Studies on the Digital Transformation of Incumbent Organizations: Causes, Effects and Solutions for Banking

Dissertation

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Preamble

Digital transformation requires organizations to develop a clear objective, a deliberate strategy. The latter's actual implementation is often observed as an emerging collection of individual transformation initiatives that ideally follow the overall strategy and pay attention to the aspired goals (Chanias et al. 2019). A cumulative dissertation project can be characterized similarly because the overarching goal is set at the beginning and the actual implementation is done through continuous work to finally achieve the goal, which is not to produce a minimum viable product but to present a coherent program, as required by incumbent organizations in digital transformation.

Both should have the extensive intellectual work involved and the many hours spent in common. The work in the context of this dissertation allowed me to attend on-site Ph.D. courses, international conferences and meetings both on-site and digitally, and the continuous study of the recent research literature on digital transformation and practice developments. In contrast to views of digital transformation as “always in the making” or being “open-ended,” a dissertation finally has to find its conclusion but also opens up new possibilities.

I want to thank my first supervisor Univ.-Prof. Dr.-Ing. Norbert Gronau for the opportunity to continue and extend my research projects as well as the possibility to discuss my results at the Chair of Business Informatics, especially Processes and Systems. I would also like to thank Univ.-Prof. Dr. Rainer Alt for being the second supervisor and the research work on digital banking, which allowed me to build connections.

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The work was encouraged by the love and patience of Emilia and our daughter. The dissertation is dedicated to them and my parents.

Abstract

Traditional organizations are strongly encouraged by emerging digital customer behavior and digital competition to transform their businesses for the digital age. Incumbents are particularly exposed to the field of tension between maintaining and renewing their business model. Banking is one of the industries most affected by digitalization, with a large stream of digital innovations around Fintech. Most research contributions focus on digital innovations, such as Fintech, but there are only a few studies on the related challenges and perspectives of incumbent organizations, such as traditional banks. Against this background, this dissertation examines the specific causes, effects and solutions for traditional banks in digital transformation − an underrepresented research area so far.

The first part of the thesis examines how digitalization has changed the latent customer expectations in banking and studies the underlying technological drivers of evolving business-to-consumer (B2C) business models. Online consumer reviews are systematized to identify latent concepts of customer behavior and future decision paths as strategic digitalization effects. Furthermore, the service attribute preferences, the impact of influencing factors and the underlying customer segments are uncovered for checking accounts in a discrete choice experiment. The dissertation contributes here to customer behavior research in digital transformation, moving beyond the technology acceptance model. In addition, the dissertation systematizes value proposition types in the evolving discourse around smart products and services as key drivers of business models and market power in the platform economy.

The second part of the thesis focuses on the effects of digital transformation on the strategy development of financial service providers, which are classified along with their firm performance levels. Standard types are derived based on fuzzy-set qualitative comparative analysis (fsQCA), with facade digitalization as one typical standard type for low performing incumbent banks that lack a holistic strategic response to digital transformation. Based on this, the contradictory impact of digitalization measures on key business figures is examined for German savings banks, confirming that the shift towards digital customer interaction was not accompanied by new revenue models diminishing bank profitability. The dissertation further contributes to the discourse on digitalized work designs and the consequences for job perceptions in banking customer advisory. The threefold impact of the IT support perceived in customer interaction on the job satisfaction of customer advisors is disentangled.

In the third part of the dissertation, solutions are developed design-oriented for core action areas of digitalized business models, i.e., data and platforms. A consolidated taxonomy for data-driven business models and a future reference model for digital banking have been developed. The impact of the platform economy is demonstrated here using the example of the market entry by Bigtech. The role-based e3-value modeling is extended by meta-roles and role segments and linked to value co-creation mapping in VDML. In this way, the dissertation extends enterprise modeling research on platform ecosystems and value co-creation using the example of banking.

Keywords: digital transformation; digitalization; digital strategy; consumer behavior; platform ecosystems; value co-creation; Fintech; incumbent; bank

Zusammenfassung

Traditionelle Unternehmen sehen sich angesichts des zunehmend digitalen Kundenverhaltens und gesteigerten digitalen Wettbewerbs damit konfrontiert, ihr Geschäftsmodell adäquat für das digitale Zeitalter weiterzuentwickeln. Insbesondere etablierte Unternehmen befinden sich dabei in einem Spannungsfeld aus Bewahrung und Erneuerung. Der Großteil jüngerer Forschungsbeiträge zum Bankwesen fokussiert sich auf digitale Fintech-Innovationen, nur wenige Studien befassen sich mit Herausforderungen und Perspektiven traditioneller Banken. Vor diesem Hintergrund untersucht die Dissertation die Ursachen und Wirkungen der Digitalen Transformation im Bankwesen und zeigt Lösungswege für traditionelle Banken auf.

Der erste Teil der Dissertation untersucht die Ursachen der Digitalen Transformation im Banking. Neuartige Einflussfaktoren und Entscheidungspfade im Kundenverhalten werden als strategische Digitalisierungstreiber für Banken identifiziert. Darauf aufbauend werden in einem Discrete-Choice-Experiment die Präferenzen deutscher Bankkunden hinsichtlich digitaler und nicht-digitaler Dienstleistungsattribute am Beispiel von Girokonten untersucht. Die Arbeit leistet einen über das Technologieakzeptanzmodell hinausgehenden Beitrag zur Erforschung des Kundenverhaltens in der Digitalen Transformation. Ein weiterer Forschungsbeitrag systematisiert anschließend wesentliche Charakteristika smarter Produkte und Dienstleistungen als Treiber von Geschäftsmodellen und Marktmacht in der Plattformökonomie.

Der zweite Teil der Arbeit befasst sich zunächst mit den Auswirkungen der Digitalen Transformation auf die Strategieentwicklung von traditionellen Finanzdienstleistern, die mittels Fallstudien entlang ihres Finanzerfolgs typologisiert werden. Die Fassadendigitalisierung wird als Standardtyp traditioneller Anbieter systematisiert, die zwar zunehmend auf digitale Kundeninteraktion setzen, aber die Geschäftsmodelldimension der Digitalen Transformation vernachlässigen. Darauf aufbauend werden in Panelregressionsanalysen die Auswirkungen der Digitalisierung auf deutsche Sparkassen auf betriebswirtschaftliche Kennzahlen untersucht. Eine weitere quantitative Studie untersucht die Wirkungen neuartiger IT-Beratungswerkzeuge auf die Arbeitszufriedenheit von Bankkundenberatern. Die Dissertation leistet hiermit einen Beitrag zur Transformationsforschung in den Bereichen Bankstrategie und Arbeitsprozesse.

Im dritten Teil der Dissertation werden gestaltungsorientiert Lösungsartefakte für die zentralen Handlungsfelder digitalisierter Geschäftsmodelle – Daten und Plattformen – entwickelt. Dies schließt einerseits eine konsolidierte Taxonomie für datengetriebene Geschäftsmodelle und andererseits ein Referenzmodell für zukünftige plattformbasierte Bankenökosysteme ein. Die rollenbasierte Referenzmodellierungsmethodik e3-value wird um Meta-Rollen und Rollensegmente erweitert, um die die strategischen Auswirkungen plattformbasierter Geschäftsmodelle aufzuzeigen. Hiermit erweitert die Dissertation die Unternehmensmodellierungsforschung im Bereich digitaler Plattform-Ökosysteme am Beispiel des Bankwesens.

Stichworte: Digitale Transformation; Digitalisierung; Digitalstrategie; Kundenverhalten; Plattform-Ökosysteme; Wertschöpfungskooperation; Fintech; traditionelle Unternehmen; Bank

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List of Abbreviations

AI	artificial intelligence
AISP	account information service provider
API	application programming interface
AVE	average variance extracted
B2C	business-to-consumer
BaaS	banking-as-a-service
BBVA	Banco Bilbao Vizcaya Argentaria
BIAN	Banking Industry Architecture Network
CBMP	Continuous Business Model Planning
CDD	capability-driven development
CDM	consumer decision-making
CI	customer interaction
CIM	customer interaction model
CRM	customer relationship management
COOP	cooperation
CORE	core banking system
DARQ	distributed ledger technology, artificial intelligence, extended reality and quantum computing
DATA	data analytics
DDBM	data-driven business model
DDS	data-driven service
DT	digital transformation
eIDAS	electronic identification, authentication and trust services
EM	enterprise modeling
FS	financial service
FSP	financial service provider
fsQCA	fuzzy-set qualitative comparative analysis
GAFA	Google, Apple, Facebook and Amazon
HTMT	heterotrait-monotrait
IoT	Internet of Things

IS	Information Systems
IT	information technology
KYC	know your customer
MSP	multi-sided platform
OBIE	Open Banking Implementation Entity
OMG	Object Management Group
PERF	firm performance
PISP	payment (initiation) service provider
PLS	partial least squares
PLS-SEM	partial least squares structural equation modeling
PSD2	Payment Service Directive 2015/2366
PSS	product-service system
QCA	qualitative comparative analysis
QES	qualified electronic signature
RoA	return on assets
SDL	service-dominant logic
SLR	systematic literature review
SMACIT	social, mobile, analytics and cloud information technology
SME	small and medium-sized enterprise
STRA	digital strategy
VCM	value creation model
VDML	value delivery modeling language
VHB	Verband der Hochschullehrer für Betriebswirtschaft
VMP	value management platform
VPM	value proposition model
WDQ	Work Design Questionnaire

List of Papers

Published:

II.1 Pousttchi, K.; Dehnert, M. (2018)

Exploring the digitalization impact on consumer decision-making in retail banking

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II.3 Dehnert, M.; Bürkle, J. (2020)

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What makes a data-driven business model? A consolidated taxonomy

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Working:

III.2 Dehnert, M.

Analyzing the contradictory impact of digitalization on the performance of German savings banks − Evidence from annual reports utilizing a text mining approach

III.3 Dehnert, M.

How does digital technology for sales and service co-creation impact job perceptions of salespeople in banks? − A study on job characteristics, IT support in customer interaction, and job satisfaction of customer advisors

IV.2 Dehnert, M.; Kruse, L.; Pousttchi, K.

The impact of digital transformation on value creation in banking − Reference models for the platform economy

Ⅰ Introduction

I.1 Motivation

Digital technologies have increasingly become part of everyday life, encompassing individuals, the economy and society. Pousttchi (2020) has systematized the technological causes of digital transformation (DT): the use of sensors and actuators, including audio and video recording; the use of mobile communication technologies for networking and automated communication; the comprehensive collection, archiving and processing of big data; data analysis using statistical techniques and computational machine learning; and advanced forms of human-computer interaction. Platform ecosystems are becoming an established digital infrastructure of traditional and new organizations to deliver digital services to customers. The corresponding effects are no longer solely in the focus of business informatics or computer science researchers but are increasingly discussed on an interdisciplinary basis, from management and sociology to law.

Consequently, we must initially delineate our understanding of DT, taking information systems (IS) and management scholars into account (Markus and Rowe 2021). There are plenty of definitions of DT in the literature.

Pousttchi (2020) distinguishes three dimensions of DT. Correspondingly, DT affects how organizations create value for their customers, what kind of novel and new products and services they provide in their business and revenue model, and how they interact with customers (Pousttchi et al. 2019; Pousttchi 2020). New value creation structures are fueled by various socio-technical factors (Sarker et al. 2019), making DT complex. Vial (2019) states that the disruptive changes induced by digital technologies in DT require a *strategic* response of organizations that changes their value creation paths. In turn, management researchers argue that DT does not necessarily have to be disruptive and that the best results come from adaptation rather than a reinvention of the organization (Furr and Shipilov 2019).

Wessel et al. (2021) advocate a shift towards an activity-centric view in the DT debate, arguing that "DT is much more about transforming work around the core *value-defining* activities of an organization" (p. 118). While Wessel et al. argue that the change in the value creation is accompanied by a change in an organization's identity in DT, many traditional organizations, such as banks, stick with their traditional business logic which follows the spirit "to remain a traditional bank but become more digital" (Dehnert 2020a, p. 6).

Against this field of tension, incumbents are the most affected by the DT. Incumbents have enjoyed the status of being the market leaders in their industries for years (often decades), and DT bears the risk of losing that status to new competitors who provide innovative product and service offerings to increasingly digital-affine customers. Many contributions in the management discipline have explored the implications of technological upheavals for incumbents (e.g., Eggers and Park 2018; Uzunca 2018; Eklund and Kapoor 2019). Most strategic change definitions point to aspects of mission or purpose, changes in value creation or organizational structures, and adaptation to changing environmental conditions, which goes beyond incremental changes (for an overview, see Kunisch et al. 2017). Many contributions refer to strategic change in general but lack the *technological core* of the developments (Markus 2004).

The various socio-technical system interdependencies between value creation activities and the enabling digital technology must be considered in DT. Companies are faced with the impact of digital technology twofold: for one thing, they source and deploy digital technologies for various reasons and motives (Kotlarsky et al. 2020). For another, the new dimension: they react to the diffusion of digital technologies across competitors, customers and partners in boundary-spanning digital infrastructures, such as platform ecosystems (Constantinides et al. 2018).

The distinctive nature of DT is induced by digital technologies' unique properties and effects. Technological causes increasingly trigger DT in various industries, such as those described under the acronyms SMACIT (Social, Mobile, Analytics and Cloud) or, more recently, DARQ (Distributed ledger technology, Artificial intelligence, extended Reality, and Quantum computing). Digital technology is a resource composed of bitstrings as carriers (bearers) in material and nonmaterial digital objects (Faulkner and Runde 2019). These bearers can be inscribed in, contained in or carried by material objects, such as smartphones (Faulkner and Runde 2019). The same applies to cloud infrastructures and extends to assemblages of material and nonmaterial bearers, such as digital platform ecosystems (Faulkner and Runde 2019). Digital technologies are generative and malleable (Nambisan et al. 2017; Yoo et al. 2010). Their properties, such as embeddedness, connectedness or reprogrammability, increase the variety of possible actions of an enterprise using digital technology for business purposes (Yoo et al. 2010). Emerging technology affords new action possibilities, such as tools, methods, interfaces, platforms, protocols or algorithms, and offers innovative recombinations of value creation activities (cf. Pentland et al. 2021). Material and nonmaterial agencies increasingly go together (Recker et al. 2021), and increasingly computed human experiences in digital platform ecosystems link or could even fuse traditional and digital businesses (Baskerville et al. 2020). The critical question for traditional companies currently is how to exploit the opportunities offered by digital technologies in all dimensions of DT.

The *banking industry* provides an exciting setting to study DT. Banking, by its very nature, was one of the first industries shaped by information technology (IT) and experienced a further wave of digitization in the 1990s with internet banking services. Since IT gained influence for market competition back then, people have expected new institutional arrangements to appear. Thus, the discussion of whether banks will be viable in the future or disappear is not new (Crane and Bodie 1996). Additionally, the underlying functions of banks have changed very little since then: basic banking functions are still legally proved transaction execution, pooling resources, transfer of economic resources, managing risk, price information and handling incentive problems (e.g., Crane and Bodie 1996; Hellenkamp 2015, pp. 7 ff.; Tolkmitt 2007, p. 97). Moreover, drivers, such as consolidation, specialization and customer orientation, impact the DT of the banking industry across all its dimensions (Alt and Puschmann 2016, p. 31).

At the same time, the Fintech evolution has led to new products, new product bundles and more competition (Gomber et al. 2018). Fintech has given rise to entirely new areas of business models, for example, in the data-based brokerage of loans or investments. One example is Klarna's BNPL (Buy Now Pay Later), lending offering to customers and retailers. In addition, the banking industry could increasingly become dominated by platform ecosystems in which banking plays its functional role following different primary customer use cases. It is also unclear whether it makes sense to resist these (inevitable) developments from the perspective of a traditional bank and what the impact of these developments could be. From the perspective of non-bank Fintech, there is an interest in integrating banking as a function (utility) in existing platform-based business models and, thus, making the traditional bank superfluous and dispensable, no longer visible at the customer interface in embedded finance. Digital platforms, such as Google, Apple, Facebook and Amazon (GAFA), have already started offering financial services to banking customers (Alt and Zimmermann 2019). Blending these influences on banks shows why DT is a complex endeavor, especially in banking (Krasonikolakis et al. 2020), and poses a competitive threat for incumbent banks' future.

One group particularly affected is savings banks, which suffer from the low interest rate policy, especially in Europe, which puts pressure on their margins. In particular, German Savings Banks ("*Sparkassen*") is an independent community bank group sponsored by municipalities with about 400 institutions in Germany that operate independently legally following the regional principle. Their primary tasks are strengthening competition in their regional business area based on market and competitive requirements and ensuring an appropriate and sufficient supply of money and credit services. They enjoy a *public mandate* to support the municipalities in fulfilling their economic, social and cultural tasks. They fulfill their tasks through their strong local presence − the high-cost branch networks. Their business model has grown historically based on strong analogous expertise about their local region but has not yet managed the transition to the digital age.

As the limitations of traditional business models become apparent, it is worth investigating the emerging digital customer behavior and business model types, the impact of banks' DT activities on the business and future value creation paths for banks in the data-driven platform economy.

I.2 Background

I briefly summarize the related research contributions on DT which are significant for the dissertation. A general research stream has made reference to the phenomenon of DT across the IS and management disciplines (e.g., Hanelt et al. 2021; van Veldhoven and Vanthienen 2021; Verhoef et al. 2021; Vial 2019; Wessel et al. 2021). Furthermore, the research stream evolving regarding digital strategies is relevant to this dissertation (e.g., Adner et al. 2019; Bharadwaj et al. 2013; Chanias et al. 2019; Matt et al. 2015; Park and Mithas 2020; Teubner and Stockhinger 2020; Yeow et al. 2018).

Other research contributions have dealt with conceptual views on DT, including changes in processes, systems and their conceptual modeling (e.g., Alt 2019; Baskerville et al. 2020; Recker et al. 2021). As digital infrastructures, platform ecosystems impact companies and their business logic strongly in DT. The relevant research contributions refer to the organizational impact of digital platform ecosystems (e.g., Hein et al. 2020; Schreieck et al. 2021; Tan et al. 2020). A lot of research on digital innovations relates to startups, whereas for this work, research in the area of DT of incumbents is more relevant (e.g., Chanias et al. 2019; Oberländer et al. 2021; Sebastian et al. 2017). Notably, only a few contributions have dealt with the subtype of small and medium-sized enterprises (SME) in DT (Canhoto et al. 2021; Jeansson et al. 2017; Li et al. 2018). Table I.2-1 summarizes the key research literature on DT.

Table I.2-1: Literature overview on key research studies on digital transformation

General research on DT	
Vial 2019	Literature review on DT from a strategic change perspective leading to building blocks
Pousttchi 2020	Definition of DT with three dimensions: value creation, value proposition, and customer interaction
Hanelt et al. 2021	Literature review of the strategy and change literature on DT to clarify boundary conditions
Verhoef et al. 2021	Research agenda on DT with structures and metrics to improve and measure firm performance
van Veldhoven and Vanthienen 2021	Interaction-driven perspective on DT at the intersection of business, society, and technology
Wessel et al. 2021	Case study differentiating DT and IT-driven organizational transformation from the perspective of value creation activities: core and supporting activities as the differentiator
Digital strategy	
Bharadwaj et al. 2013	Digital business strategy as a new paradigm interconnecting products/services and processes
Matt et al. 2015	Systematization of elements of DT strategies: technology use, value creation, structures, and finance
Yeow et al. 2018	A dynamic capability view on digital strategizing for the alignment of strategy and resources
Adner et al. 2019	Novel aspects of digital strategies: representation, connectivity, and aggregation
Chanias et al. 2019	Digital strategy-making in pre-digital organizations: emergent and open-ended
Teubner and Stockhinger 2020	IS strategizing in the digital age: reasoning for the continued distinct role of the IT/IS department
Park and Mithas 2020	Complex configurations of digital business strategy and their firm performance relationship
Conceptual perspective on DT	
Majchrzak et al. 2016	MIS Quarterly Special Issue on “Designing for DT”: emergent designing for societal challenges
Alt 2019	Electronic Markets on “Methodologies in DT”: software, process, and value development
Baiyere et al. 2020	New logics of business process management in DT: flexibility in process, infrastructure, and agency
Fischer, Imgrund et al. 2020	Strategy archetypes for DT and business process management: communication/learning, unification/optimization, and automation/certification as meta-objectives
Baskerville et al. 2020	Ontological reversal in DT: research implications of digital technologies creating/shaping reality
Recker et al. 2021	Implications for conceptual modeling in DT that represents and mediates physical and digital reality
Digital transformation at incumbents	
Hess et al. 2016	Options for digital strategies along technology use, value creation, structures, and finance
Sebastian et al. 2017	Customer engagement and digitized solutions as incumbent DT strategies upon a digital backbone
Svahn et al. 2017	Competing concerns for incumbents: capability, focus, collaboration, and governance
Oberländer et al. 2021	Resource-centric perspective on DT for incumbents: customers, products, and assets and capabilities
Siachou et al. 2021	Absorptive capacity and strategic interdependence as boundary conditions for DT of incumbents
Digital transformation at SME	
Jeansson et al. 2017	Digital channel expansion of SME in DT: primary and secondary activities across transition stages
Li et al. 2018	DT induced by SME entrepreneurs: the important role of cognition renewal, social capital development, team building, and capability building
Canhoto et al. 2021	SME DT alignment across passive acceptance, connection, immersion, fusion, and transformation
Platform ecosystems in DT	
Hein et al. 2019	Catchword on digital platform ecosystems: the role of platforms, complementors, and value creation
Tan et al. 2020	Case study on DT in pop industry: impact of boundary spanning practices on business ecosystems
Riasanow et al. 2020	Study on cross-industry platform ecosystems: intertwined clusters with infrastructure at the core
Cozzolino et al. 2021	Incumbents and entrants on platform ecosystems: from selective cooperation to selective coopetition
Schreieck et al. 2021	Value co-creation for platform ecosystems: technology- and relationship-related capabilities

Furthermore, research contributions deal with the specific context of DT in banking (e.g., Graupner and Maedche 2015; Kaniadakis and Constantinides 2014; Lauterbach et al. 2020; Liu et al. 2011; Schmidt and Buxmann 2011; Scott et al. 2017; Tallon 2010). However, few studies examine the DT strategies of incumbent banks (Chanias et al. 2019; Sia et al. 2016; Tallon 2010). Some contributions in the field of digital innovation research systematize the field of Fintech innovations in general (e.g., Gomber et al.

2018). More specific scholarly work examines concrete technologies, such as robo advisory (e.g., Jung, Dorner, Glaser and Morana 2018), identity and payment platforms (Bazarhanova et al. 2020; Eaton et al. 2018; Kazan et al. 2018) and crowdfunding/-lending platforms (e.g., Burtch et al. 2018; Drummer et al. 2017; Xu and Chau 2018). In addition, decentralized infrastructures based on blockchain technology are discussed (e.g., Chong et al. 2019; Du et al. 2019; Ziolkowski et al. 2020). Further research has addressed banking customer behavior in digitalization (e.g., Carbo-Valverde et al. 2020; Tam and Oliveira 2019; Zhou et al. 2020). Table I.2-2 summarizes the key research literature on DT in banking.

Table I.2-2: Literature overview on key research studies on digital transformation in banking

Digital transformation in banking	
Tallon 2010	Corporate strategies, IT impact, and performance outcomes for banks: the struggles between customer intimacy and operational excellence strategy for scalability
Schmidt and Buxmann 2011	Enterprise architecture management in banks: architectural governance as the main contributor
Kaniadakis and Constantinides 2014	Transforming legacy assets in digital infrastructure innovation: data accuracy validation as core
Graupner and Maedche 2015	Process digitalization: sensory and control requirements as main inhibitors for process use
Alt and Puschmann 2016	Primer on digitalization in the financial services industry: banking model and network, bank IS
Scott et al. 2017	Long-term impact of digital innovation on bank performance (SWIFT)
Lauterbach et al. 2020	Changing work processes in a European bank: representational complexity constraints from system and semantic dependencies on effective use
Digital strategies of incumbents in banking	
Sia et al. 2016	Digital business strategy (case study at DBS): digital leadership, agile core, data, and continuity
Chanias et al. 2019	Digital strategy-making in a financial service provider: emergent and open-ended
Niemand et al. 2021	Digitalization in banking: the positive impact of entrepreneurial orientation and the interaction with strategic vision on firm performance, innovation and risk taking as potential benefits
Sund et al. 2021	Business model exploration in European banks' innovation labs: conflicting expectations from top management and core business areas as an obstacle for balancing the strength of innovation
Fintech innovations in banking	
Gomber et al. 2018	Overview article on technology, process, and service disruptions in the Fintech evolution
Jung, Dorner, Glaser and Morana 2018	Catchword on robo advisory: characteristics of customer assessment and portfolio management
Eaton et al. 2018	Governance in e-identity platforms: negotiating conflicting social and political values
Kazan et al. 2018	Strategic groups of mobile payment infrastructures: integration and access mode as constituents
Bretschneider and Leimeister 2017	Study on online crowdfunding services: self-interest, pro-sociality and herding as motivators
Drummer et al. 2017	Digitalization of the financialization of credits: slow progress in data-driven risk management
Burtch et al. 2018	Online crowdfunding study: the role of network based incentives
Beck et al. 2018	A framework and research agenda on blockchain governance: decision rights, accountability, and incentives as the core dimensions
Du et al. 2019	A blockchain implementation study: direct settlement, automated transactions, and loan securitization as main affordances
Chong et al. 2019	Case studies on blockchain applications: platformer, disintermediator, mediator, transformer, and co-innovator as business model types
Ziolkowski et al. 2020	Decision problems in blockchain governance: boundary, legitimacy, discretion, and time management as reoccurring organizational problems
Consumer behavior in banking	
Iqbal et al. 2003	Foundational discrete choice study on customer preferences in electronic banking services
Königsheim et al. 2017	Customer demand for digital financial services: knowledge and risk tolerance as usage drivers
Tam and Oliveira 2019	Culture impact on mobile banking use: individualism and uncertainty avoidance as moderators
Carbo-Valverde et al. 2020	A machine learning analysis of customer behavior in mobile banking towards personalization
Zhou et al. 2020	Omnichannel customer behavior and branch networks: synergies between on- and offline
Fang et al. 2021	Impact of digital-only banks on the customer demand of traditional bank services in Korea

I.3 Research questions

The central research question of this dissertation entails three parts: How does DT change customer behavior and business models in B2C banking; how does DT impact the business of incumbent banks; and how can these banks respond to the challenges of DT?

From the leading research question on the causes of DT in banking, the impact on the business of incumbent banks and the necessary responses, I deduce further research questions in each area. In doing so, I take up the building blocks from Vial's integrative literature review on DT (2019). Table I.3-1 summarizes the research goals and research questions of the thesis.

Thus, the *first main part* deals with the causes of DT, i.e., the disruptive changes emanating from customer behavior and the possibilities of digital technologies that affect B2C industries such as banking. The *second main part* focuses on the financial, organizational and competitive effects of DT on incumbent banks. This research includes the strategic responses in the context of DT strategies, structural changes in the organizations and organizational barriers. In this regard, paper III.3 builds directly on a conference publication that is not part of the dissertation. The *third main part* identifies possible solutions by changing value pathways. The two main drivers here are the data and platform economies. Accordingly, the two contributions address the building blocks of data-driven and platform-based business models. Finally, the conclusion discusses future research options regarding DT management and its impact on organizations. Table I.3-1 summarizes the research questions to be addressed for banking in response to Vial's identified building blocks of DT.

Table I.3-1: Research questions as a response to Vial's building blocks of digital transformation

DT building block	Paper	Research goals and questions
Causes: Which changes in customer behavior and digital technologies affect banks' B2C business in DT?		
Disruptions	Paper II.1	Exploring the impact of digitalization on consumer decision-making in retail banking along with the influencing factors and the decision process. - How does digitalization impact the latent personal preferences and the decision-making process of banking customers?
	Paper II.2	Uncovering the value of service attributes of checking accounts in banking, the impact of influencing factors along with latent customer segments in digitalization. - What digital and non-digital service attributes do banking customers prefer regarding checking accounts and what is the quantitative impact of the influencing factors on CDM?
Use of digital technologies	Paper II.3	Examining smart product-service systems with their properties and business model patterns for B2C industries. - What kind of business models are connected to properties of smart product-service systems along with their impact on B2C industries such as banking?
Effects: What are the financial, organizational and competitive effects of DT on incumbent banks?		
Strategic responses	Paper III.1	Exploring the DT strategies of financial service providers and how these strategies are systemically connected to firm performance. - How do international banks and insurance companies face DT on different levels of firm performance?
	Paper III.2	Examining the contradictory impact of digitalization on the firm performance of savings banks. - What is the digitalization impact on the productivity and profitability figures of German savings banks?
Structural changes	Paper III.3	Examining the threefold impact of IT support in customer interaction in the context of banking customer advisory. - What is the impact of digital technology for customer co-creation in sales/services on customer advisors' job perceptions?
Organizational barriers	Paper not included (Dehnert 2020a)	Exploring the relationship between the value creation and customer interaction dimension in the DT of banks. - What affordances and constraints occur in banking customer advisory?
Solutions: How should banks react to the challenges of DT, and what are the key ingredients of future digitalized business models in banking?		
Changes in the value creation paths	Paper IV.1	Developing a taxonomy of data-driven business models to determine their core elements. - What constitutes a data-driven business model across the dimensions of DT?
	Paper IV.2	Developing reference models for the platform economy in banking, exploring its impact on value creation in banking ecosystems and the opportunities and threats of platform competition. - What are the current and future roles and activities for platform-based banking; how can value co-creation be realized between actors in a platform ecosystem?
Impact	Conclusion	Developing future research options on realizing DT. - What are related research avenues on DT management in banking?

The theoretical scientific goal of business informatics is to gain knowledge to explain human-task-technology systems; the pragmatic scientific goal is to utilize the knowledge gained for the design of these systems (Heinrich et al. 2011, p. 140). Accordingly, business informatics is predestined, on the one hand, to increase the understanding of the effects of DT in banking on individuals, the economy and society and, on the other hand, to design solution artifacts (Heinrich et al. 2011, p. 47). The dissertation uses a broad methodological spectrum to answer the research questions in business informatics (Heinrich et al. 2011, pp. 97 ff.).

I use qualitative methods in papers II.1, II.3, III.1 and IV.1. Paper II.1 is based on the analysis of qualitative consumer data using analytical techniques of grounded theory, which enable an understanding of the essential decision-making processes and influencing factors of digital customer journeys in banking. Paper II.3 and IV.1 conduct Nickerson's taxonomy development based on empirical case studies, resulting in classifications for describing and developing digital business models. Paper III.1 uses fsQCA as a set-theoretical method for the case study analysis of DT strategies. I provide a categorization tool for describing and explaining the digital maturity of incumbent financial service providers.

I rely on quantitative methods in papers II.2, III.2 and III.3. Paper II.2 applies a discrete choice experimental design to investigate customer behavior and then performs comprehensive structural path and segmentation analyses on the choice data collected. The paper pursues explanatory and predictive goals of systematizing customer behavior for checking accounts within the influencing factors and latent customer segments. Paper III.2 draws on panel regression methods to analyze longitudinal annual report data on digitalization obtained through text mining. Digitalization effects on business figures of savings banks are identified by using inferential statistics. Paper III.3 applies structural equation modeling and analysis to management and employee survey data collected in savings banks. The results improve the understanding of the effects of digital technology for customer co-creation in banking customer advisory.

I work design-oriented in papers II.3, IV.1 and IV.2. Paper II.3 and IV.1 use the morphological method to develop building blocks of business models in DT. Paper IV.2 uses e3-value and VDML modeling on the impact of the platform economy for banking. The enterprise modeling artifacts demonstrate the value creation roles, activities and actors in banking platform ecosystems.

I.4 Structure of the dissertation

The dissertation consists of five parts. Following the introduction, the main body includes three parts of causes, effects and solutions of DT among incumbent organizations using the example of banking (see Table I.3-1 before).

The first main body part on the causes consists of three papers. *Paper II.1* uses a qualitative research approach to analyze the impact of digitalization on consumer decision-making in banking. Based on comprehensive qualitative data from online consumer reviews, we analyze what factors influence consumers' journey towards a banking product in the digital age. The paper's outcome consists of four detailed partial models of the respective decision stages and an integrated model of CDM in current retail banking. *Paper II.2* takes up the research findings of the first paper and conducts a discrete choice experiment to investigate the preferences of German bank customers. The direct influence of service attributes and the moderating influence of latent influencing factors on consumer choice are examined. Subsequently, segment analyses are conducted to determine unobserved heterogeneity, and the influence of latent personal characteristics of customers on segment membership is determined. In *Paper II.3*, we develop and evaluate a taxonomy with 56 empirical case studies and subsequently identify empirically consistent smart product-service system configurations leading to different value proposition types.

The second main body part on the effects consists of three papers. *Paper III.1* analyzes the DT strategies of incumbent banks using case study analysis in fsQCA. The DT strategies are categorized across firm performance levels. Sustainable competitive advantages, such as the strategies' implications, are discussed. In this course, theoretical propositions about the configurations of banks and their future viability are developed. *Paper III.2* uses panel regression analyses to examine the effects of digitalization on important business figures of German savings banks from 2009 to 2017. *Paper III.3* examines this banking group concerning the effects of digitalization on the work perceptions of customer advisors. Utilizing PLS-SEM, I analyze executive and customer advisor survey data on a new IT core banking system release for customer advisory, which focuses on customer co-creation, including new processes, user interfaces and improved data analytics.

The third main body part on the solutions includes two papers. *Paper IV.1* develops a consolidated taxonomy for data-driven business models following the Nickerson approach and validates it with innovative case studies in DT. *Paper IV.2* shows the effects of the platform economy on the value creation of banking along with three phases and develops a role-based reference model in e3-value. The potential business model implications are demonstrated using the example of payment/identity platform ecosystems in VDML and discussed and evaluated with practitioners. On the theoretical level, strategic archetypes for platform-based banking at the B2C customer interface are derived.[1]

The concluding section summarizes the main findings of the dissertation and highlights the key contributions, practical implications as well as the limitations of the research. Future research options are discussed in the outlook.

[1] The "we" form is consistently used across all papers included. The publications were unified concerning their citation style.

II Causes

II.1 Exploring the digitalization impact on consumer decision-making in retail banking

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Abstract: Retail banking has undergone a massive transformation in the last few years. A major aspect is changing consumer behavior. The aim of the paper is to better understand retail banking consumers regarding the impact of digitalization. Consequently, we acquired online consumer review data from Germany, the UK and US. We analyzed the data using coding techniques of grounded theory, supported by interdisciplinary literature to identify and categorize the relevant influence factors. The outcome of the paper is an integrated model of consumer decision-making in today's retail banking along with four detailed partial models of the respective decision stages.

1 Introduction

Retail banking has undergone a massive transformation in the last few years. The former stable and protected retail banking market has taken on a new dynamic of competition and demand for customer orientation (Alt and Puschmann 2012; Bons et al. 2012; Homann et al. 2004; Nüesch et al. 2015). Incumbent banks are challenged by Fintech companies that started to offer standardized retail banking products and services, such as accounts, loans, and mortgages, to consumers. Traditional and strong banking relationships based on trust and loyalty are increasingly questioned by many consumers in the light of new innovative offerings and decreasing switching costs (Kinting and Wißmann 2016).

Digitalization is transforming the nature of interactions between companies and their customers, such as the cross-channel and holistic design of the customer relationship and the inclusion of automated communication and modern forms of data analysis (Pousttchi 2020). A very closely connected, but still under-researched subject is consumer decision-making (CDM) in retail banking, especially regarding the impact of digitalization on the decision process.

Relevant literature for this area can be found in three major fields of research. The first topic is *consumer behavior* (e.g., Blackwell et al. 2002; Kroeber-Riel et al. 2009; Schiffman and Kanuk 1997; Solomon et al. 2013 and, especially for financial behavior, van Raaij 2016). Consumer behavior research increasingly examines the impact of digital technologies (e.g., Belk 2013; Gunter 2016; Hoffman et al. 2013; Labrecque et al. 2013; Lehdonvirta 2012; Sheth and Solomon 2014). Decision-making is a special field of consumer behavior research (e.g., Bettman et al. 1998; Häubl and Trifts 2000; Punj and Stewart 1983). In the field of decision-making, there are few specific research studies regarding retail banking (Babakus et al. 2004; Devlin 2002; McKechnie 1992; Milner and Rosenstreich 2013). The second research topic is the *influence of new media on consumer interactions*. This is examined both in general (e.g., Kim and Han 2009; Nysveen 2005; Pousttchi and Goeke 2011) and specifically for retail banking (e.g., Gu et al. 2009; Ha et al. 2012; Hoehle et al. 2012; Kim et al. 2009; Laukkanen 2016; Laukkanen and Lauronen 2005; Pousttchi et al. 2015). Moreover, research also examines new media channel choice and channel paradigms (e.g., Leeflang et al. 2014; Verhoef et al. 2015) and the impact of self-service technologies, both in general (e.g., Cetto et al. 2015; Curran and Meuter 2007; Meuter et al. 2000) and specifically for retail banking (e.g., Berger 2009; Graupner et al. 2015). There is further research on new media referring to decision-making and buying processes (e.g., Dellaert and Häubl 2012; Frambach et al. 2007; Xiao and Benbasat 2007). The third topic deals with *DT in retail banking*. Research in this field focuses, for instance, on banking information systems, processes, business networks and business models (Alt et al. 2009; Alt and Puschmann 2016; Auge-Dickhut et al. 2014; Reitbauer 2009).

Practitioner literature in the field of retail banking focuses on customer orientation regarding digitalization (e.g., Drobe 2014; Everling and Lempka 2013; Görg 2015; Melles 2014; Melles 2014) and the digital customer of the future (e.g., Accenture 2015a; King 2013; Roland Berger 2015; Sinn et al. 2012; Skinner 2014). Moreover, the implications of digitalization on the banks' market position and business models (e.g., Accenture 2014, 2015b; Alcocer et al. 2014; Alt and Ehrenberg 2016; Everling and Lempka 2016) as well as on bank processes (Accenture 2014) are discussed.

While academic research treats all three major topics more or less separately, practitioner literature tends to integrate the areas. In all cases, there are only a few specific pieces of research on CDM in retail banking, and none regarding the impact of digitalization.

Against this background, the aim of the paper is to understand CDM in retail banking with special regard to digitalization. Consequently, we acquired online consumer review data for market players from Germany, the UK and US. We analyzed the data using coding techniques of grounded theory, supported by interdisciplinary literature. This includes the identification of core consumer activities and the corresponding influencing factors along with the impact of digitalization on these. After identifying and understanding all relevant aspects of consumer decisions in retail banking, we model the different stages of CDM in detail. In a third step, we develop an integrated model that combines the stages and shows the impact of digitalization.

The outcome of the paper consists of four detailed partial models of the respective decision stages and an integrated model of CDM in current retail banking.

The rest of the paper is organized as follows: Firstly, we describe our methodology. In the second step, we use the grounded theory approach to derive the influencing factors from empirical data in open coding and the resulting constructs from literature and relate them to the core activities of CDM identified in four partial models by axial and selective coding, assessing the impact of digitalization on these. In a third step, we develop a general process model of CDM by composing the four partial models with the help of CDM literature, assessing the impact of digitalization on the overall CDM process. We conclude with implications regarding research and practice.

2 Methodology

Our research process consists of three phases: data analysis, theory building, and model construction. In the first phase, we acquired empirical data from online consumer reviews of major platforms: Apple App Store, Google Play Store (both accessed via appannie.com), kritische-anleger.de, ciao.com, wallethub.com, and consumeraffairs.com. Focusing on typical product categories, such as checking accounts, credit cards, and saving plans, we gathered more than 10,000 consumer reviews from the period between January 2012 and August 2016. The data covers the current retail banking market with financial service providers from Germany, the U.K., and U.S., such as Deutsche Bank, DKB, N26, Fidor, Sparkasse, Comdirect, George, Mint, Atom Bank, Moven, Bank of America, Chase, Citibank, and Wells Fargo. We used the Textstat text analysis tool in the theoretical sampling to collect and sample all relevant data regarding consumer decisions.

In the second phase, the identification of influencing factors and CDM activities requires an exploratory approach that combines empirical data from consumers with a high amount of relevant literature from the different fields. This is in line with the postulation of Hess et al. (2014) that the investigation of digital life aspects requires interdisciplinary approaches. We use *grounded theory* for the structured analysis of empirical user data to build our theory. Grounded theory is an “inductive, theory discovery methodology that allows the researcher to develop a theoretical account of the general features of a topic while simultaneously grounding the account in empirical observations or data” (Martin and Turner 1986, p. 141). Moreover, grounded theory allows for “the generation of theories of process, sequence, and change pertaining to organizations, positions, and social interaction” (Glaser and Strauss 2009, p. 114). Consequently, all samples undergo a three-part process of analysis: *open*, *axial,* and *selective coding.*

Open coding is “the analytic process through which concepts and categories are identified and their properties and dimensions are discovered in data” (Strauss and Corbin 1990, p. 101). In this process, we use the constant comparative method and follow (Matavire and Brown 2013; Strauss and Corbin 1990), using interdisciplinary literature from IS, marketing, sociology and psychology, as well as literature on the purchase of financial products and services from retail banking research and practice.

In *axial coding*, we put those data back together in new ways by making connections between the categories. Axial coding is defined as “the process of relating categories to their sub-categories, termed ‘axial’ because coding occurs around the axis of a category, linking categories at the level of properties and dimensions” (Strauss and Corbin 1990, p. 123). Strauss and Corbin (1990) suggest the use of a paradigm model to identify how a category relates to its sub-categories: Causal conditions are those categories that have a releasing influence on the phenomenon and, thus, on the actions/interactions of subjects, while intervening conditions affect the impact of causal conditions on the phenomenon.

Selective coding involves the integration of the categories. We determine the core categories (the central phenomena of the theoretical model), relate them to other categories, and validate these relationships with data. A core category is central, in that all other major categories relate to it and that, with almost all cases, there are indicators pointing to it. The relationships between categories are established and validated through literature and the empirical data.

In the final phase, we develop a partial model for each of the core categories and compose them into an integrated CDM process model. Consequently, the results of the coding phases are aggregated to four partial models of the core categories and the according influencing factors by connecting the categories identified from the coding stages with their intervening conditions. The resulting CDM process model is derived inductively by the interlinkage of the core categories identified from the partial models with help of CDM literature. The impact of digitalization appears in two different ways in the model: On the one hand, we consider a leverage on every single influencing factor in any of the partial models. Based on our findings from the data, we reflect this with their assignment to one of three degrees of digital change: *Low-change* refers to a largely unchanged environment, *mid-change* to a balanced impact and *high-change* to a strong impact of digitalization on the respective influencing factor. On the other hand, we consider a top-tier impact on the model, particularly on the order or even appearance of stages in the decision-making process. This is examined based on our data and on prior research and reflected in the construction of the integrated CDM process model.

Figure II.1-1 shows the complete research process.

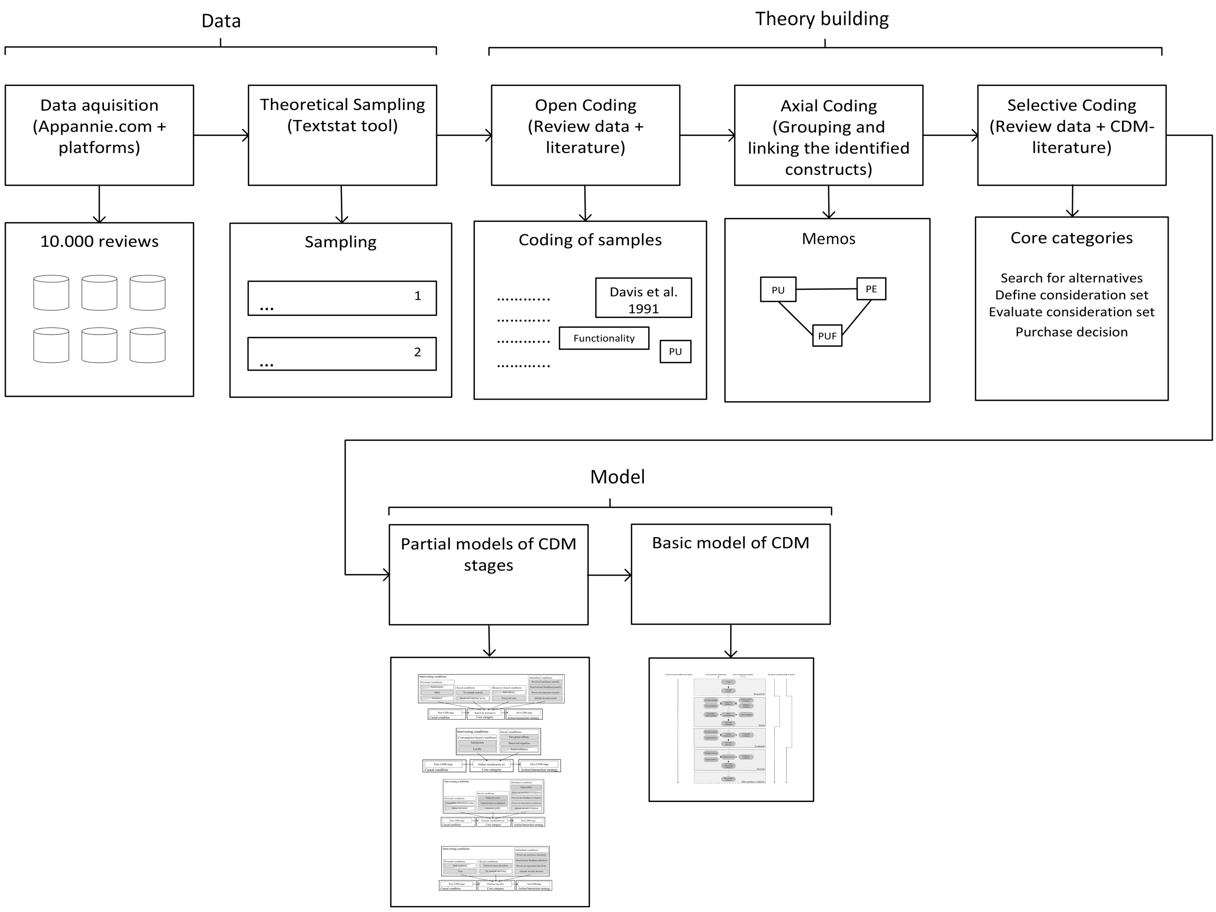

Figure II.1-1: Research process

3 Theoretical framework

In this section, the empirical insights and the theoretical analysis obtained from our research will be presented. We first show the results of the coding phases and the development of the partial models.

As described in the methodology section, TextStat serves as a text collection and retrieval tool in the initial open coding of the data analysis phase. We code our empirical data with open codes until no new aspects are mentioned. We identify constructs to the respective coding with help of the interdisciplinary literature. Table II.1-1 gives an example of the open coding phase (see appendix for a complete list of open coding).

Table II.1-1: Example of open coding

Data (extract)	Coding	Literature	Construct
"Why has the bank aroused my interest?" "I opened the account at first only for interest, but soon was very convinced." "The somewhat different concept and the variety of possibilities (community, foreign currencies, etc.) made me curious."	Interest, curiosity in a product category	e.g., Aldlaigan and Buttle 2001; Howcroft et al. 2007; Zaichkowsky 1985	Involvement

In axial coding, we identify all relevant interrelationships between the constructs using the paradigm model and group them into one of different types of intervening conditions: *Personal conditions* refer to personal consumer preferences, *social conditions* describe societal influences, *attitudinal conditions* arise from the attitudes towards the respective activity under consideration, *consumption-based conditions* are based on earlier consumption experiences, and *resource-based conditions* reflect a consumer's personal resources and capabilities.

Table II.1-2 exemplarily shows a 'memo' of the axial coding phase, according to Strauss and Corbin (1990, p. 138).

Table II.1-2: Example of a memo "perceived usefulness" in axial coding phase

<table>
<tr><th colspan="3">Perceived Usefulness</th></tr>
<tr><td>Causal Condition</td><td>Start CDM of a financial product/service</td><td rowspan="6">Comments

Price is an important aspect of perceived usefulness in financial services, especially for customers of direct banks.

Mavens value digital product innovations such as mobile apps.

Proof:
Open coding [PU]</td></tr>
<tr><td rowspan="2">Phenomena</td><td>Perceived Usefulness</td></tr>
<tr><td>Properties: perceived utility (e.g., service quality)
Dimensions: high/mid/low
Occurrence: initiation, comparing, deciding, after-purchase
Frequency of occurrence in data: high</td></tr>
<tr><td>Intervening conditions</td><td>Self-efficacy, market mavenism, consumer values, observability, user friendliness, enjoyment, trust</td></tr>
<tr><td>Action/Interaction strategy</td><td>Preference development of customer</td></tr>
<tr><td>Consequences</td><td>Go to next CDM stage</td></tr>
</table>

In the final coding phase, selective coding examines the core categories of the CDM process with the help of data and literature. Table II.1-3 shows the results after this coding phase. The constructs identified and the intervening conditions are grouped around the *core categories*. Those represent the CDM stages identified that customer behavior centers on with the respective influencing factors.

We examine these more closely in the following, developing a partial model for each of the core categories and assessing the impact of digitalization on the level of single factors. If an influencing factor appears in more than one core category, its name is complemented with the respective category to ensure unique category identifiers.

Table II.1-3: Axial and selective coding phase

Constructs	Conditions	Core category
Involvement Habit Awareness	Personal conditions	Search for alternatives
Tie strength Perceived consumer power	Social conditions	
Self-efficacy Perceived costs	Resource-based conditions	
Perceived usefulness Perceived user friendliness Perceived enjoyment Attitude	Attitudinal conditions	
Satisfaction Loyalty	Consumption-based conditions	Define consideration set
Perceptual affinity Perceived expertise Trustworthiness	Social conditions	
Compatibility with consumer values Market mavenism	Personal conditions	Evaluate consideration set
Subjective norm Expressiveness Argument quality	Social conditions	
Observability Perceived usefulness Perceived user friendliness Perceived enjoyment Attitude	Attitudinal conditions	
Self-regulation Trust	Personal conditions	Purchase decision
Expressiveness Tie strength	Social conditions	
Perceived usefulness Perceived user friendliness Perceived enjoyment Attitude	Attitudinal conditions	

3.1 Search for alternatives

Regarding the search activity of the CDM process, the retail banking consumer screens the market for suitable alternatives, activating knowledge stored in memory and/or gathering information from the environment. Search fulfills four functions for consumers: reducing perceived risks, building up buying efficiencies to better understand products and services, perceiving fun, and (potentially) gaining personal influence (Bloch et al. 1986). We analyze the influencing factors in detail in the following.

3.1.1 Personal conditions

Involvement: 'Interest,' 'curiosity' and 'excitement' are attributes often mentioned in the review data, as well as the wish to take out 'the best offer,' which implies the high amount of cognitive processing involved. The according factor *involvement* is a key construct in marketing literature (e.g., Zaichkowsky (1985). The overall engagement of the consumer depends on the level of involvement as a hypothetical state of activation (Weinberg 1981, p. 17). Depending on this level, motivation to process information can range from inertia to passion, obsession, and elaboration (Solomon et al. 2013, p. 322), implying the different amounts of cognitive control used (Bettman et al. 1998); research shows a mid to high involvement level for most decisions about retail banking services (Aldlaigan and Buttle 2001). The major impact of digitalization on involvement is that it may initiate the *arousal* paradigm at any time, based on upcoming big data capabilities and smartphones. Even if the overall impact of digitalization on involvement in the general consumer life course might be rather low for a lot of customers, this capability warrants an assessment as mid-change.

Habit: Several descriptions of user patterns hint at the influencing factor *habit* as learned, automatic behavior (Limayem et al. 2007). Consumers had a rather small set of options for search in the non-digital past of retail banking. Most consumers switched to PCs or use mobile devices for searching in times of digitalization. Consequently, search engines, online communities, marketplaces, provider websites, app stores, or comparison portals have become established entry points for retail banking consumers (e.g., Berger and Messerschmidt 2009). These new media often bypass traditional forms of searching, such as branch visits, that left consumers often unsatisfied. Thus, the digital impact is to be assessed as high-change.

Awareness: The influencing factor *awareness* is derived from our findings in the data and from studies on banking channel adoption (Hoehle et al. 2012). The factor comprises both non-digital and digital channels, such as new types of branches, mobile apps, banking communities or online banking portals, resulting in a mid-change digitalization impact.

3.1.2 Social conditions

Tie strength (search): The influencing factor *tie strength* is motivated by our review data and literature on viral marketing (e.g., Palka et al. 2009) covering the combination of the amount of time, degree of emotional intensity, level of intimacy, and degree of reciprocity between two individuals (Granovetter 1973). Research has found that more strongly tied pairs communicate more frequently, maintain more and different kinds of relations, and use more media to communicate. Information especially of a personal nature is more likely to be shared by strong ties than by weak ties (Norman and Russell 2006). We expanded this factor to business-to-consumer relationships to integrate new behavioral patterns of consumers that we derived from our data. Consumers assess their everyday financial concerns showing numerous complaints that prevent them from contacting their bank in new financial matters. Many banks offer monetary incentives like 'shopping coupons,' which was confirmed to work well for some users, to strengthen ties. The increasing number of branch closures weakens the ties between consumers and banks. Moreover, customers regret the frequent change of personal advisors. These strong ties between individuals, groups, and organizations are about to be transformed in the rise of new media, introducing new behavioral patterns and leading to an assessment as high-change.

Perceived consumer power: The factor *perceived consumer power* is motivated by our findings in empirical data, where we recognized that unsatisfied users threaten their banks with a provider change in an unprecedented way. This is in line with marketing literature, which confirms increasing consumer power (Labrecque et al. 2013) and decreasing information asymmetry, a former major reason for consultation and visits to branches. With the rise of the Internet, not only does information become increasingly accessible for almost all consumers, but phenomena such as social banking also enables the exchange of knowledge with like-minded people or even consumers developing their own financial products (Berger and Messerschmidt 2009). The resulting new manifold interactions between users in new media lead to so-called “pinball effects” on business-to-consumer relationships (Hennig-Thurau et al. 2010), with strategic relevance for retail banking: Experts expect banking customers to have fewer direct interactions with customers and more interactions via third parties or impersonal channels (Pousttchi et al. 2015). We regard this factor as mid-change, because it is not exclusively a result of the digital change, but is highly influenced by the expertise of the banks.

3.1.3 Resource-based conditions

Self-efficacy: The influencing factor *self-efficacy* is defined by IS literature as the self-assessment of an individual’s capability to use information systems (Compeau and Higgins 1995). We expand this factor to ‘self-efficacy in financial matters’ considering *financial literacy*. In the data, we observed the importance of financial literacy to get things into perspective while searching for financial products and services. One consumer, for instance, argued that he 'had at that time no idea; my adviser was, however, of course totally enthusiastic.' Such consumer decisions are generally complicated by temporal information and capacity limitations, as well as by a lack of cognitive problem solving skills (Crozier and Ranyard 1997). With the introduction of self-service technologies, the rise of the Internet, and the reduction of advisory services, banks started to push products and services towards the consumer. Self-efficacy becomes a major prerequisite for the quality of search results and for the acceptance (Hsu and Chiu 2004) and the intention to use (Wang et al. 2013) of proposed digital services in such a DIY mentality. However, informational and strategic digital skills have not well developed by many consumers (van Dijk and van Deursen 2014, pp. 63 ff.). A recent consumer study among the working population confirmed even a decreasing financial literacy of German consumers (GfK market research 2014). Experts expect new forms of personal contact, such as virtual banking and augmented reality, in the future to address these issues in retail banking (Pousttchi et al. 2015). We refer to this factor as mid-change because it comprises both non-digital and digital elements.

Perceived costs: Costs associated with banking services usage were frequently found to be inhibiting factors (Hoehle et al. 2012). This factor was dominated by human communication and mass media in the past. Digitalization brought a high speed and range of information (van Dijk 2012, p. 1) and a higher complexity of products and self-service approaches. Although perceived costs of search are significantly reduced on the Internet (Miyazaki 2003; Rowley 2000; Tang and Lu 2001), the identification of relevant information depends increasingly on consumer skills that are very costly (i.e., time-consuming) to develop. Comments in the data on search efforts dealt with troubles to overcome to understand the products and services offered. Exemplarily, one user argued that, 'It took me a lot of calls and nerves until I was able to disclose all the hidden traps of the credit agreement to understand the entire structure properly.' This factor is significantly changed by digitalization and considered as high-change.

3.1.4 Attitudinal conditions

Perceived usefulness (search): The influencing factor *perceived usefulness* is motivated by findings in data and literature where it is frequently mentioned by authors studying consumers' use behavior related to e-banking services (Hoehle et al. 2012). The factor in IS literature measures "the degree to which a person believes that using a particular system would enhance his or her performance" (Davis 1989). Our review data shows that consumers paid attention to the quality of retail banks' websites and mobile apps in frequent comments regarding being 'practical' and 'useful.' We refer to this factor as high-change, because perceived usefulness expectations are strongly influenced by the digital age.

Perceived user friendliness (search): We found in our review data that perceived user friendliness is assessed, for instance, based on website quality, processing times and the visual appearance of mobile apps. *Perceived ease of use* in literature is introduced as a measure of "the degree to which a person believes that using a particular system would be free of effort" (Davis 1989, p. 320). The related factor *convenience* was found to be influential for consumers' intentions to use e-banking services (Hoehle et al. 2012), because access convenience has a direct impact on behavioral intentions (Berry et al. 2002; Seiders et al. 2007). Appropriateness of branch locations was very important in the past (Laroche and Taylor 1988), as were waiting times, comprehensibility of paper-based front ends, and the friendliness of a bank's workforce. Digital users, however, turn their backs on the branch regarding less complex activities, such as searching, due to lower *perceived costs* and higher *perceived consumer power* through new media (Honka et al. 2017). Digital banking customers prefer convenient information sources, such as search portals with clearly arranged and rather complete information, so that they have to search less (Honka et al. 2017). This factor is clearly high-change.

Perceived enjoyment (search): There is strong evidence on this factor in our data, with consumers entitling banking channels as 'awesome,' 'superior' or 'fun to work with.' Users confirmed 'enjoying' using information systems in cases of 'simplified flows.' Davis et al. (1992, p. 1113) state that "enjoyment refers to the extent to which the activity of using the computer is perceived to be enjoyable in its own right." In mobile, perceived enjoyment is not simply a factor to enhance acceptance of a service – "the truth is that a service that is not fun to use is simply not perceived as useful" (Pousttchi and Goeke 2011, p. 41). Perceived fun is a major factor for consumers' intentions to use e-banking channels (Hoehle et al. 2012). This reflects current consumer expectations and leads to an assessment as high-change.

Attitude towards search: Categorizing phrases such as 'annoying,' 'good,' 'interesting,' 'new,' or 'cool' in our review data confirmed the importance of this factor for consumers. Literature defines *attitude* as "the positive or negative feeling of an individual about performing a behavior" (Fishbein and Ajzen 1975, p. 302). The factor comprises the consumer attitude towards search activities, for instance, in the branch, on websites, in online marketplaces or with mobile apps. This is deeply influenced by digital technologies, therefore, we refer to it as high-change.

Figure II.1-2 shows the complete partial model *search for alternatives*.

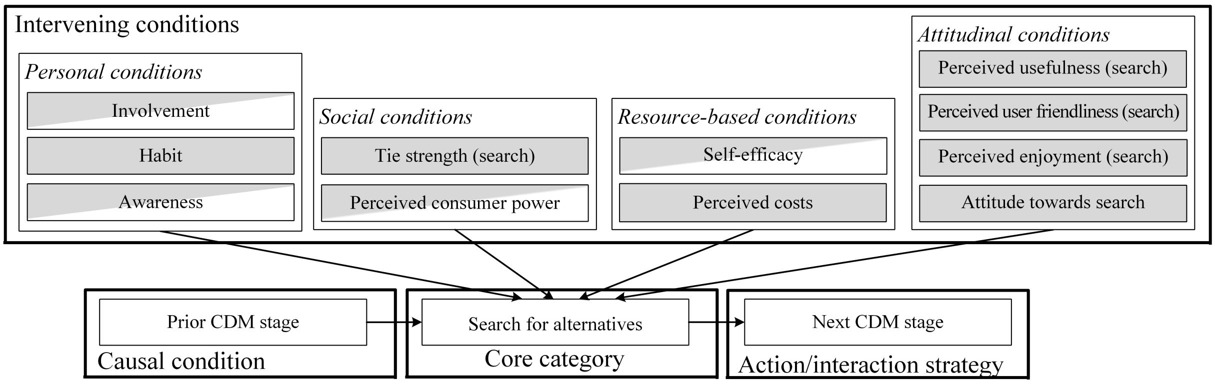

Figure II.1-2: *Search for alternatives* model

3.2 Define consideration set

Consumer behavior research showed that consumers only consider a subset of the product available and service alternatives to reduce the efforts on later evaluation (Bettman et al. 1998). This subset is referred to as the *consideration set* (Blackwell et al. 2002, ch. 3).

3.2.1 Consumption-based conditions

Satisfaction: Satisfaction measures the distance between expectations and the product's perceived performance (Kotler and Keller 2016). The data showed a lot of reviews describing both positive and negative experiences with financial products and services, very often linked to the digital experience. This leads clearly to an assessment as high-change.

Loyalty: Brand loyalty is introduced in marketing literature as a concept to avoid switching risks (Kroeber-Riel et al. 2009, p. 438). Research on bank loyalty refers to the degree to which consumers constantly support their banking institution (Methlie and Nysveen 1999). Previous banking studies elaborated that bank loyalty was affected by perceived quality (Bloemer et al. 1998) and perceived ease of banking (Moutinho and Smith 2000). Apathy and laziness were considered the main switching barriers (Colgate and Lang 2001) as well as a lack of time and an overall lack of differentiation between banks (Howcroft et al. 2003). The consumer search for variety increasingly diminishes those factors within the lure of new experiences in the digital age; the reasons for apparent consumer disloyalty also include a multi-brand loyalty by many consumers (Oliver 1999). Some consumers described in the data that major drawbacks made them dismiss their loyalty. The data also shows the trend of having interactive banking accounts, at least in addition to the main account. We found evidence of a new emerging culture of 'interactive,' 'cool' apps to try out. Overall, we see decreasing loyalty levels of consumers and a high affinity towards new media. Therefore, we propose it as high-change.

3.2.2 Social conditions

Perceptual affinity: Findings in our review data and in literature on viral marketing motivate us to integrate the influencing factor *perceptual affinity*, which is defined as the degree to which recipients and informants are similar in terms of values, likes, dislikes and experience (Bruyn and Lilien 2008). In the data, consumers value 'appealing,' 'modern,' 'contemporary' and 'clear' websites or expressed identification with mobile apps that 'perfectly match the bank style' (and the users' own style). This is especially true for customers with a digital lifestyle who consider themselves to be hyper-social in the "bubble" of new media (Llamas and Belk 2013). Banking advisors in the past knew their customers and took their time to speak to people in local branches, being the center of most consumers' financial lives. Common values were exchanged face-to-face in these encounters. In recent years, however, constraints in time and place (Belk 2013) are about to be eliminated and new patterns of how people meet and interact are observable (e.g., using mobile messengers). Many consumers nowadays prefer to get their financial matters done online in the mobile channel and on the desktop – still a major information source for "digital omnivores" (Fulgoni 2015). New channels reflect the increasing *perceptual affinity* towards new media and interactivity beyond online banking (e.g., chat, video, co-browsing; Kinting and Wißmann 2016) for preselection. This leads perceptual affinity to high-change.

Perceived expertise: Research found that consumers are more inclined to seek advice from experts than non-experts (Gilly et al. 1998). However, our data showed many statements that advisors had no 'clue' about product details, while others confirmed that advisors 'showed expertise and knew what they talked about.' From the consumer perspective, a communicator is an expert if he or she is by virtue of "his or her occupation, social training, or experience in a unique position" (Schiffman and Kanuk 1997, p. 335). However, increasing information transparency gives an information advantage to those people working intensively on an interest and mobile connectivity allows consumers to compare products and prices instantly on the spot – resulting in a "loss of authority" of banking advisors (Kinting and Wißmann 2016). We refer to this factor as high-change.

Trustworthiness: Trustworthiness becomes an important factor in the preselection of alternatives, because financial services and products such as investments often show first results years after contracting, at the earliest (Rieck 2016). Bankers historically had a high reputation and advising was their primary function. However, recent years have led to a (perceived) selling mentality to which many customers respond with resistance and lack of trust. Ongoing branch closures and, consequently, less personal contact will have a further diminishing impact. The factor also applies to online banking portals which are very anonymously organized and to social trading in which the community serves their members with guidance (Brylewski and Lempka 2016). However, we assess this factor as mid-change since it is not only influenced by technology.

Figure II.1-3 shows the complete partial model *define consideration set*.

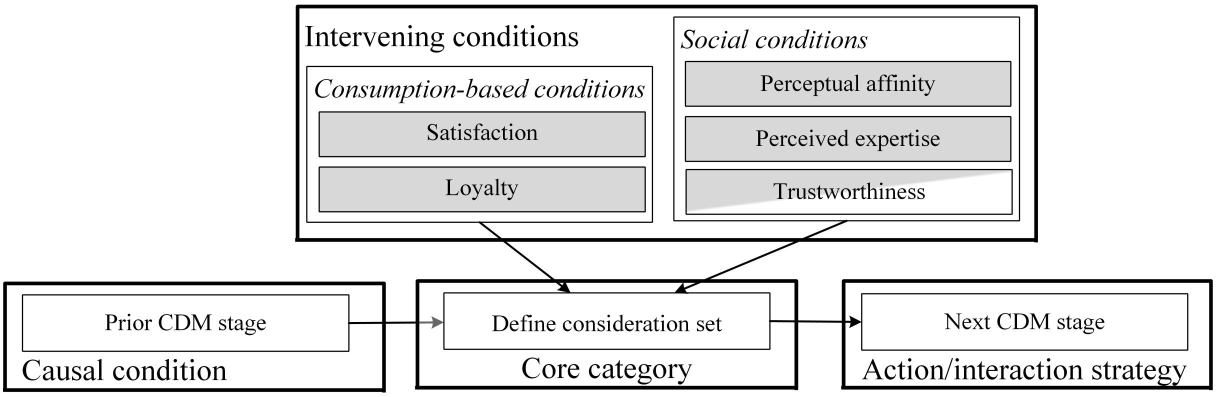

Figure II.1-3: *Define consideration set* model

3.3 Evaluate consideration set

Consumers apply different patterns to evaluate and compare products, often developed on the spot, depending on the complexity and importance of the decision (Bettman et al. 1998). In this regard, consumers rate the relative attractiveness of different options (i.e., 'This is by far the best banking app compared to others'). In most cases, consumers have already memorized judgements or beliefs about the performance of the choice alternatives. Otherwise, consumers will rely on acquiring further external information to form their beliefs and evaluate the options from the consideration set.

3.3.1 Personal conditions

Compatibility with consumer values: Compatibility with consumer values was frequently found to be an important factor for e-banking use (Hoehle et al. 2012). In IS, it describes "the degree to which an innovation is perceived as being consistent with the existing values, needs and past experiences of potential adopters" (Moore and Benbasat 1991, p. 195). Surveys found that younger consumers especially tend to evaluate products regarding their emotional fit and the personal identification (Barton et al. 2014). Holbrook (1999) introduced eight typical consumer values, from which we describe four especially important in the retail banking context and influenced by digitalization to a greater extent. Consumers demand a higher *efficiency* of products and service in scarcity of time and haste (Pine and Gilmore 1998). The value of *play* relates to the mobile apps culture that permeates all spheres of consumers' lives (e.g., Llamas and Belk 2013) and enjoyment is sought after in products and services. This is also examined by the attitudinal conditions of our model (e.g., *perceived enjoyment*). In addition, a shift of *aesthetic* values to the digital domain is recognizable. Regarding *quality*, the data shows that not every consumer is dazzled by design when the decision is between style and substance. Digital banks especially divided communities, getting praise such as 'best bank solution that I can think of' and hate, in the case of unfulfilled expectations. Altogether, consumer values are influenced by digitalization in different foci, however, strong traditional values, such as the quality and pragmatism of service provision, remain important. Thus, we refer to this factor as mid-change.

Market mavenism: Our empirical data shows that most people relate to their own manifold experiences with banks, such as 'I do not know these unfriendly practices from other banks.' Users generally appear to be very familiar with prices that they first observe (e.g., monthly fees, interest rates, overdraft fees, and hidden fees). Marketing literature on the phenomenon of word-of-mouth introduced different user types to identify influential people. In this regard, *market mavenism* identifies “individuals who have information about many kinds of products, places to shop, and other facets of markets, and initiate discussions with consumers and respond to requests from consumers for market information” (Feick and Price 1987, p. 85). The exchange of information often moves to the digital sphere and increases reach, whereas the concept itself remains a non-digital one; we refer to it as mid-change.

3.3.2 Social conditions

Subjective norm: “The person’s perception that most people who are important to him think he should or should not perform the behavior in question” (Fishbein and Ajzen 1975, p. 302) was identified as an important factor for banking consumers’ use intentions (Hoehle et al. 2012). While branches were the center of financial matters in the past, nowadays, various aspects of the structural change, mainly domestic migration (Stettler 2011), lead to a decreasing impact of these traditions. Mobile connectivity is often perceived as a substitute. When branches have already been shut down, with them, local subjective norm often eroded. Moreover, the move of socialization away from traditional institutions, such as family, school, and mass media, towards new media (van Dijk 2012, p. 2) has reduced the influence of the family on youth behavior. Adolescents weigh friendships increasingly higher than family relations (Gerrig et al. 2008, p. 397) and typical modern youth behavior is characterized as “variety-seeking” (Kroeber-Riel et al. 2009, p. 491). Here again, mobile connectivity is an important substitute: ‘My friends asked me all the time about this app’ is one exemplary comment in our data next to ‘I will recommend your solution to my friends’: Opinions are shared, apparently having an impact on product evaluations. We see strong digital influence here and assess it as high-change.

Expressiveness (evaluation): Expressiveness describes how well a channel expresses below instrumental utility (Mittal 1994). The impression management theory states that individuals establish and maintain impressions that are congruent with the perceptions they want to convey to their public (Goffman 1959, pp. 160 f.). Traditional retail bank branches expressed value, status, and tradition, attracting consumers to visit. In digital realms, however, a growing number of users have switched to new ways that represent the current mode in fashion and lifestyle, for instance, online communities or app stores. The results of Katz and Sugiyama (2006) suggest that young people use the mobile phone to express their sense of self and perceive others through a ‘fashion’ lens, apart from utilitarian arguments. Our data indicates this for retail banking products and services. Very enthusiastic consumers, for instance, find digital banks to be the ‘very cool new way of banking’ or ‘the future of money.’ Digital banking solutions seem to express the current mode of lifestyle in numerous consumers’ eyes. This is to be assessed as high-change.

Argument quality: Zhang et al. (2014) found in online reviews that *argument quality* has a significant effect on consumers’ purchase intentions. This is true for both non-digital and digital banking channels. We regard this factor as mid-change.

3.3.3 Attitudinal conditions

Observability: This factor measures “the degree to which the results of an innovation are observable to others” (Moore and Benbasat 1991). While the observability of financial products and services was rather limited in the past, digitalization increases transparency greatly and users might easily acquire online reviews or compare prices on specialized platforms. In addition, digital solutions often allow consumers to try banking solutions (e.g., for checking accounts, personal finance management and payment solutions) beforehand (e.g., ‘I have now tried the account for some time, and must say that it convinces me entirely’). Various studies found that consumers wished to try banking channels before adopting them in the long-term (Hoehle et al. 2012). We refer to observability as high-change.

Perceived usefulness (evaluation): When it comes to usefulness, the data show a wide variety of preferences. Many users show a preselection in favor of traditional branch networks or direct banking with an online focus. Users often mention criteria for choice such as ‘free account management’ and comparatively ‘low overdraft interest.’ Other users prefer to pay account fees, but are rewarded because they ‘have a super advisor, self-service terminals, and a 24-hour service.’ Multiple studies in retail banking also confirmed that service quality is essential for consumers (Hoehle et al. 2012). We regard perceived usefulness as mid-change.

Perceived user-friendliness (evaluation): User-friendliness affects consumers’ product evaluations (Berry et al. 2002). Users prefer bank interfaces that make ‘banking easy and understandable.’ Consumers were used to waiting in the past, often completing and submitting paperwork in the interim. However, digital consumers are used to a much higher service pace and transfer these expectations to banking. As a result, today’s consumers increasingly avoid banks that make the ‘processing and delivery of the necessary documents complicated and long-winded.’ Our data also reveals that many users generally perceive banking services as ‘complicated’ and restrictive. As a major consumer expectation in digitalization, we refer to user-friendliness as high-change.

Perceived enjoyment (evaluation): We already reasoned the relevance of *perceived enjoyment* on consumers’ intentions to use channels by review data and literature in the search model. The importance of product evaluation is also confirmed by service research (e.g., Xin Ding et al. 2010) and can be assessed as high-change.

Attitude towards evaluation: Regarding consumer values, some users change their attitudes in favor of evaluating products via new media, while others remain and request professional advice in non-digital media. Since this comprises influences from both non-digital and digital, we refer to it as mid-change.

Figure II.1-4 shows the complete partial model *evaluation of the consideration*.

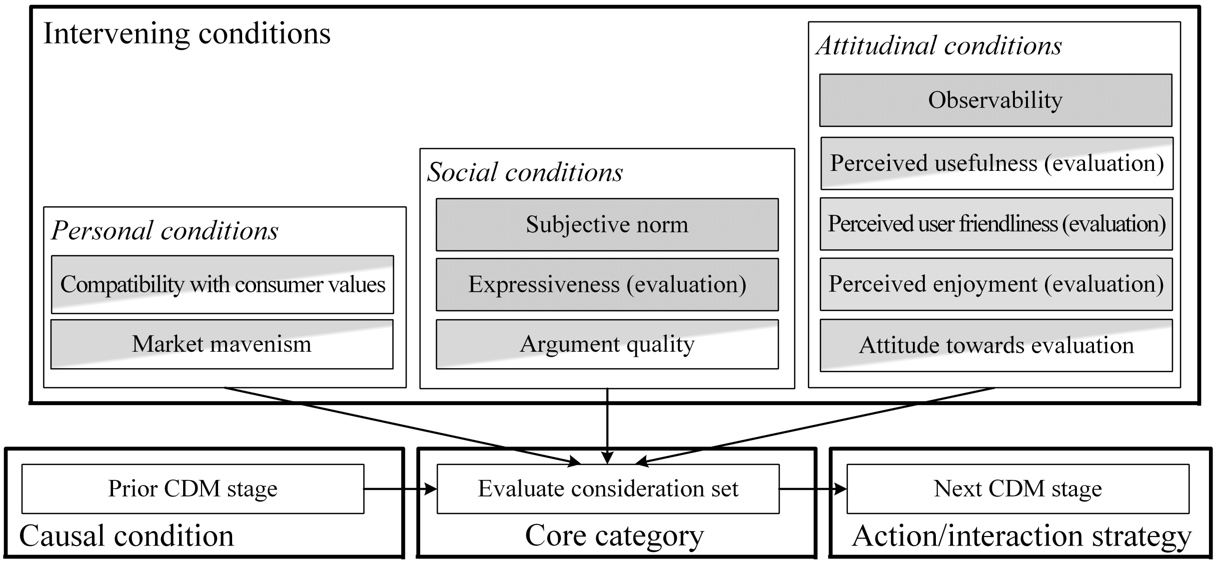

Figure II.1-4: *Evaluate consideration set* model

3.4 Purchase decision

Final decision-making includes three subjects: choice of provider, time, and method of completion with respect to the intervening conditions.

3.4.1 Personal conditions

Self-regulation: Potential future consequences of decisions are often considered in the data. Literature on financial behavior shows two important aspects influencing final decisions in retail banking (van Raaij 2016, p. 212). The first aspect describes the control of impulsivity to prevent from overspending, reflecting the decreasing limitations by non-digital cash and increasing levels of *arousal* (e.g., mobile shopping). The second aspect refers to budgets and expenses in personal finance. Fintech, such as Mint, constitute an opportunity to get in touch with personal finance more frequently to prevent overspending. However, the concept remains traditional with digital impact and is referred to as mid-change.

Trust: Trust in IS measures "the willingness to make oneself vulnerable to actions taken by the trusted party" based on feelings of confidence or assurance (Gefen et al. 2003, p. 55). The factor is often found to be influential for adoption and usage in retail banking studies: Users who believe channels to be risky do not use them and choose alternative channels (Hoehle et al. 2012). However, the times are over when traditional banks were trustworthy and Internet players were not. Trust levels are, for instance, influenced by financial crises these days (Anneli Järvinen 2014; Hurley et al. 2014). Only 30 percent of citizens between 18 and 34 years of age trust a private bank, and two-thirds trust the Internet payment system PayPal, whose popularity even among young German users is now 96 percent (Cofinpro 2014). Our data reveals that consumers show high trust towards new challengers at the beginning with high enthusiasm. One reason might be that services that include perceived interactivity, perceived user control, and perceived contextual offers are more trusted in general (Lee 2005). Another finding is that people tend to evaluate long-established relationships to retail banks rather complete and critical, as they had many (sometimes unpleasant) experiences over the years. However, people's positive attitude towards bank challengers can change quickly under disappointing circumstances. Most of these trust losses occur at the customer interface. Users of Fintech, for instance, emphasize that they 'want and must be able to rely on a bank' and 'cannot trust any bank that might expel me.' Another representative user review about a mobile banking app ('if the clarity becomes even better, it will confirm my trust') shows that what counts among young people is, above all, the uncomplicated handling of services. Since trust comprises major digital consumer expectations, we refer to it as high-change.

3.4.2 Social conditions

Expressiveness (decision): The data shows that users prefer 'cool' products, for instance, paying via NFC or mobile apps 'recommended by friends.' As research found decision-making closely related to expected future emotions (Lerner et al. 2015), we reason that expressiveness is also important in purchase decisions. This leads to an assessment as high-change.

Tie strength (decision): Critical decisions are seldom taken alone by the customer. Strength of ties towards people and institutions should also be considered in purchase decisions. Several trends in recent years have changed the role of the family for the individual, such as the increasing number of singles, a decreasing number of marriages, and an increasing percentage of couples living separately (Destatis 2008). Moreover, the influence of external non-family groups increases with social media, as in our empirical review data. Sociologists even argue that the individual linked by networks is increasingly becoming the basic unit of social coexistence (van Dijk 2012, p. 2). However, digitalization is only a part of this development, and we refer to it as mid-change.

3.4.3 Attitudinal conditions

Perceived usefulness (decision): This influencing factor is important regarding the final decision. Many of the routine processes are already fulfilled by the customers themselves, for instance, in online forms or mobile apps. However, our data revealed frictions, such as inconsistent check-out processes, non-completion routes, or media breaks, that imply a lack of effectiveness and enjoyment which is avoided by many consumers. Since this factor reflects major consumer expectations in the digital age, we regard it as high-change.

Perceived user friendliness (decision): Similar to the search and evaluation partial model, user friendliness is closely related to the other attitudinal conditions. As before, we regard it as high-change.

Perceived enjoyment (decision): Perceived enjoyment is not simply a factor to enhance acceptance of a mobile service – "the truth is that a service that is not fun to use is simply not perceived as useful" (Pousttchi and Goeke 2011, p. 52). Mobile services for purchase completion are becoming increasingly important in digital technologies. As before, we regard this as high-change.

Attitude towards decision: This factor reflects the attitude towards final decision-making, for instance, in the branch, on websites, in online marketplaces, or with mobile apps. Categorizing phrases such as 'complicated,' 'very cool,' and 'good' in our data confirmed that consumers adopt an attitude towards their choices. Since attitude towards decision-making is strongly influenced by digital technologies, we refer to it as high-change.

Figure II.1-5 shows the complete partial model *purchase decision*.

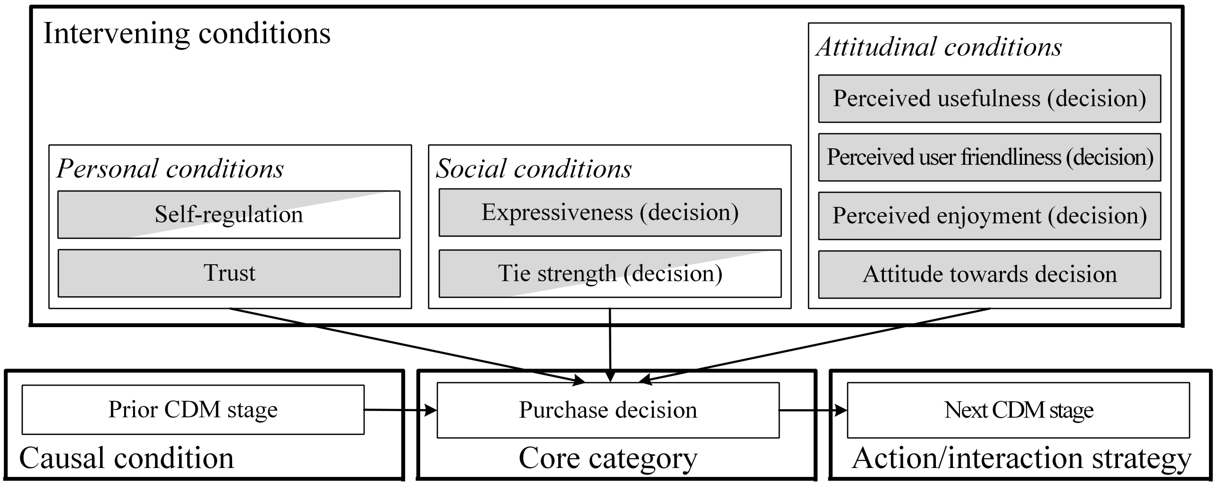

Figure II.1-5: *Purchase decision* model

4 Integrated model

In this section, we build on the four partial models to develop an integrated model for CDM in retail banking. Given the results for the core categories, we apply the relevant literature to identify the interconnections between these. On the research side, discrete but interconnected stages can be found in, for example, Nicosia 1966, Howard and Sheth 1968, Perreault and McCarthy 1996, and Blackwell et al. 2002 in chapter 3. On the practitioners' side, relevant retail banking studies on CDM are, for example, Devlin 2001; McKechnie 1992; Milner and Rosenstreich 2013.

The overall decision-making process is started by an initial *trigger* (causal condition) for the consumer. This might be either the recognition of a *need* for a product or a service that initiates a planned decision, or the *arousal* of a desire which reflects a trigger that initiates unplanned decisions (Lee et al. 2001; Mortimer & Shanahan 2003; Moschis 2007). The next step in a standard case is a search stage.

In the search stage, the core categories *search for alternatives* and *define consideration set* reflect the core activities of the decision-maker (Bettman et al. 1998; Blackwell et al. 2002). In this case, the intervening conditions follow Figure II.1-2, respectively, Figure II.1-3 and the subsequent action/interaction strategy is to proceed to the next stage evaluation. In the case where the consumer has decided successfully on a set of potential alternatives exposed to intervening conditions, the process is continued by the evaluation stage. Otherwise, the process is aborted.

In the case where the process is continued, the evaluation stage implies the evaluation of the consideration set (Bettman et al. 1998; Blackwell et al. 2002). In the evaluation stage, the core category *evaluate consideration set* reflects the core activity of the decision-maker. In this case, the intervening conditions follow Figure II.1-4 and the subsequent action/interaction strategy is to proceed to the next stage decision. In the case where the consumer has successfully identified a set of potential alternatives exposed to intervening conditions, the process is continued by the decision stage. Otherwise, the process is aborted.

In the case where the process is continued, the consumer enters the decision stage, including the core category *purchase decision* (Blackwell et al. 2002). In this case, the intervening conditions follow Figure II.1-5 and the decision is taken.

In the case where the consumer completes the final decision and chooses a product or service, the next stage, *after-purchase evaluation* (Blackwell et al. 2002), relates to the use and evaluation of the product or service chosen, which is not discussed in detail here.

The causal conditions are not depicted separately in the basic model for reasons of clarity, except for the initial trigger. The overall structure of the basic model is organized by defining prerequisites and relationships between the stages (causal conditions, core categories, intervening conditions, and action/interaction strategies).

Figure II.1-6 shows the complete CDM process model.

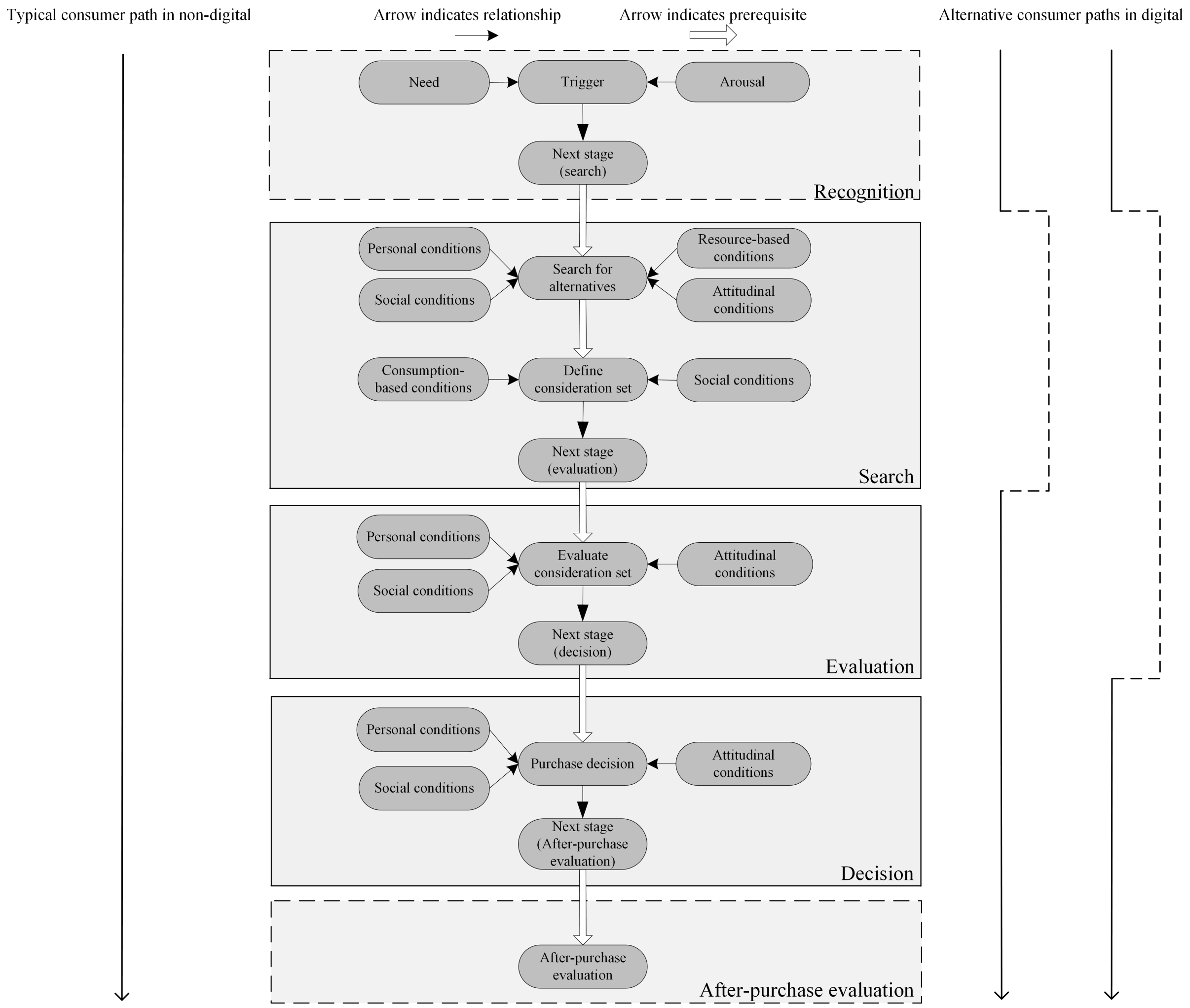

Figure II.1-6: Process model of CDM in retail banking

The integrated model shows the traditional decision-making path with all stages of the linear process. Consumers typically reside a certain time within the respective stages depending on the respective influencing factors that occur. It is possible to skip single phases of the process in the traditional path, but rather unlikely.

A shorter decision process might become increasingly typical in a digital world. Digital data-based (especially mobile) marketing might initiate a decision process or even a customer relationship. Digital banks already include recommend-a-friend options (e.g., 'I received an email stating that I would receive 5000 bonus points for each friend I referred'). In addition, digital consumers tend to use online comparison sites or recommendation systems during CDM. That is, recommendations often cause consumers to search in "choice mode," common when choosing from predetermined sets of alternatives, and one consequence of that evolution is to search less (Dellaert and Häubl 2012). Such recommendations may come from various sources. It is obvious that the consumer's bank – if tech-savvy enough – might be a recommender. Viral effects, such as recommend-a-friend, are also viable. However, the ownership of large and rich consumer datasets and the application of big data techniques in combination with direct access to the consumer via smartphones might enable any non-bank to provide according recommendations (Pousttchi and Hufenbach 2014).

Consequently, not only might the stages be influenced, but consumers might take a shortcut in the process and go from a well-targeted recommendation directly to the evaluation or even to the decision stage. While this is also possible, but rather unlikely in a non-digital environment, it might become increasingly typical in the digital world – especially if a data-driven recommendation enables the use of the trigger *arousal* instead of *need* in the recognition stage.

This potential represents the major impact of digitalization on the overall CDM process. Figure II.1-6 includes the different customer journeys as vertical arrows, with the classic path to the left and the two alternative paths to the right side of the model.

5 Conclusion

The starting point for our considerations was to better understand the motivations, attitudes and behaviors of today's retail banking customers. We explored the phenomenon of financial decisions using empirical data and relevant literature from diverse disciplines to develop four partial models using the grounded theory approach. Based on that, we developed an overall CDM process model by linking our findings of the detailed partial models with the traditional CDM literature. Finally, we showed how this traditional process might be modified by digitalization.

The analysis of our data reveals that traditional IS factors, such as those described in technology acceptance model, are not sufficient to cope with all the effects of digitalization in the retail banking domain. This is in line with the more general considerations of (Bagozzi 2007). Digital technologies, such as mobile phones, shape the individual and society in different ways. We discovered remarkable interdependencies between IS and related disciplines, such as Marketing and Sociology, for the analysis of personal, consumption-based, or social factors. The respective influencing factors, such as perceptual affinity, tie strength, or expressiveness, have an impact on retail banking consumers and customer relationships throughout the whole CDM process. Further research on digitalization calls for a deeper interdisciplinary analysis of the interdependencies of technology and social life aspects. The assessment of the impacts on the respective CDM factors reveals that digitalization is a challenging endeavor, having a considerable transformational impact on any of the factors identified in the CDM model, traditional ones and newly integrated ones.

The results contribute to research from a theoretical standpoint in three ways: Firstly, the paper contributes to consumer behavior and decision-making literature by investigating financial products and services. Secondly, our work adds several constructs from existing theories to the area of CDM in the field of retail banking. Finally, our model represents the first complete approach to CDM in the digital era and, thus, lays the foundation for further quantitative analysis – within the field of retail banking and beyond.

From a practitioner's point of view, the results provide not only additional and new insights into what is up to now a poorly-understood, complex and dynamic situation, but also a structured process view and a map of digitalization impacts on the operational and strategic level.

If traditional banks want to keep up with new entrants, they need to address these challenges, from new digital habits and values to the shift of consumer power and loyalty. This requires investing significant resources into designing and delivering services that are timely, up-to-date, and personalized. Traditional assets must be integrated with digital capabilities to fit personalization and rapid processing consumer demands. The younger generation is especially looking for services that reflect their perception of modern life. Coping with these changes is a major challenge for every bank which remains in the market. However, our results suggest that a lot of current approaches might not turn out to be effective, as the stages they are targeting can be bypassed by competitors' approaches (e.g., at the search stage). Since consumer decisions in digital technologies might be increasingly shortened, it is essential to address the right customers, in the right manner and at the right time, first and foremost, by data-driven approaches to compete with new digital entrants.

The alteration of CDM in a digital world might be highly relevant and timely, but is a very extensive field. This paper represents the first step in our research area. Further research will have to measure the influences in our model with quantitative methods, try to generalize the results beyond banking, and develop strategies to address the challenges identified.

Appendix

Table II.1-4: Complete list of open coding phase with exemplary data

Data (extract)	Coding	Literature	Construct
"Why has the bank aroused my interest?" "I opened the account at first only for interest, but was so convinced (...)." "The somewhat different concept and the variety of possibilities (community, foreign currencies, etc.) made me curious."	Interest, curiosity in a product category	e.g., Aldlaigan and Buttle 2001; Howcroft et al. 2007; Zaichkowsky 1985	Involvement
"Nowadays, I use online banking several times a week." "I compared prices and read the reviews on this site."	Habits (esp. channel use)	e.g., Duhigg 2014; Limayem et al. 2007; Verplanken 2006; Wang et al. 2013	Habit
"I became aware of the account due to a campaign..." "I was attracted by the 200 € Amazon vouchers." "I became aware of the offer from a price comparison site."	Awareness of a product or channel, advertising	e.g., Honka et al. 2017; Lee et al. 2007	Awareness
"We feel that the offer only serves to attract interested customers to the branch to sell other products." "And even if I do not have an interest, advisors take note of my wishes." "I was welcomed by the friendly consultant and offered water and coffee."	Intensity of customer relationship	e.g., Granovetter 1973; Lang and Colgate 2003; Marsden and Campbell 1984	Tie strength
"… bank consultant who wants to sell something." "I actually went in search of a better app for what I need and haven't been able to find one." "Actually, I had considered whether I should change the bank connection. Laziness triumphed, and I regret that."	Customer autonomy, empowerment	e.g., Fuchs et al. 2010; Labrecque et al. 2013; Martin 2013; Rucker et al. 2012; Zureik and Mowshowitz 2005	Perceived consumer power
"I've blocked the area directly as I have only limited knowledge about securities." "I can do the banking business all by myself." "I had a lot of stupid questions (...), but my counselor showed a lot of patience."	Perceived capability to search, evaluate, and use financial products (financial literacy)	e.g., Bandura 1982; Compeau and Higgins 1995; Hsu and Chiu 2004; Wang et al. 2013	Self-efficacy
"I have to search the website for a long time to find the phone number for personal contact." "I can easily withdraw money without having to search." "You have to search for a longer period of time and have a certain discipline to obtain the information desired."	Different types of costs (e.g., search)	e.g., Laukkanen and Lauronen 2005; Lee and Lee 2004; Miyazaki 2003; Rowley 2000; Tang and Lu 2001	Perceived costs
"However, what should be improved, in any case, is the search for keywords (...)" "The app is absolutely superior, the functionality and simplicity unbeatable." "The best mobile banking app (...), both in terms of design and functionality."	Product quality, functionality, price, utility	e.g., Davis 1989; Ricci and Caratelli 2014; Stamenkov and Dika 2016	Perceived usefulness
"The so-called mailbox is somewhat bad to use." "Searching for names is not bad, but you have to enter (...) each time again." "I feel very positive about the clear layout of the website." "I like the warm colors and the clarity very much." "It's all there where you'd look for it"	Usability, design, service friendliness, ease of use	e.g., Davis 1989; Johnston 1997; Joseph et al. 1999; Jun and Cai 2001; Setia et al. 2013	Perceived user friendliness
"It's fun to work with (...) Paying with NFC is easy." "This makes banking fun." "Enjoy banking on the go." "I enjoy it because the function scan and pay works so perfectly."	Fun, enjoyment	e.g., Dabholkar 1996; Pousttchi and Goeke 2011	Perceived enjoyment
"However, this experience has changed my attitude." "Super cool app!" "I like the online banking as much as it is." "Overall, I like the bank very much."	Attitude towards banking products and services	e.g., Fishbein and Ajzen 1975; Howcroft et al. 2002; Kaynak and Harcar 2005; Moutinho and Smith 2000; Shu and Cheng 2012; Voss et al. 2003	Attitude

Data (extract)	Coding	Literature	Construct
"I had to look for a new bank because I was absolutely dissatisfied with the service of my last bank." "I'm super satisfied with this app. Everything works perfectly and I can only recommend it." "My requests could always be answered to the fullest satisfaction." "I am very satisfied with my bank and I am trying to explain why…" "The appearance of the bank contributes to my satisfaction."	Satisfaction	e.g., Aldlaigan and Buttle 2005; Bloemer et al. 1998; Levesque and McDougall 1996; Oliver 2014; Wang et al. 2013; Wirtz and Bateson 1999; Xin Ding et al. 2010	Satisfaction
"I will continue to remain loyal to the bank as I am very satisfied with it." "I will probably look for another bank after the free cash withdrawal was limited in September." "I have been a client for many years and have decided to go to another bank because there is simply a better offer now."	Consumer loyalty, switching behavior	e.g., Beerli et al. 2004; Methlie and Nysveen 1999; Oliver 1999; Selnes and Hansen 2001; Yavas et al. 2014	Loyalty
"You can also visit many (mostly sporting) events free of charge with Visa card." "Other banks cannot be visited before 9 o'clock. Conclusion: more than pleasing and contemporary." "… is simply top: young and fresh!" "Beautiful and modern!" "I've been looking for a modern banking app for a long time and found it!" "Personal advice was always important to me – quite different from the anonymous Internet."	Similarity between consumer (lifestyle) and product	e.g., Belk 2013; Bruyn and Lilien 2008; Kinting and Wißmann 2016; Llamas and Belk 2013; van Dijk 2012	Perceptual affinity
"The employees have little knowledge in the banking sector." "In my opinion, these offers have little to do with my investor profile, but are more in the interest of the bank."	Expertise of bank (advisors)	e.g., Gilly et al. 1998; Kinting and Wißmann 2016; Schiffman and Kanuk 1997	Perceived expertise
"Simply do a web search to take a look at the cases against this company." "We feel that the offer only serves to lure interested customers to the branch." "They want to know a lot of details that no other provider would like."	Trustworthiness, reliability, credibility of bank (advisors)	e.g., Anneli Järvinen 2014; Gefen et al. 2003; Hurley et al. 2014; Kim et al. 2009; Lee 2005; Schwartz et al. 2011	Trustworthiness
"The app does exactly what it should. Registration within five minutes." "In combination with the app, everything that I need is available." "Of course, I noticed the differences in the branch network compared to other banks." "I praise the anonymity of direct banks."	Value dimensions of consumption (e.g., quality, efficiency)	e.g., Holbrook 1999; Holbrook and Hirschman 1982; Moore and Benbasat 1991; Pine and Gilmore 1998	Compatibility with consumer values
"Online banking is very clear (...) compared to competitors, and I know some." "The account will be the most expensive account that I know." "Personally, I like the online banking service best in comparison to all other (...)"	Product and market experience	e.g., Feick and Price 1987	Market mavenism
"I need to get my whole family to use this app!" "I am posting on social media not to do business with … to all my family and friends." "I received a nice recommendation through my friends."	Use of products in the social environment, normative pressure	e.g., Fishbein and Ajzen 1975; Kroeber-Riel et al. 2009; Stettler 2011; van Dijk 2012	Subjective norm
"I've made several friends of mine aware of the app." "I hope you keep going. I have recommended you to many of my friends and all of them were very enthusiastic." "Friends to whom I recommended (...) also told me about similar experiences."	Extroversion, recommendation behavior	e.g., Katz and Sugiyama 2006; Llamas and Belk 2013; Mittal 1994	Expressiveness
"My son finally convinced me to change my account." "… my adviser was, of course, totally enthusiastic."	Persuasiveness, informativeness	e.g., Zhang et al. 2014	Argument quality
"I have now tried the account some time, (...) it convinces me entirely." "I had initially opened the account only from interest, but was so convinced right after the first few days!"	Trialability, app testing	e.g., Hoehle et al. 2012; Moore and Benbasat 1991	Observability
"Luckily, I've rethought the matter of the salary account." "If you are still thinking about it, you should consider that … has good offers for new customers."	Self-control, consideration of future consequences	e.g., Strathman et al. 1994; van Raaij 2016	Self-regulation
"I am really confident and full of trust." "Actually, very happy, but the current wave of layoffs is responsible for a lot of mistrust."	(Mis-)trust	e.g., Gefen et al. 2003	Trust

Data (extract)	Coding	Literature	Construct
"To become a customer was difficult in this case, because the first application at the … was simply lost in the system." "At first, I thought it would be very difficult (...) to open an online account." "Great app with real-time control of all account activity."	Difficulties of performing behaviors, financial control	e.g., Ajzen 1991	Perceived behavioral control
"Compared to other direct banks, few data are collected or required as mandatory fields." "They want to know a lot of details that no other provider would like."	Personal data, privacy	e.g., Berendt et al. 2005; Hoehle et al. 2012	Privacy
"I am not concerned about the security of my deposits." "Many banks are simply not up to date with encryption."	Security (technical dimension)	e.g., Littler and Melanthiou 2006	Security
"Banking cannot be easier and more convenient." "This is fast, easy and convenient when you do not have time."	Convenience	e.g., Berry et al. 2002; Collier and Kimes 2013; Seiders et al. 2007;	Convenience
"I'm currently looking for another bank to do my business with." "I came across this provider while looking for a free checking account." "So, if you are looking for something new, this account is definitely worth a look." "I found this bank during my search for a free checking account." "I'm still looking for a really good and secure app for all my bank accounts."	search, information acquisition	e.g., Bettman et al. 1998; Lee 2000; Moorthy et al. 1997; Payne et al. 1993	Search for alternatives
"If I had to open another savings account, I would consider … as my first choice again." "I will certainly never consider … for any business transaction in the future." "I strongly urge anyone thinking of doing business with … to reconsider." "If you want to have a free, secure and easy account, you should consider this one."	pre-choice, consideration	e.g., Bettman et al. 1998; Erdem and Swait 2004; Punj and Moore 2009; Shocker et al. 1991	Define consideration set
"Some standout features compared to other banking apps…" "This is by far the best banking app compared to others." "It has great notifications, works more real-time compared to other banks." "I set up and compared a few different vendors beforehand." "Conditions are rather bad in many fields compared to the online competition."	evaluation, comparison	e.g., Collier and Kimes 2013; Dabholkar 1996; Devlin 2001; Zeithaml 1981	Evaluate consideration set
"I decided on … and I couldn't be happier." "After trying a variety of prepaid debit cards, I decided to go with ..." "If I had known that … banking is so easy, I would have decided on this bank much earlier." "One reason I chose … is the dense branch network." "I chose … because it offers me the most modern and innovative online banking."	decision, purchase	e.g., Bonaccio and Dalal 2006; Hastie and Dawes 2010; Tam and Ho 2006	Purchase decision

II.2 Uncovering the digitalization impact on consumer decision-making for checking accounts in banking − Insights from a discrete choice experiment

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Abstract: Checking account providers must understand the importance of digital and non-digital service attributes across different customer segments to achieve a product-market fit in digitalization. In particular, various latent personal characteristics influence customer choices in digital banking. However, there is only limited research on bank customer behavior beyond the technology acceptance model, and none that explores customer preferences for checking accounts experimentally. Against this background, we present the results of a discrete choice experiment on customer preferences towards checking accounts in Germany. The outcome of the paper is a detailed quantitative assessment of the relationships between checking account service attributes and a set of latent influencing factors on choice. While customer service experience, the scope of services, and professional expertise are identified as re-occurring critical aspects for customers when choosing their banking service provider, the type of provider and digital product innovation showed little impact on customer choice overall. In multigroup analyses, we reveal the moderating impact of influencing factors on the preference of checking account service attributes. Additional segmentation analyses point to six customer segments from which four still prefer a traditional operating model. The largest segment of traditional product-innovative customers prefers digitalized, i.e., data-driven checking accounts in a mixed-mode with human customer advisory and on-site branch services from a traditional bank. At the other end of the spectrum, a small innovative Fintech customer segment, influenced by non-pragmatism and social norms, prefers a purely digital operating model with data-driven applications in banking.

1 Introduction

The primary checking account has always been an anchor point for house bank relationships of the traditional banking business. However, as digitalization is changing the nature of product and service offerings in banking, customer preferences for traditional products such as checking accounts may also have changed. Based on digital financial technologies, new market players ("Fintech") have introduced new innovative offerings to the banking industry (e.g., Alt and Puschmann 2012; Gomber et al. 2018). Neobanks such as Revolut or N26 already provide fully digital checking accounts. Such innovative digital offerings increasingly challenge the traditionally strong customer relationships with incumbent banks. Incumbent banks have started to react to these developments and innovated their product offerings in many places (Dehnert 2020b).

Many studies have been conducted on the usage and adoption of checking accounts. However, few studies go beyond the limited technology acceptance model to examine customer preferences in banking (Carbo-Valverde et al. 2020). Influencing factors, such as trust, expressiveness, or personal values, may also impact customer preferences for checking accounts (Pousttchi and Dehnert 2018). While survey studies still predominate, only very few experimental studies have been conducted in banking (Hoehle et al. 2012). Moreover, the future of checking accounts is also widely debated in practice. There is a broad opinion spectrum between bank traditionalists and Fintech evangelists on which service attributes will remain relevant in the future and what banking innovations will catch on. Hence, the future role of traditional banks as checking account providers and a trusted money depository on the one hand and the necessity of branches and human customer advisory on the other is highly controversial (Skinner 2021).

Against this background, this paper analyzes the customer preferences towards primary checking accounts with a discrete choice experiment. Against this background, this paper analyzes the customer preferences towards primary checking accounts with a discrete choice experiment. We answer the following research questions: *What traditional and digital service attributes do German customers prefer, and how are latent influencing factors linked to their choices?* Researching the observed heterogeneities, we explore how the choice of service attributes is moderated by influencing factors, such as personal trust-related, social, and attitudinal conditions. We further explore the unobserved heterogeneities to derive a set of latent customer segments. The outcome of the paper is a set of tested hypotheses on the importance of digital and non-digital service attributes, their interaction with latent influencing factors, and the description of customer segments. We contribute to digital product and service innovation research. Our findings provide bank managers with new insights to achieve a product-market fit for primary checking accounts.

The paper is structured as follows: In the next section, we introduce the theoretical background of our study. In section three, we describe the methodology for our quantitative analyses. Section four presents the results, i.e., direct effects analysis, moderating effects analysis, and the segmentation results for the unobserved heterogeneities. In section five, we discuss our results from a checking account service attribute perspective. In the last section, we establish theoretical and practical implications, provide avenues for future research, and discuss the limitations of the study.

2 Theoretical background

In this section, we provide the theoretical background and the research model for this study regarding the service attributes and the latent influencing factors on the choice of checking accounts.

2.1 Consumer-decision making in digital banking

Understanding consumer decision-making (CDM) is key to solving market planning problems, given the increasing spread of digital product offerings across customer segments (Blackwell et al. 2002; Schiffman and Kanuk 1997; Solomon et al. 2013), especially in the financial services domain (e.g., Milner and Rosenstreich 2013; van Raaij 2016). In particular, digitalization changes *CDM in banking* (Pousttchi and Dehnert 2018). However, studies that explored the digitalization impact on CDM in banking in developed countries are already quite outdated (Dick 2008; Iqbal et al. 2003; Verma et al. 2004). More recent results suggest that consumer characteristics, needs, and perceptions drive CDM in banking, providing the opportunity for customer segmentation (Carbo-Valverde et al. 2020). Related research also examines the omnichannel behavior of banking customers (Fang et al. 2021; Zhou et al. 2020). Practitioners instead speculate that traditional customer segmentation is no longer effective and that customer usage paradigms must be considered (e.g., The Financial Brand 2017). Therefore, we would like to explore this field of tension across numerous publications, especially from practice.

2.2 Random utility theory

We opted for a discrete choice experiment to examine consumer preferences in this study. Discrete choice experiments represent the decision complexity adequately and more realistically than survey studies since *compensatory CDM* can be measured appropriately. Hence, discrete choice experiments are precious for research on checking accounts that are low to mid involvement products (Pousttchi and Dehnert 2018). Discrete choice experiments present combinations of product or service attributes. Accordingly, we develop hypothetical decision situations for the participants of our experiment who have to decide between different product alternatives in a competitive market scenario (Hair et al. 2019). For each choice set, the participants must decide on one concrete product alternative or choose a 'none' option that is included to increase the realism of the experiment. The different choice sets presented as stimuli are evaluated based on latent personal preferences and finally trigger a choice decision (Solomon et al. 2013). The underlying choice model is based on *random utility theory* (Louviere et al. 2010). An individual study participant is regarded as a rational decision-maker who wants to maximize the utility relative to his or her choice. A customer is most likely to choose a product that provides the highest utility (McFadden 1984). The utility attributed to the good or service consists of a systematic component, which depends on the characteristics, and a random component. The systematic component can be statistically inferred via the observation of choices. Thus, the path coefficient for the choice of a specific attribute can be estimated. The random utility component is not observable and is an error term in the statistical sense. Depending on the assumption about the distribution of the error terms, different statistical models can be used for choice model evaluation. To this end, influencing factors such as latent personal characteristics can also be included in choice modeling (Ben-Akiva et al. 2002; Louviere et al. 2008).

2.3 Research model

2.3.1 Service attributes

The service attributes must be identified first. When designing discrete choice experiments, there is always a tradeoff between the number of attributes and the number of choice sets on which a participant can meaningfully decide in a concentrated manner. The CDM literature recommends that a discrete choice set consist of *five* to *nine* attributes (Street and Burgess 2007, p. 243). This literature also recommends creating suitable categories to reduce the number of attributes in a meaningful way.

For this purpose, we evaluated available practitioner studies on checking accounts and collected the attributes which find recurring relevance in recent discussions (e.g., King 2019; Kinting and Wißmann 2016; McKinsey 2019b; Roland Berger 2015; Skinner 2014). Many practitioner studies have focused on the role of Fintech as novel checking account providers and the future of traditional banks (Skinner 2020, Chapter 1), the accessibility of the account service (esp. the role of the branch: Roland Berger 2021; or new forms, such as pop-up stores: King 2019, p. 138), as well as the service experience and quality related to traditional and digital services (Loadwick et al. 2019; PwC 2018, 2021). The rise of digital channels to access banking (King 2019; PwC 2020a, 2020b), such as chatbots, is accompanied by a discussion around the future role of human customer advisory and expertise (Accenture 2021). The debate on digital technologies further evolves around specific Fintech solutions, such as personal finance management (Pickford 2019). Additional offerings beyond the core of a checking account are also discussed, such as credit cards or payment services (McKinsey 2019a; Shevlin 2021). Pricing is especially relevant regarding the low interest rate situation in European Banking and the necessary adaptations to tackle cost pressure across all providers (Simon Kucher 2019).

After collecting the relevant attributes from practice, we conducted 15 additional qualitative interviews with customers across different age groups. We asked them to describe and rank the most relevant attributes to complement our findings. The interviewees essentially stated the categories from the practitioner literature. Service attributes such as the availability of a personal contact person, branch accessibility, product innovation, and the experience, reliability, and pricing (costs) were important reoccurring aspects. While pricing is an important aspect to consider, we decided not to include this attribute as we wanted to focus on digital product and service innovation attributes. Free checking accounts are no longer economically feasible, so a pricing study would have required determining what people are willing to pay for primary and additional account services. Thus, we decided to keep the number of choices manageable for the participants and excluded the price attribute. Through the interviews, inconsistencies or overlaps in the combination of some product attributes could be identified, and our choice experiment design could be concretized.

Our selection was narrowed down to a final set of five service attributes strongly related to the impact of digitalization on CDM for checking accounts in banking. Altogether, the identified attributes address the provider type, the scope of services, the customer service experience, the digital product innovation (technology), and the human professional expertise. The attribute levels are varied with their characteristics related to the digitalization degree, resulting in eight hypothetical service offerings (i.e., choice sets). We conceptualized the following attribute levels:

– *Provider type*: Traditional bank, Fintech
– *Service scope:* Digital and analog access (branch/store), purely digital access
– *Customer service experience*: Very good service and intuitive operations, average service and cumbersome operations
– *Digital product innovation*: Standard app (only digital readouts), AI-based app (product and action recommendations matching personal financial/life situation)
– *Professional expertise*: High (personal experts available), low (digital assistants only)

In the following, we develop a set of hypotheses for the overall direct impact of the service attributes on choice.

Firstly, the *provider type* is an important criterion to account for in digital banking. Traditional incumbent banks and their Fintech counterparts, the neobanks, constitute the two types of customer account providers in the banking environment (Alt and Puschmann 2016; Eickhoff et al. 2017; Zavolokina et al. 2016). About one-third of the respondents could imagine switching from a traditional provider to a Fintech in a recent study (Jünger and Mietzner 2020). Personal brand preferences and the compatibility of brand types with consumer values might impact this. There could be a higher or lower valuation of traditional banks as the provider type. We suppose that German customers could still prefer a traditional bank due to its heritage value and nostalgic attachment. *We hypothesize that the provider type "traditional bank" positively influences choice (H1).*

Secondly, the *scope of services* is another potentially important criterion in digital banking. This attribute refers to the availability of stationary (i.e., non-digital) or purely digital services. Accordingly, a high scope of services includes the possibility of accessing one's account via a branch or store. Almost 75 percent of customers are still visiting bank branches (ING Group 2019), although the frequency of branch visits decreases rapidly. However, the habits of customers might be changing in digital banking (Berger and Messerschmidt 2009). The dense traditional bank branch system is threatened to be replaced by digital distribution channels, such as mobile, video, and voice banking (Alt and Puschmann 2012). Fintech might also consider opening pop-up branches or integrating their digital services into existing stationary advisory settings of partners in the future. Considering this, we expect both digital and non-digital services to be regarded more positively than digital services only (Zhou et al. 2020). *Therefore, we hypothesize that a "high" scope of services positively influences choice (H2).*

Thirdly, the *customer service experience* is an elementary attribute of services (Ding et al. 2011; Mbama and Ezepue 2018; Xin Ding et al. 2010). It entails positive affect, customer mistreatment, and customer service behavior, including customer orientation (Groth et al. 2019). Convenience largely shapes the overall customer service experience (Berry et al. 2002; Collier and Kimes 2013; Dai and Salam 2014). Plus, an overall positive customer service experience improves customer satisfaction (Helkkula et al. 2012; Homburg et al. 2017; Mocker and Ross 2013). However, both traditional banks and Fintech are reporting an increasing number of technical problems and failures. Depending on how much customers pay attention to this attribute, they seek information, including their own or external experiences with checking account providers. Customers access information traditionally through exchanging personal experiences (e.g., word-of-mouth) or, increasingly, digitally via online reviews. *Therefore, we hypothesize that customer service experience has a positive influence on choice (H3).*

Fourthly, *digital product innovation* is referred to as banking innovations (Gomber et al. 2017; Gomber et al. 2018). A digitalized bank could provide new types of applications based on transaction data analysis. Regarding checking accounts, AI-based digital assistants have gained currency (Maedche et al. 2019), such as in mobile apps, for example, the personal assistant "Erica" from Bank of America or the personal finance manager "Mint." These tools support customers in managing their personal finances (Gupta and Tham 2019, pp. 21 f.; King 2019, p. 120). Despite its potential, the propensity to use digital personal assistants is still relatively low (Bud 2020). On the other hand, standard mobile banking apps usually include financial overviews such as accounting records and overviews of monthly expenses. It is reasonable that customers are skeptical about novel digital products for checking accounts. *Therefore, we hypothesize that "standard" digital product innovation positively influences choice (H4).*

Finally, the importance of *professional expertise* is connected to the increased information transparency that gives self-efficacious customers an information advantage and power (Acar and Puntoni 2016). Customers obtain information on the Internet and carry out banking themselves. The information transparency may result in a loss of authority of customer advisors in banks (Kinting and Wißmann 2016).

However, customers might also have complex financial issues that they would like to clarify personally with their house bank. Some customers may also not need additional advisory services linked to their primary checking account. Consultations by human experts do not necessarily have to occur on-site but can also be provided digitally, for instance, via video channels, which are becoming more popular (Alt and Puschmann 2014). Although banking customers are increasingly engaged in self-service (Collier and Kimes 2013; Scherer et al. 2015), a customer advisor's availability and competence might still significantly influence the decision for a checking account (Laumann 2013). *Therefore, we hypothesize that "human" professional expertise exerts a positive influence on choice (H5).*

2.3.2 Influencing factors

This section introduces a set of influencing factors on CDM for digital banking that we identified in a prior study (Pousttchi and Dehnert 2018), and we derive specific hypotheses regarding their moderating impact. We will refer to a moderating influence when we find that the service attributes' regression paths on choice differ significantly between the groups we formed from the influencing factors. The population of the respondents may, for example, favor a specific type of provider, but this may be different across the influencing factor segments.

2.3.2.1 Personal trust-related conditions

We first distinguish consumer preferences that point to *personal trust-related conditions*. Trust is an essential prerequisite in many business-to-consumer interactions as it reduces uncertainty between transaction partners (Gefen et al. 2003). As it continues to be an essential aspect of digital commerce (Kim and Peterson 2017), it might especially be crucial for the banking industry (Breinich-Schilly 2020). *Calculative-based beliefs* involve the emotional connection between individuals and the calculated compromises between perceived gains and pains in cost and benefit calculations (Lewis and Weigert 1985; Ologeanu-Taddei and Vitari 2020; Rousseau et al. 1998). Customers value when service providers are professionally reliable and act in their interest (Gefen et al. 2003). *Structural assurances* are defined as "the belief that success is likely because of contextual conditions such as promises, contracts, regulations and guarantees" (McKnight et al. 1998, p. 478). The perception of structural assurances could likely influence banking account choice. Traditionally, customers could judge the bank's trustworthiness, for instance, by the body language of the advisor and clues from the environment, such as the appearance of the on-site business. This interaction between trust and personal expertise diminishes because banking is increasingly shifting to online environments with less personal contact (Hurley et al. 2014). What remains is that customers are more likely to think that the checking account provider does not fit them if they have problems with customer service or feel that their needs are not adequately understood (Xu et al. 2011). However, digital banking innovations might also be closely related to trust (Brewster 2016). Research shows that perceptions of interactivity could induce trust in mobile commerce (Lee 2005). Recent surveys have shown that customers are increasingly willing to consider PayPal and Amazon for banking (Mistry 2019; PYMNTS 2019). We suppose that the greater the tendency to trust is, the more customers are inclined towards less traditional products. On the contrary, customers who attach greater importance to trust could prefer more traditional attributes. For those people, traditional banks might enjoy a heritage value (Almquist et al. 2016). *Therefore, we hypothesize that personal trust-related* *conditions have a moderating influence on consumer choice (H-TRU)* to positively influence the preference of traditional service attribute levels.

2.3.2.2 Social conditions

We further look at the social conditions to reflect on consumers' socially constructed motives in banking, such as expressiveness (Nysveen 2005), market mavenism (Feick and Price 1987), or subjective norms (Li et al. 2008). The *expressiveness* construct addresses the ability to express style, image, and symbolic capital (Nysveen 2005). More expressive consumers need to perceive that a bank product expresses below instrumental utility. We expect that more expressive people are more likely to be enthusiastic about a specific provider type than less expressive people. A certain range of services might also be necessary for expressive people to express their personality in banking. More expressive people might value customer service experience higher concerning their choice. They could be more engaged with service quality and digital banking innovations. It could also be reasonable that more expressive customers value professional expertise higher, being more critical of the necessary competence of service personnel. In this regard, *market mavenism* is a related influencing factor. Market mavenism characterizes "people who have information about many types of products, shopping opportunities, and other facets of the market, initiate conversations with other consumers and respond to information requests from other consumers" (Feick and Price 1987, p. 83). Hence, market mavens constitute a reference group with high expertise (Solomon et al. 2013, p. 416). In this regard, we argue that more market-affine people could be more likely to choose a traditional provider type as these have a higher level of maturity. Since market mavens try to cover the market more and extend their knowledge greatly (Feick and Price 1987), we suppose that they might also be more interested in a higher scope of services than non-mavens. Customers familiar with the market might know more about the banking innovations of individual providers and evaluate them either more positively or more critically. It is also reasonable that market mavens place more value on professional competence. Furthermore, subjective norms point to the similarity of offerings to the customer, social environments, and the corresponding norms (i.e., *situational normality*). People who value situational normality higher could also prefer more traditional banking modes as these still constitute the norm. *Therefore, we hypothesize that social conditions have a moderating influence on consumer choice (H-SOC*) to positively influence the preference of traditional service attribute levels.

2.3.2.3 Attitudinal conditions

We further analyze *attitudinal conditions* resulting from attitudes towards the particular stimuli under consideration, such as perceived usefulness (Davis 1989) and perceptual affinity (Bruyn and Lilien 2008). People could be rather pragmatic or rather value-oriented to specific banking products and services. The *perceived usefulness* construct can be traced back to the technology acceptance model (Davis 1989; Lee 2009; Okazaki and Mendez 2013). Customers are likely weighing up which product is more practical, looking at their preferable checking account's functionality and task fulfillment. For the pragmatic, usefulness-oriented segment, this could mean that a specific provider type plays a significant role. The compatibility of consumer values is another aspect in forming attitudes that could impact banking account choice (Pousttchi and Dehnert 2018). The *perceptual affinity* construct measures the degree to which recipients and informants are similar in values and experiences, especially in a world of increasing digital interactions (Bruyn and Lilien 2008). The condition describes the value orientation that points to the functional or emotional similarity with the service offering. We presume that perceptual affinity could impact the customer service experience and digital product innovation positively. In turn, value orientation could also positively impact traditional service attributes such as the bank provider type or human customer advisory. *Therefore, we hypothesize that attitudinal conditions have a moderating influence on consumer choice (H-ATT)* to positively influence the preference of specific traditional and digital service attribute levels.

2.3.2.4 Controls

We include additional control variables to explain possible differences in consumer choices, such as the consumption-based experience of loyalty (i.e., prior checking account switching behavior), education, or age. *Loyalty* could play a considerable role in customer relationships for digital banking. Less loyal customers might especially be more open to other types of providers than the traditional bank. Personal characteristics, such as *age*, *education,* and *gender*, might also influence CDM in digital banking. We expect that older people might prefer a traditional bank because it might be thought of as a symbol of trust and heritage (Almquist et al. 2016). People might be especially more traditionally oriented for higher age groups. It is reasonable that the propensity for a higher scope of service increases with age. On the contrary, older people might not be keen on digital AI-based banking products but prefer higher professional expertise, such as a human customer advisor. Accordingly, we conducted additional analyses on the moderating influence of education (degree) and gender. Personal distress is included to measure the degree of ambiguity, uncertainty, or stress the participants perceive in CDM.

Figure II.2-1 shows the final research model with the direct effects and the interaction of choice attributes and influencing factors on choice.

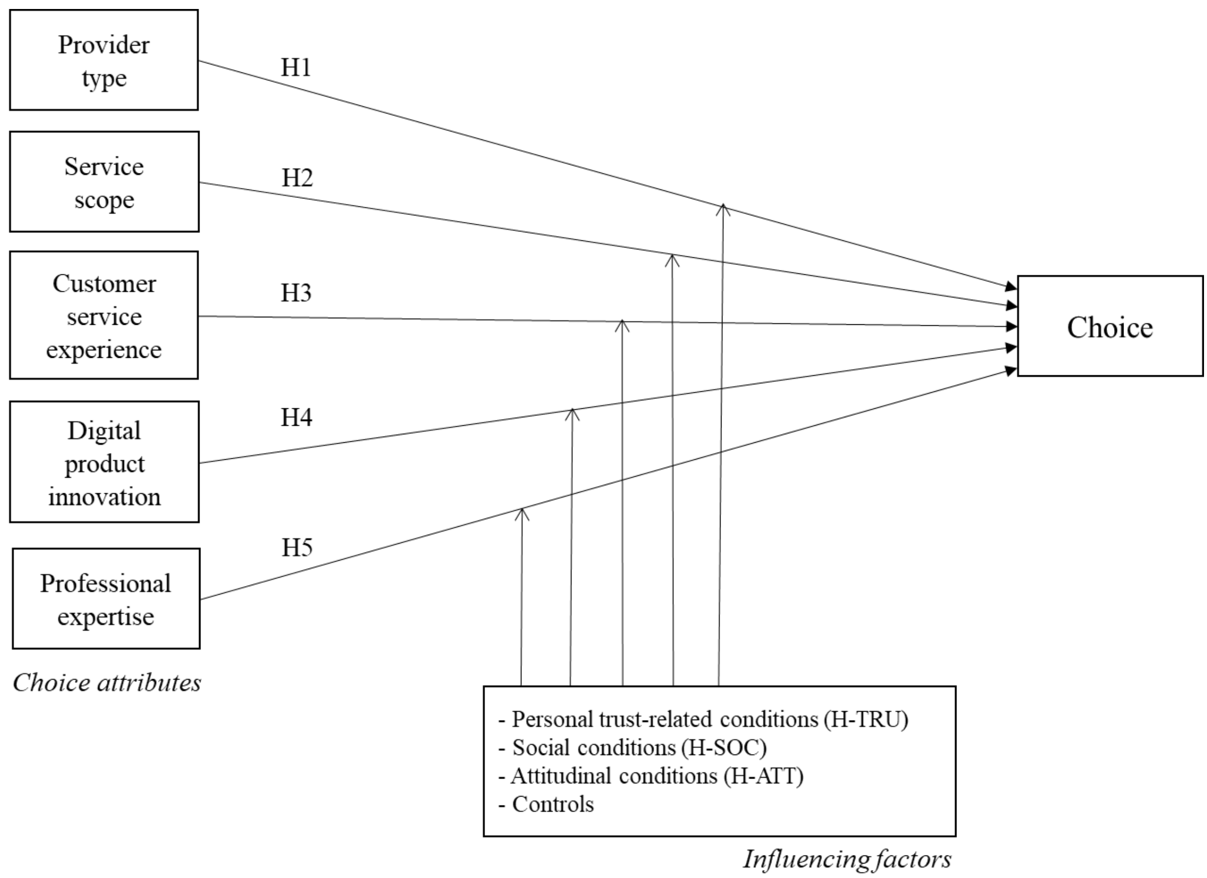

Figure II.2-1: Research model

3 Methodology

Our research approach follows three steps. After developing our research model, the survey, data collection strategies, and instruments were developed. We analyzed the data with SmartPLS 3.32, including structural and measurement model checks. We conducted flexible mixture modeling in "Flexmix" in R, a regression model framework using an expectation maximization procedure for latent class segmentation. In the following, we describe our survey design, data collection, and data analysis strategy in detail.

3.1 Survey design

The survey questionnaire entailed three parts. After the initial demographic questions and initial construct measurement, the second part was the discrete choice experiment with eight choice sets through which each participant was guided. An introductory text explained what a traditional bank and a Fintech are and the further experiment procedure to sharpen participants' awareness. We added an introductory page explaining the experiment. Before experimenting, participants were familiarized with the study using ex-ante explanations: A decision should be made about the primary checking account. A listing of bank types and potential representatives followed for traditional banks (e.g., savings banks, cooperative banks) and Fintech (e.g., N26, Apple, Google), plus the explanation of the experiment with an example.

We decided to follow a complete full factorial 2^5 discrete choice model from the literature (Street and Burgess 2007, p. 220), leading to eight choice sets each participant must choose on. Accordingly, eight choice sets were built systematically using an established choice experiment design software. We included our five service attributes for checking accounts with two levels each to preserve the orthogonality of the experimental design (Kuhfeld et al. 1994; Naous and Legner 2021; Street and Burgess 2007, p. 89). Each participant had to rate all the choice sets so we could conduct the multigroup analysis. Thus, block building was avoided. An exemplary choice set is depicted in Figure II.2-2.

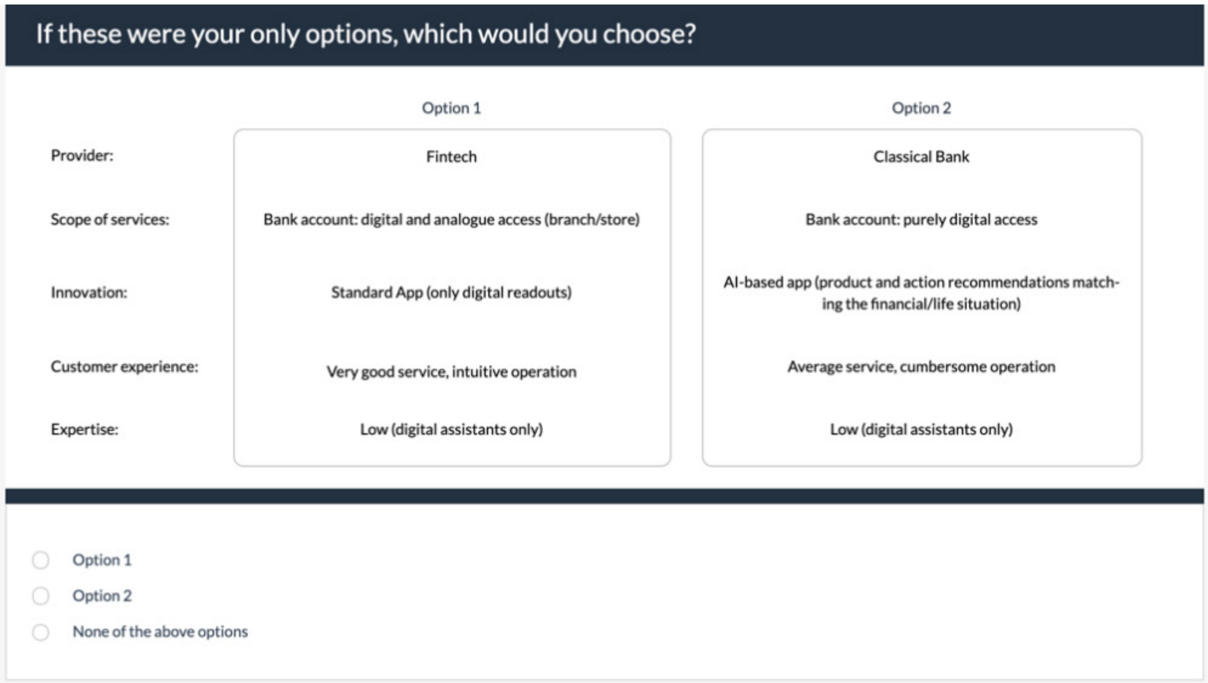

Figure II.2-2: Exemplary choice set (translated)

Each participant went through the randomized eight choice sets having three options: Choosing option 1, option 2, or a 'none' option. In case the participant took an option, this choice option became "1," otherwise "0," and both options in a choice were set at "0" in the case of choosing the 'none' option. Thus, each participant has implicitly made 16 decisions.

The third part of the survey included further questions on CDM influencing factors afterward. With this, we collected data on the remaining influencing factors. We did not measure the latent variables after each choice specifically but asked the respondents about the overall impact of different aspects on their decisions. These questions included a questionnaire with 6-point Likert scales ranging from *Do not agree at all* to *Totally agree*. The constructs were measured reflectively. The questions are based on scales from the relevant literature (see section 2). We used a single item for loyalty, age, gender, and education (degree). The construct items are listed in the appendix. All questions relevant to the evaluation were mandatory.

We conducted a *pre-test* with university students collecting over 50 responses to test comprehensibility and then solicited comments and suggestions for improvement via a free text field. Overall, the participants confirmed that they understood the experiment and felt their CDM process had been adequately considered.

3.2 Data collection

Our data were collected using the developed anonymous survey conducted with a German market research firm in summer 2020. The data collection entailed an online panel in a cross-sectional sample of adult customers with 992 valid participants. Additionally, we placed a short announcement of our online experiment in a major German financial magazine ("Finanztest") to reach more offline participants, with 205 valid responses. Participants with short processing times were excluded ex-post. We removed 34 implausible responses from the online panel and four responses from the magazine. Overall, we evaluated 1197 valid responses. We checked the overall results and compositional invariance for both groups afterward but did not identify remarkable differences. The participants had the possibility of determining time and place independently. Since the participants were not observed directly, social desirability bias can be regarded as low. Another measure to reduce bias was randomizing the question order, such as the sequence of choice sets. The scales in the survey questionnaire were generally kept consistent to avoid common method bias (Podsakoff et al. 2003). The sample demographics distribution is depicted in Table II.2-1. Due to the balanced sample and the orthogonal experiment design, it is possible to derive more detailed statements about the preferences of the subgroups. The participants are relatively evenly distributed among the different age groups and slightly predominant among the 30- to 39-year-old people. There was a slight surplus of survey participants without a university degree, the same for the male gender.

Table II.2-1: Sample demographics

Age	
18-20	0.6%
21-29	16.2%
30-39	32.0%
40-49	18.1%
50-59	22.6%
Above 60	10.4%
Education	
Lower secondary school graduates or equivalent qualification	6.3%
Secondary school certificate or equivalent qualification	23.3%
Advanced technical college entrance qualification or equivalent	8.8%
A-levels or equivalent	16.3%
Ungraduated university studies	3.3%
Bachelor's degree	16.8%
Master's degree	22.8%
Doctoral degree	2.4%
Gender	
Male	56.2%
Female	43.8%

Note. n = 1197.

3.3 Data analysis

We used *partial least squares structural equation modeling* (PLS-SEM) and *finite mixture modeling* (Flexmix) to estimate the effects. The analysis of discrete choice data in PLS-SEM is based on linear probability models (Hair et al. 2019; Naous and Legner 2021). We chose this novel analysis approach to conduct multigroup analysis for moderation effects. The estimated regression coefficients correspond to the utility values of a service attribute (i.e., part-worths) on our binary dependent variable, "choice." The coefficients finally represent relative instead of absolute influences on choice. The orthogonal experimental design causes the values for attribute levels to differ in their magnitude ("−1"). For instance, if the attribute level "traditional bank" is positively valued with a coefficient of "0.2," the "Fintech" attribute level would be precisely orthogonal and valued at "−0.2."

We first used the discrete choice data and estimated the direct effects using the PLS-SEM algorithm, bootstrapping with 5000 samples. As expected, the results for the path coefficients of the service attributes were identical for PLS-SEM and Flexmix.

Next, we elaborated on the *observed heterogeneity* in PLS-SEM, i.e., the influence of the surveyed latent characteristics of the experiment participants on the weighting of their preferred choice attributes (Hair et al. 2018, pp. 135 ff.). A conventional moderator analysis is not recommended for continuous independent and binary dependent variables in PLS-SEM (Bodoff and Ho 2016). However, a comparative multi-group analysis is possible for binary target variables, and we can create these groups using the latent variables. We used the *PLS-SEM multi-group analyses*, i.e., PLS-MGA and permutation procedures (Hair et al. 2018). Hence, subpopulation samples are analyzed as separate groups, and the significance levels of the group differences are estimated afterward (Henseler 2012). PLS-SEM comes into its own here since we can calculate the regression coefficients and determine the significance levels for group differences by bootstrapping, which is a pragmatic approach for a moderation analysis. We took the center value of our 6-point Likert scales as the differentiation criterion for the membership into a low or high group and the lower and upper boundaries ("2" and "5") for very low and very high group memberships.

PLS-SEM currently does not support the analysis of *unobserved heterogeneity* with aggregated choice data. Therefore, we performed the latent class regression analysis in R. The Flexmix package was used to segment the data by assigning each participant observation to latent classes to derive divergent CDM clusters. Finite mixture models are estimated with a maximum likelihood estimator and the expectation-maximization algorithm (Leisch 2004). We integrated the binary service attributes and the construct score values for the influencing factors (calculated in SmartPLS) for hybrid choice modeling (Louviere et al. 2008). For estimation, we used a method known as the "joint approach" that produces less error in latent class segmentation (Andrews and Currim 2003). The method is implemented in Flexmix as the "concomitant variable model" with two parts (Grün and Leisch 2008). The variables in the regression model influence the dependent variable, choice, while the influencing factors in the concomitant variable model explain the segment affiliations (sizes). While the choice model can be estimated with the binary service attributes, the Likert scaled influencing factor data must be estimated as a multinomial logit model. The procedure then involved a parameter estimation in maximizing the log-likelihood values. This procedure delivered the path coefficients for the binary service attributes on choice. The influences of the latent personal characteristics on the various segments were determined in the multinomial logit model. For this purpose, we have set the largest segment as the baseline. The coefficients show the change in log odds when one predictor changes by one unit, holding all other predictors constant. In principle, their interpretation is identical to multiple linear regression coefficients. The significance of the results was tested in Flexmix by bootstrapping and log-likelihood tests (Train 2009, pp. 71 ff.). We checked for identifiability problems by comparing the bootstrapped results for different numbers of segments (Dolnicar and Leisch 2010; Leisch 2004). While minimizing the Akaike and Bayesian Information Criterion and log-likelihood values, the derived assignments became a stable compromise of segment size, empirical explanatory value, and model quality leading to a *six-segment* solution (cf. Hair et al. 2018, pp. 182 ff.). Here, we found the highest practical explanatory value and theoretical generalizability. For bootstrapping with 1000 samples, the likelihood ratio test was passed with a p-value of 0.026. The segment assignments remained stable; however, the regressors varied slightly due to the probabilistic nature of the expectation-maximization algorithm.

3.4 Construct evaluation

The construct evaluation includes reliability and discriminant validity tests (Hair et al. 2014). The PLS-SEM literature recommends using composite reliability. The constructs' composite reliability values are above 0.7 and below 0.9, as recommended in the literature. The PLS-SEM calculation of Cronbach's alpha is sensitive to the number of items, underestimating alpha (Hair et al. 2014, p. 101). A minimum alpha value of 0.5 is recommended for constructs with two indicators, 0.6 for three and 0.7 for four or more indicators (Ohlwein 1999, p. 224). All constructs met this requirement. The outer loadings are all well above the recommended value of “0.708” for the reflective constructs. The average variance extracted (AVE) is also well above the recommended minimum value of “0.5” (Hair et al. 2014, p. 103). Thus, the constructs show no issues regarding composite and convergent reliability. The results are listed in Table II.2-2.

Table II.2-2: Construct validity and reliability

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Importance of trust	0.822	0.826	0.894	0.738
Calculative based beliefs	0.756	0.759	0.891	0.804
Structural assurances	0.846	0.852	0.907	0.764
Expressiveness	0.835	0.978	0.893	0.738
Market mavenism	0.894	0.931	0.933	0.823
Situational normality	0.619	0.831	0.825	0.705
Perceived usefulness	0.880	0.881	0.926	0.807
Perceptual affinity	0.806	0.821	0.872	0.632
Personal distress	0.886	28.143	0.902	0.824

Regarding discriminant validity, the Fornell-Larcker criterion was satisfied. The heterotrait-monotrait ratio of correlations (HTMT) indicated that the importance of trust and calculative-based beliefs on the one hand and expressiveness and market mavenism on the other was perceived somewhat similarly by respondents as they show slightly higher HTMT values than recommended in the literature. Accordingly, it can be assumed that these constructs show similar effects on choice, which is not an issue for our purpose of analysis as they were assigned to the same respective group of conditions. The collinearity statistics with the variance inflation factor showed values below “2” and a single value of “3.5,” which is still below the recommended threshold of “5” (Hair et al. 2011). We also checked the configural and compositional invariance of the constructs for the multigroup analysis (cf. Hair et al. 2018, pp. 139 ff.), with no identifiable issues. The results are listed in Table II.2-7 to Table II.2-9 in the appendix.

4 Results

In the following, we examine the direct and moderating effects of the influencing factors on choice and derive the latent segmentation results. We have chosen the typical configuration of a *traditional universal bank* as the reference point in the results section (see Table II.2-3, left column). The utility values for the respective contrary (i.e., typically digital) attribute levels are orthogonal.

4.1 Direct effects

Firstly, we describe the overall results of the direct effects. Table II.2-3 presents the results for the total sample. We also report interesting path coefficients in brackets in the text.

The overall direct effects show that the average survey respondent was rather *traditionally oriented* towards checking accounts. The *average customer* still prefers a traditional bank, the possibility of both digital and a branch or store service, as well as appreciates a high customer service experience, a standard mobile app, and the possibility to contact a personal advisor. While all direct regression paths are significant, we found that the provider type (0.042) and digital product innovation (0.023) are way less decisive service attributes compared to customer service experience (0.280), professional expertise (0.210) and the scope of services (0.186).

Table II.2-3: Overall direct effects (total sample)

Dependent Variable: Choice	Path coefficient
Provider type (“traditional bank”)	0.042***
Scope of services (“both digital and branch/store”)	0.186***
Customer service experience (“high”)	0.280***
Digital product innovation (“standard app”)	0.023***
Professional expertise (“human customer advisor”)	0.210***

Note. Significance level: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

The latter factors influence customer choice more strongly. Although the average participant in the cross-sectional sample slightly tends to favor a traditional bank, the customer service experience of the provider is ultimately seven times more important to them than the provider type. A high level of professional expertise is about ten times more decisive criteria than digital product innovation. These results highlight that, on average, checking accounts are evaluated primarily based on customer service experience, service scope, and human professional expertise. Accordingly, digital product innovation, on average, is only a means to an end in CDM. However, our findings indicate that all service attributes still significantly impact the choice of checking accounts. Hence, we support *H1 to H5*. An additional analysis of the observed and unobserved heterogeneities is vital to identify the moderating impact of the influencing factors and the underlying customer segments for checking account choice.

4.2 Moderating effects

Secondly, we present the results of the multigroup analyses on the observed heterogeneities, i.e., the interaction of the influencing factors with the service attributes on choice. Figure II.2-3 summarizes the results graphically with coefficient plots. The tables for the multigroup analyses can be found in the appendix.

4.2.1 Personal trust-related conditions

The majority of participants with low importance of trust emphasized the service scope, customer service experience, and human customer advisor in their choices. These results differed for the more trust-sensitive participants who weighted the traditional bank as the provider even above the human customer advisor. The results for calculative-based beliefs reveal a similar picture with slight differences on the periphery. People with such trust perceptions put less emphasis on the traditional branch-based operating model or a human customer advisor. They would prefer a traditional bank and AI-based mobile app (−0.072) even more. Our analysis thus reveals that traditional banks are chosen if a customer values or perceives trust intensely. Moreover, choosing digital product innovations also requires trust perceptions. People who perceived structural assurances in CDM were more likely to choose a traditional bank as the provider and more prone to the traditionally high service scope. Hence, branches can be considered contributors to structural assurances. Overall, our results indicate that trust beliefs have a moderating influence on choice. We support H-TRU due to the identified significant group differences. Table II.2-10 in the appendix shows the results of the multigroup analysis for H-TRU.

4.2.2 Social conditions

Regarding social conditions, the majority of participants reported being among the more expressive and knowledgeable customers. We found that more expressive and experienced customers value a traditional bank as the provider and high service scope, indicating a strong imprint of the traditional operating model. At the lower end of the expressiveness spectrum, people slightly preferred a Fintech as the provider (−0.049) but were still indefinite about the level of digital product innovation. The traditional bank provider type, a high scope of services, and a human customer advisor is essential for the high maven group, regardless of the consistently high value of customer service experience. Thus, digital banking innovations surprisingly play more of a subordinate role for both mavens and non-mavens. The high norm group gives customer service experience also a higher priority. We found significant changes in the segments, supporting H-SOC. Table II.2-11 summarizes the results of the multigroup analysis for H-SOC.

4.2.3 Attitudinal conditions

We further observe the impact of attitudinal conditions on CDM. Regarding perceived usefulness, a pragmatic customer has a higher preference for the traditional bank as the provider type, a lower customer service experience orientation, and a lower affinity towards a human customer advisor. Both the high and low segments do not put much emphasis on digital product innovation. However, the very pragmatic users would favor an AI-based mobile app (−0.064) in managing their personal finances. For perceptual affinity, we found less apparent changes in CDM. The more perceptually oriented consumers emphasize customer service experience even more. Surprisingly, human customer advisors are significantly less important for the very perceptually affine consumers than for the non-affine users. Still, the focus remains on traditional product categories across these segments. The influencing factors are less impactful than expected, as perceptual affinity primarily affects the peripheral groups. We support H-ATT based on the identified significant group differences. Table II.2-12 shows the results of the multigroup analysis for H-ATT.

4.2.4 Controls

Other aspects of CDM have been considered as controls, such as loyalty, gender, or age. A majority of the participants claimed to be less loyal customers. The very loyal customers would consider a Fintech (−0.057) as the provider type than their peers. The analysis on *degree* revealed that the more educated people value customer service experience even more than people without a university degree. However, these participants showed significantly less demand for a traditional branch-based operating model (but still do). Regarding *gender*, we found only very few group differences. A broad service scope including branches was a bit more important to women than men. It became clear that with increasing age, people favor a traditional bank as the provider type; this was particularly significant for the over 59-year-olds. Accordingly, our data show that customer service experience is more important for older people. Surprisingly the younger participants are only slightly more digitally affine than their older peers. We also find it interesting that the younger participants show a slightly higher demand for a human customer advisor. For reasons of space, we have not included the coefficient plots for distress in CDM. Table II.2-13 in the appendix exhibits the results of the multigroup analysis for the controls.

Notes. PT = Provider type ("traditional bank"), SS = Service scope ("digital and analogue access"), CE = Customer service experience ("high"), DI = Digital product innovation ("standard app"), PE = Professional expertise ("human customer advisor").

Figure II.2-3: Results for the observed heterogeneities (influencing factors)

4.3 Latent class segmentation

Thirdly, we present the results for the analysis of unobserved heterogeneities, including six latent customer segments. Table II.2-4 shows the segmentation results sorted by descending segment size. The segments are designated according to their characteristic service attributes. Table II.2-5 shows the multinomial logit model results for the impact of the influencing factors on the segment assignments compared to the baseline.

Table II.2-4: Identified segments in the latent class regression analysis

Dependent Variable: Choice	Segment 1 "Traditional product-innovative segment"	Segment 2 "Advisory-focused segment"	Segment 3 "Direct banking segment"	Segment 4 "Fintech segment"	Segment 5 "Experience-focused segment"	Segment 6 "Branch-focused segment"
Provider type ("traditional bank")	0.203***	−0.123***	0.006	−0.219***	0.022	0.143***
Scope of services ("both digital and branch/store")	0.270***	0.080***	−0.158***	−0.051**	0.226***	0.742***
Customer service experience ("high")	0.174***	0.324***	0.012	0.485***	0.750***	0.174***
Digital product innovation ("standard app")	−0.124***	0.189***	0.272***	−0.329***	0.200***	0.056***
Professional expertise ("human customer advisor")	0.243***	0.561***	−0.001	−0.028	0.211***	0.046**
Segment size (share)	416 (33.7%)	220 (17.8%)	165 (14.6%)	134 (11.3%)	133 (11.3%)	129 (11.3%)

Note. Significance level: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

The first and largest cluster differentiates the "traditional product-innovative segment" of customers that prefer a traditional but digitalized operating model. This segment favors traditional banks as their provider but would prefer a more digital product offering and is thus open to data-driven, innovative banking applications. These customers do not (over-) emphasize customer service experience compared to the overall results. They still value the opportunity to visit a branch and prefer a "human" touch of banking, including the possibility of contacting a human customer advisor. The analyses show that this segment primarily entails usefulness-oriented, middle and higher-aged customers compared with the other segments.

The second solution shows the "advisory-focused segment" of customers with a low propensity for digital product innovation and a strong focus on the human aspects in banking, i.e., customer advisors. These customers, surprisingly, would also be inclined towards alternative offerings of Fintech. Moreover, the customer service experience is essential to customers in this segment. Accordingly, a standard app would be sufficient for them. They attach the least importance to bank branches among the attributes. These customers are less concerned with trust than the baseline, younger than those in the largest segment, and more oriented towards subjective norms (situational normality). They come from a higher educational background and have a greater perceptual affinity for values that are primarily oriented towards traditional banking expertise.

The third “direct banking segment” shows a very pragmatic attitude towards banking. These customers prefer purely digital access to their checking accounts and want to manage their finances without human customer advisors (but are also not inclined to digital assistants). Standard app functionalities are also sufficient for this customer segment. Both the provider type and the customer service experience are irrelevant choice criteria. Thus, direct bank customers are, in principle, open to both types of providers. These customers are typically less frequent bank switchers than the baseline customers. We found higher importance of trust compared with the traditional product-innovative customers. Direct banking customers are less likely to be market mavens than customers in the largest segment.

We further identified a fourth “Fintech segment” that entails customers who value a purely digital checking account. They consciously choose a Fintech provider, demand advanced AI-based digital product innovations, and prefer to do their banking digitally without branches and human customer advisors. However, the outstanding attribute for this customer segment is the intense focus on the customer service experience, which is expressed in the digital realm. Still surprisingly, this segment is also relatively small, reflecting the market share of these providers in Germany. Fintech customers are also more trust-oriented than traditional bank customers, presumably as they prefer novel market offerings. This customer group is clearly among the youngest customers among the segments. They perceive CDM situations as more stressful than their peers. Their decisions are less pragmatic, i.e., not as usefulness-oriented as those of traditional product-innovative customers. They may value playfulness, ease of use, and perceived enjoyment. In addition, these young customers are significantly more oriented towards their environment and the prevailing social norms. Interestingly, they tend to have less detailed knowledge of the market from their perception, although this was barely not significant. These customers do not count themselves as frequent product switchers, maybe as many of them could be rather new to banking.

The fifth “experience-focused segment” suggests that the customer service experience is paramount to these customers. They value seamless operations without interferences or malfunctions. Yet, the remaining traditional attributes, such as bank branches and personal customer advisors, are also crucial for them. These customers are not interested in digital product innovations. Thus, the customer service experience is primarily expressed in standard processes that may still involve human interactions. However, when it comes to the provider type, they are undecided and could principally be open to new market offerings. These customers have a higher level of education than the traditionally innovative customers. They are more loyal and value-oriented (perceptually affine) but less pragmatic than the customers from the baseline segment. This value orientation thus relates to traditional banking attributes such as a positive customer experience, including a personal human touch. Accordingly, private banking customers could be found among them.

Finally, the sixth “branch-focused segment” has a strong demand for traditional branch access to banking. Other than that, this segment is rather unremarkable. These customers prefer a traditional bank but are somewhat undecided about digital product innovations. Interestingly, however, the human customer advisor is not very important to this segment, so these customers are primarily interested in retaining on-site self-services. Customers in this segment come from a lower educational background compared to the traditional product-innovative customer segment.

Table II.2-5: Multinomial logit model results

Dependent Variable: Choice	Segment 2 "Advisory-focused segment"	Segment 3 "Direct banking segment"	Segment 4 "Fintech segment"	Segment 5 "Experience-focused segment"	Segment 6 "Branch-focused segment"
Importance of trust	−0.212	**0.539*****	**0.280***	−0.110	0.152
Calculative beliefs	**−0.330**†	0.263	0.256	0.091	0.185
Structural assurances	−0.043	−0.076	−0.202	−0.010	−0.196
Expressiveness	−0.135	−0.002	−0.112	−0.006	0.062
Market mavenism	0.125	**−0.327***	−0.220	−0.130	0.022
Situational normality	**0.175***	−0.075	**0.224***	0.076	−0.033
Perceived usefulness	−0.168	**−0.260**†	**−0.597*****	**−0.624*****	0.001
Perceptual affinity	**0.264***	0.214	0.187	**0.564*****	0.062
Loyalty	0.044	**0.205***	**0.308*****	**0.284*****	−0.055
Age	**−0.203***	−0.123	**−0.338****	−0.114	−0.135
Gender	0.286	0.121	0.037	−0.138	−0.178
Education	**0.105***	−0.083	0.004	**0.151****	**−0.131***
Distress in CDM	0.017	**−0.192***	**0.207***	−0.132	0.109

Note. Significance level: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

From the path coefficients, we can draw inferences on CDM behavior. The results for the largest first segment indicate a very balanced CDM involving all service attributes. For segments two, four, five, and six, we can infer from the single high path coefficients that these customers are very focused on particular service attributes, i.e., human personal advisory for segment two, customer service experience for segments four and five, and branch operating model for segment six. Participants in segment three have focused on the fulfillment of the digital operating model criterion.

5 Discussion

We conducted a discrete choice experiment to analyze the personal preferences for checking account services among German banking consumers.

All hypotheses on the *direct effects* are supported to impact choice significantly, with different strengths. The overall results show that the majority of participants opted for a traditional banking model. We can state: On average, customers prefer a modern digital service offering from a traditional bank that provides branches and human customer advisory (at least) on demand. We found that the customer service experience is the most important aspect for customers regarding their choice. Our results indicate that the average bank customer does not need fancy digital features *per se* but bases its choice more on a positive customer service experience. Regarding this, our results show how fatal increasing reports of technical problems at banks can be for customer retention and acquisition in almost all customer segments (Charette 2020).

Our findings allow statements on the damping or strengthening *moderating effect* of the influencing factors on the service attribute preferences. Overall, we see that our conditions help explain customers' preferences towards digital properties of checking accounts to varying degrees.

Considering the role of the *provider type,* we gained the insight that the personal trust-related, social, and attitudinal influencing factors as well as age all have a positive (i.e., strengthening) influence on the traditional bank preference. People who strongly emphasize trust choose the traditional bank as provider type, which is a reasonable finding. However, we would have expected a more substantial influence. A key factor certainly is that customers assume that a traditional bank could be more likely to act in the customer's interests and be perceived as more reliable. Those customers also perceive structural assurances more strongly. We further found that social conditions have the greatest impact on this attribute, as mavens opt for a traditional bank while non-mavens prefer a Fintech as their provider type, given the perception of professional intelligence. Market experts favored traditional products, possibly reflecting traditions in the German banking market. Overall, the traditional bank still holds a heritage value as a safe harbor for money that attracts and builds trust with the oldest group of customers (and with the younger, more indecisive people).

Regarding the *scope of services*, we found that the more maven and expressive people value a broader service offering, including the possibility of accessing these services via non-digital ways. On the contrary, loyal customers tend to hold on to this form of customer access less, although the effect remains positive. Interestingly, the non-maven and low expressive customers place the least value on a branch-based operating model. Apparently, they lack a strong connection to this traditional service attribute, being among the direct banking and Fintech customers.

In addition, *customer service experience* turned out to be even more important for older and more expressive customer segments, while there is a constantly strong overall influence from this attribute. The very loyal customers value this attribute by far the highest, whereas the social and the attitudinal conditions also have an effect but do not make a vast difference here. In contrast, the segment of the usefulness-oriented (i.e., pragmatic) users do value experience considerably less high. We have seen that this attribute will also involve analog personal interactions for four segments, whereas, for direct banking and Fintech customers, it will involve mostly digital interactions.

Remarkably, we also found that *digital product innovation* is not very decisive for people *on average*. Customers who strongly perceive structural assurances prefer innovative data-driven digital products. Furthermore, we found that a strong usefulness orientation can explain the choice of digital product innovations. Plus, *age* can explain innovative choices here, as the under 30-year-olds tend to be a bit more open to digital innovation but remain somewhat indefinite. For customers in the largest segment, digital AI-based products are initially a companion factor, while for Fintech customers, they are a critical decision-making factor.

Consumer preferences for *professional expertise* typically could remain with human customer advisors for the primary checking account. Remarkably, those customers who strongly emphasized calculative-based beliefs were the most indecisive on human personal advisory. This finding is interesting as we could infer a lack of trust in banking customer advisors (and their benevolence). Also, a very high perception of structural assurances indicated that customers are more likely to dispense with the expertise attribute or pay less attention to it. Moreover, the market mavens, the expressive, highly educated, and (surprisingly) the younger customers would rely on the possibility of contacting a human customer advisor the most. We assume that the mavens are more familiar with the banking products and the necessary expertise behind the product. We have seen customers from the largest segment and the second higher educational segment opt for human advisory. They belong to the group of customers who might have more complex banking needs and might know more precisely what requirements they have of their checking account provider. We can infer that banking market expertise should not be equated with Fintech innovativeness.

All moderators considered individually could have led to strong preference shifts, but none of the influencing factors pushed the overall choice firmly into the digital realm. Overall, strong digital attribute preferences could not be adequately explained through the singular observation of observed heterogeneities. Quite contrary, the latent class segmentation analysis explained the participant memberships to the more digital segments. Our analysis revealed that four customer segments would prefer both branch-based and digital access to banking checking accounts, which points to our sample's predominantly traditionally-minded German customers. Here, our influencing factors also contributed to explaining the segment assignments.

We want to discuss two further exciting findings from the segmentation results. Firstly, the largest, rather traditionally oriented customer segment still prefers a high service scope. Nonetheless, a stronger propensity towards digital product innovations becomes evident for this customer segment. Hence, pragmatic customers are open to digital innovations for data-driven banking, which must coincide with a positive customer service experience. Secondly, a smaller segment was identified that opts for purely digital checking accounts from Fintech at the other end of the spectrum. Some Fintech advocates might have chosen these offerings out of sheer inexperience, as we found some indications on this. However, social aspects and a non-pragmatic attitude towards banking strongly influence the preference of Fintech checking accounts. In this regard, most of the younger Fintech customers have shown a significantly stronger orientation towards subjective norms than the traditional product-innovative bank customers. Hence, these customers are likely more aware of Fintech products in their daily lives, including everyday encounters with the peer group or the sheer urge to experience novelty. We could also imagine that one reason for the different choice patterns is a change of customer journeys, primarily in the digital realm, such as online communities or social media platforms. We highlight several implications for research and practice in the following.

6 Conclusion

6.1 Implications for research

This paper provides a novel perspective on the interactions between service attributes and latent customer preferences for CDM in banking. We used a novel research approach for conducting IS studies on consumer behavior. Random utility theory posits that consumer preferences generally are a good predictor of customer choices. The choice design followed strict requirements of a full factorial model with the service attributes derived from current practice developments. The results show a broad spectrum of customer preferences that adequately reflect the market. Our findings provide novel insights into the diffusion of banking innovations, especially regarding the role of the novel Fintech provider and digital product innovations (Alt and Puschmann 2012; Gomber et al. 2018). In particular, we extend prior studies on banking service choice (e.g., Iqbal et al. 2003; Matsuo et al. 2018; Verma et al. 2004). Almost 20 years later, our results support Verma et al. (2004) that traditional bank attributes such as human professional expertise still matter. However, the increasing demand for digitalized products and services becomes apparent for latent customer segments.

We enrich the discussion on the influencing factors on the choice of banking providers, with traditional banks enjoying some historical merit, especially among trust-sensitive customers (Ologeanu-Taddei and Vitari 2020). Our study also updates the Iqbal et al. (2003) results for choice preferences among social conditions. We discovered market mavens to be very prone to traditional banking attributes, while Iqbal et al. found that high e-familiarity online consumers seemed to be the least demanding consumers. Furthermore, our results confirm the findings by Matsuo et al. (2018), indicating that social influences such as market mavenism go hand in hand with a more conservative approach to banking. However, the traditional pragmatic customer segment makes very balanced decisions and is probably less prone to adapt these products solely for making new digital experiences. Our results also suggest the impact of a cultural value dimension on CDM in banking (Tam and Oliveira 2019). Perceptual affinity was not very informative as a moderator solely, however, it helps identify the more traditional experience- and expertise-focused customer segments. Although positively related, perceptual affinity did not significantly explain the participant assignment to the Fintech customer segment. Overall, our analysis shows that our latent influencing variables can still explain the assignment to customer segments, including more digital ones. Likewise, the moderation analysis showed several significant results but only partially explained a shift towards digital service attributes. Our quantitative analysis thus confirmed prior qualitative research (Pousttchi and Dehnert 2018) that various latent personal characteristics influence preference formation in digital banking.

Our findings indicate that customer service experience plays a vital role for traditionally and digitally oriented customers, contributing to the research on service experience (Groth et al. 2019). Regarding this, we provide updated and more fine-grained results for the developments around Fintech. The Fintech segment demands digitalized service experiences and product innovations, pointing to embedded finance to attract these customers as early adopters (Alt, Ehmke et al. 2019; Chen et al. 2018; Nüesch et al. 2015). We expect these products to spread the market if they provide a positive customer service experience in the digital realm.

6.2 Implications for practice

Several practical implications can be derived from our results. Checking account providers must find an appropriate product-market fit in digitalization (Bloch 1995). Particularly, the dialectics of traditional and digital bank service attributes must be resolved strategically. While many banks claim to preserve the status quo, the Fintech innovators instead claim that future banking will be purely digital. Our results indicate that the truth lies somewhere in between as the optimal or preferred level of digitalization differs between the identified latent customer segments. The results show that traditional service attributes, in which traditional banks are powerful, could remain relevant in the future − albeit with a different integration due to varying use frequencies. Related research also shows that adopting digital-only bank services could increase the total transaction volume of customers but keep the traditional primary banking transactions stable (Fang et al. 2021). Accordingly, the digital business primarily offers new revenue potentials that traditional banks could leverage. Other scholars showed that maintaining a minimized stationary customer interface is helpful in the omnichannel to prevent declining transaction volumes among all channels (Zhou et al. 2020). Our results suggest that further resources should be invested in digital service offerings, particularly addressing the human-technology interface, to enable seamless banking operations and a more accurate allocation of specialist expertise to customer needs, especially for advisory services.

While the type of provider plays a subordinate role overall, banks still enjoy customers' historical merit here. In Germany, at least, digital Fintech offerings are primarily attractive for peripheral groups. In this regard, traditional banks should find ways to fulfill the identified digital expectations of the largest traditional product-innovative segment. Traditional banks need to score with a well-thought-out combination of traditional and digital service attributes. In addition to traditional values such as a broad service scope, digitalization should be pushed forward to improve the customer service experience and provide digital product innovations. The primary asset of traditional banks is still their professional expertise. This competency must be better played out with digital and non-digital advisory interfaces to the customer. Traditional banks must focus again on providing added values for customers with an affinity for advisory, which does not necessarily have to include in-branch consultations but can also be done digitally. Some of these customers may not be satisfied with the established advisory settings as they might even be open to Fintech providers. Customer advisory services may no longer be seen as trust builders after customers have been driven out of branches for years for cost reasons. While most customer-bank interactions can be carried out independently through self-service, video consultations could be offered to reduce branch network costs. Since customers still attribute a lot of value to stationary forms of banking, new operating models must be found to guarantee cost-efficient integration of banking offerings. In other words: Traditional banks can only try to instill the desired usage behavior for unprofitable customers through re-established customer relationships and increasingly shifting it towards digital channels. Notably, this is already the strategy of many banks, but both the customer affection and processual implementation of omnichannel customer interaction are lacking.

Traditional banks also need to focus on customers with a substantial experience focus as these are also potential switchers to Fintech. Such a strong customer service experience orientation could likely be the primary driver of Fintech adoption in the future, also from the traditional bank customer segment. Banks should focus on improving the frictional points of the customer interaction, which depend greatly on the bank's ability to control its operational business, such as legacy core banking. At the moment, traditional banks are poorly constituted to win Fintech customers back, as these customers seek the antithesis of traditional banking – innovative digital checking accounts. However, none of the Fintech neobanks offer advanced data analytics yet. One decisive factor here will be developing trustworthy digital innovations that fulfill these very digital-oriented customers' subjective norms.

From a traditional banks' perspective, one worrying aspect is that the customers who have switched their bank less often in the past, in particular, would consider a Fintech as the provider type. Thus, an openness to new providers can be observed among long-standing customers. Loyal customers also put less emphasis on the traditional branch-based operational model than their less loyal peers. Plus, they prefer a high customer experience and are comparatively less reliant on branches. Also, the direct banking customers are more loyal than the traditional product-innovative customer segment. Thus, traditional banks could face customer churn in the future. Thus, our findings are both an opportunity and a warning signal for traditional banks to enhance their products and services in the digital realm and find new ways to interact with customers personally.

From a Fintech perspective, one future path to consider is attributing their products and service more traditionally without neglecting their modern digital core to expand their market share beyond the niche. Fintech could be predestined to win customers from the direct banking segment. However, Fintech would have to demonstrate real professional expertise in banking to win more traditional customer segments, which could be realized via video consulting offerings. Thus, more substantial banking expertise would be needed to occupy additional customer segment shares. Fintech would have to build up stationary factors such as (pop-up) branches/stores to address the customer needs of the traditional product-innovative and the branch-focused segments. However, this could probably be outside the scope of these digital-native providers.

Our results underscore that managing the digital and non-digital services continuum is a determining element of a traditional bank's future strategy. Digital product innovation is a differentiating factor for Fintech and traditional product-innovative customers, while probably primarily an accompanying factor to improve the customer service experience for at least three further customer segments. While Fintech customers demand a distinctive, purely digital offering in line with subjective norms, the traditional product-innovative customers still demand personal advisory and access to on-site branch services. Banks could aim to become fully digital but would thus have to demonstrate their existing competencies in a purely digital way. Hence, traditional banks should find the right balance between digital and non-digital services to underscore their traditional values, such as professional expertise. However, the number of physical touchpoints probably decreases as the generated value of each stationary touchpoint increases. Hence, cost-intense branch structures should only be maintained if these structures contribute to valuable transactions through personal advisory interactions. We find evidence for three segments that they could likely draw on branches for advisory purposes, but we only measured preferences and not actual transactions. Customer interaction should therefore be skillfully played via digital channels whenever possible to keep in touch with customers.

Furthermore, our results suggest that personal advisors could be of little value to attract direct banking and branch-focused customers, which is surprising for the latter. These customers with a self-service tendency showed no or only a slight preference for human advisory via digital or stationary channels. This insight underscores the complexity of selling higher-value products to specific retail banking customers, thus perpetuating the current dilemma of difficult access to particular customer needs and wants as a primary house bank. Traditional universal banks will have to make the benefits or advantages of their monetizable products and services clearer to these customers who prefer standardized digital products and little human intervention. Banks could help the less-educated customers navigate more complex financial products to revive the primary house bank relationship. Precisely these branch-focused but rather advisory-averse customers could be encouraged on-site to increasingly switch to digital channels, using learning spillover effects (cf. Zhou et al. 2020). Regionally shared service centers or pop-up branches could be appropriate structures to address basic needs, such as access to stationary services, while reducing overall costs (King 2019). Pop-up branches could greatly increase flexibility in managing supply and demand for brick-and-mortar services and thus improve the interaction with digital services. Another option is cost-efficient transaction-oriented (direct) banks that could serve these customers. Fintech could also provide attractive alternative offerings for direct banking customers.

Quite the contrary, individualized branch concepts could complement the standardized digital products and services to serve the experience- and advisory-focused customers. Mainly the experienced-focused customers show echoes of higher-value private customer business as they place less value on pure usefulness but personal value fit. More niche, i.e., specialized and expertise-rich products and services could address these customer needs. The benefits of an on-site presence seem to shine through most clearly in this context, whereas standardized digital services can be helpful facilitators.

While only some customers prefer a purely digital user experience, most customers could likely switch between digital and non-digital channels or conclude a contract on-site after several digital interactions. Therefore, digitalized banks would provide omnichannel services with professional expertise across several channels, including the stationary one. The stationary channel could reinforce the digital interactions, just as these could be necessary to reinforce the physical touchpoints. In the future, customer behavior could be shaped through innovative digital and non-digital solutions towards more cost-efficient digital services. However, such a stepwise adaption towards the optimal digital service offering will not work for paper-based banks. Thus, the DT of banking structures demands corresponding digitalized processes, products, and revenue streams for increasingly digital customer interactions (Fang et al. 2021).

Beyond that, one possible future market scenario is bundling innovative digital services by a Fintech provider in cooperation with the operations of a traditional bank. This could eliminate the respective structural disadvantages by establishing open interfaces in financial market infrastructure (Alt and Puschmann 2012). Banks would become a trusted brand partner in the digital ecosystem business as they might not fulfill digital customer expectations themselves. Banks could generate additional revenues as a complementor of digital platform ecosystems on the one hand, along with the disadvantage of losing control of customer access and paying provisions on the other (Fang et al. 2021). In contrast, the ecosystem orchestrators could mediate stationary advisory services and the settlement of regulated banking products to its partnering banks. It could especially be possible for Fintech to win more trust-sensitive customers through such partnerships that combine the best of both worlds. Although Google has recently abandoned (or postponed) its "Plex" banking solution, the international market could likely be developing in this direction. Bigtech players could build partnerships with established banks, such as Goldman Sachs in the U.S. The relevance of such banking services for a customer likely depends on how mature its platform-based relationship with a provider already is (Carbo-Valverde et al. 2020). Here, the future customer path to the checking account could lead via the digital services of Fintech or Bigtech, and not the other way around (Pousttchi and Dehnert 2018).

6.3 Limitations

Despite its strengths, this study is not without limitations. Firstly, our stated preference experiment could not perfectly represent the market reality by its very nature. In selecting service attributes, we had to make trade-offs. We did, for instance, not work with brand names, so our results might not be one-to-one transferable to the GAFA banking world since greater brand attributions are expectable here. We measured a low level of trust importance in the hypothetical choice experiment, which could likely be higher for real choices. Although we have drawn on established scales, the relatively high proportion of expressive customers and mavens is questionable. Our participants may perceive and know digital banking innovations and thus have consciously decided against them (as our results indicate), probably as they perceive them as still immature. Another possibility is that these services have not yet become sufficiently widespread in German society, so they did not reach the participants' awareness (who assessed themselves as expressive and knowledgeable despite their preference for traditional banking products). Here, our experiment's entry page provided a short market overview, but future studies could also survey market mavenism via a knowledge test. We also decided not to include price as a service attribute. Taking this into account would have led to a pricing study, which was not our goal. Pricing experts also state that bank customers' price sensitivity is low (Fischer-King and Grabbe 2019). Several studies show the abandonment of price attributes does not lead to an omitted variable bias (Pedersen et al. 2011). The order of other attribute preferences remains the same for unforced choices, including a 'none' option. However, we could have included *perceived costs* as a construct in the moderator analysis to explain better the choice of specific offerings such as direct banking. It would be exciting to investigate the willingness to pay for human advisory services, for example, by working with so-called "menus" in future choice experiments.

Secondly, the consumer research literature highlights that there can be problems related to studying personality traits (Solomon et al. 2013, p. 238). Therefore, we selected influencing factors that we identified in a previous study based on consumer reviews and the prior literature as sufficiently valid, reliable, and actionable constructs to explain the impact of digitalization on CDM in banking. However, situational factors can make a difference in CDM (Punj and Stewart 1983). The circumstances of the decision could bring changes, such as whether a customer is currently actively looking for a banking product or not. We have not included or considered all possible factors in this study. We included control variables of possible influences, such as loyalty, distress in CDM, age, gender, or degree.

Thirdly, we did not measure real purchase decisions. Especially the moderating analyses showed the impact of the influencing factors across all choices, rather reflecting the consumers' consideration sets (Blackwell et al. 2002, ch. 3). The segment analyses, in turn, assigned participants to one of the estimated preference clusters that reflected their preferred product choice holistically. Moreover, possible demand effects are rather unlikely due to the 'none' option included, and only 40 percent of the offerings have led to choice. Experimental reliability is increased by design as each participant had to proceed with eight replications (i.e., choice sets). Regarding validity, we saw the conceptual understanding confirmed from our pre-test. Our discrete choice experiment with a full factorial design is more rigorous than streamlined variants with only a few decisions about many attributes. We have made the appropriate significance statements with caution due to the large sample size (Lin et al. 2013). Wherever possible, we pointed out the practical relevance and significance of the results bound to the respective group of conditions (Mohajeri et al. 2020).

6.4 Future research

Further research avenues may follow this study. The preference formation for digital checking accounts may differ following situational norms in the digital realm, which is challenging to study. This development is accompanied by increasingly digitalized access paths to checking account providers. In the future, the primary bank relationship could be chosen via platform ecosystem providers, as the collaboration between Bigtech and major banks in the U.S. already demonstrates. Some customers (especially those prone to Fintech) may choose their checking account provider based on personalized recommendations in a digital product and service ecosystem they have already joined. Accordingly, it would make sense to examine the access paths to checking accounts and the relationship between checking accounts and additional banking services more in-depth in the future when customers are contracting with platform ecosystem providers. Mapping the customer journey and linking it to other banking or complementary ecosystem services could be indicated to gain further insights into Fintech customer choice. The frequency of digital interactions likely plays a role here, besides the innovative use cases that may lead to relationships with several checking accounts providers. For example, choice sets could be used to examine different usage scenarios for platform-based checking accounts in an experiment. This requires new experimental designs that integrate concrete usage patterns within the selection decisions. In this regard, scholars could also conduct revealed choice studies at digital platforms or comparisons portals. The uniqueness of the customer journey and new ways to access customers could be considered in future studies as situational factors, as we have not considered dynamic customer behavior in this study. Here, customers would have to evaluate concrete usage scenarios as influencing factors (instead of latent construct variables) to analyze how the customer segments can be mapped to complementary usage patterns. This could also be investigated ex-post, for example, with click-stream data from digital banking platforms in the future. However, platform-based offerings to investigate embedded finance customer journeys in a meaningful way are currently found primarily in Asia. Hence, this study would also need to be replicated with participants from other cultures. Further research should be conducted on the human-technology interface to enable seamless banking operations and a more accurate allocation of human resources, especially for advisory services. Analyzing established personality traits such as the "Big 5" would be another research opportunity (cf. van Raaij 2016, p. 145). It would be exciting to see exactly which personality traits contribute to customers' resistance or openness to new types or forms of checking account providers. Finally, other industry sectors, such as insurance services, would provide a fruitful avenue to analyze the impact of digitalization on CDM.

Appendix

Table II.2-6: Survey questionnaire (translated)

Construct	**Source**
Importance of trust	Gefen et al. 2003
With the chosen bank accounts, it was important to me	
... that I feel that they are honest with their customers.	
... that I feel like they're taking care of the customers.	
... that they have high expertise.	
Calculative-based beliefs	Gefen et al. 2003
With the chosen bank accounts, it was important to me	
... that they provide customers with expert advice.	
... that I feel that they are acting in the best interest of the customers.	
Structural assurances	Gefen et al. 2003
I would feel secure in doing business with banks	
... because the general requirements of a banking license to be fulfilled by every provider protect my money.	
... because the security and bank guarantee of the providers strengthened my confidence.	
... because they will keep my personal information confidential.	
Market Mavenism	Feick and Price 1987
My friends seek my advice when they ask about bank accounts.	
People ask me for my opinion before they sign up for a new bank account.	
If someone asks me what the best bank accounts on the market are, I could tell them.	
Expressiveness	Nysveen 2005
I often show my friends or family which digital banking products and services I use.	
I often talk with other people about banking products and services that I use.	
The banking products and services I use should leave an impression on other people.	
Situational normality	Gefen et al. 2003
With the chosen bank accounts, it was important to me	
... that the products offered are most similar to the typical banking products currently available.	
... that the products offered are similar to those used by my friends or family.	
Perceived usefulness	Lu et al. 2005
With the chosen bank accounts, it was important to me	
... that the services offered can be used productively.	
... that the services offered fulfill their tasks.	
... that the services offered are functional.	
Perceptual affinity	Bruyn and Lilien 2008
With the offerings I selected, it was important to me	
... that I can identify with the offering personally.	
... that I like the offering personally.	
... that the offering meets my personal values.	
... that the services offered appeal to me emotionally.	
Loyalty	Methlie and Nysveen 1999
I have been a loyal customer at the same bank for years.	
Personal distress	Koller and Lamm 2015
I feel anxious and uncomfortable in decision-making situations.	
Sometimes I feel helpless when I am in the middle of a decision-making situation.	
Demographic	
Please mark your gender.	
Which of the following age categories do you belong to?	
What is your highest school or university degree?	

Table II.2-7: Fornell-Larcker criterion

	ASS	CALC	EXP	MAV	PA	PD	PU	TRU
ASS	0.874							
CALC	0.509	0.897						
EXP	0.116	0.048	0.859					
MAV	0.109	0.011	0.818	0.907				
PA	0.453	0.519	0.202	0.155	0.795			
PD	0.016	0.058	0.049	−0.041	0.137	0.908		
PU	0.531	0.554	0.057	0.099	0.436	−0.047	0.898	
TRU	0.565	0.85	0.089	0.049	0.539	0.059	0.574	0.859

Table II.2-8: HTMT

	ASS	CALC	EXP	MAV	PA	PD	PU	TRU
ASS								
CALC	0.631							
EXP	0.120	0.068						
MAV	0.131	0.087	0.925					
PA	0.535	0.650	0.294	0.186				
PD	0.026	0.055	0.114	0.043	0.166			
PU	0.615	0.676	0.097	0.120	0.490	0.075		
TRU	0.674	1.076	0.097	0.058	0.646	0.054	0.675	

Table II.2-9: Cross Loadings

	ASS	CALC	EXP	MAV	NORM	PA	PD	PU	TRU
EXP1	0.088	0.032	0.908	0.733	0.113	0.156	0.016	0.055	0.073
EXP2	0.136	0.052	0.935	0.777	0.104	0.162	0.024	0.089	0.099
EXP3	0.039	0.037	0.719	0.575	0.265	0.280	0.162	−0.071	0.034
MAV1	0.085	0.019	0.767	0.942	0.121	0.156	−0.026	0.075	0.049
MAV2	0.096	0.013	0.773	0.935	0.131	0.137	−0.026	0.067	0.049
MAV3	0.128	−0.010	0.684	0.841	0.062	0.126	−0.072	0.146	0.033
PERC1	0.348	0.422	0.209	0.158	0.431	0.842	0.147	0.308	0.426
PERC2	0.379	0.447	0.166	0.129	0.386	0.854	0.135	0.340	0.485
PERC3	0.411	0.447	0.066	0.067	0.254	0.744	0.023	0.539	0.462
PERC4	0.278	0.300	0.231	0.152	0.430	0.732	0.145	0.125	0.303
PU1	0.461	0.484	0.082	0.102	0.145	0.416	−0.051	0.886	0.501
PU2	0.477	0.501	0.026	0.072	0.114	0.367	−0.040	0.898	0.529
PU3	0.491	0.507	0.047	0.092	0.162	0.393	−0.036	0.911	0.516
PD1	0.007	0.026	0.076	−0.008	0.123	0.114	0.805	−0.080	0.002
PD2	0.016	0.058	0.048	−0.042	0.133	0.136	1.000	−0.046	0.060
ASS1	0.859	0.394	0.107	0.106	0.249	0.337	−0.005	0.461	0.440
ASS2	0.894	0.459	0.123	0.128	0.285	0.424	−0.001	0.455	0.516
ASS3	0.869	0.477	0.074	0.055	0.239	0.418	0.044	0.476	0.519
CALC1	0.399	0.889	−0.003	−0.053	0.348	0.457	0.061	0.436	0.736
CALC2	0.511	0.904	0.086	0.068	0.300	0.473	0.043	0.553	0.788
NORM1	0.310	0.372	0.072	0.061	0.940	0.402	0.082	0.216	0.361
NORM2	0.148	0.194	0.248	0.192	0.725	0.402	0.187	−0.027	0.179
TRU1	0.504	0.744	0.077	0.035	0.266	0.477	0.050	0.524	0.866
TRU2	0.499	0.769	0.057	0.020	0.321	0.489	0.075	0.486	0.888
TRU3	0.452	0.674	0.098	0.076	0.307	0.420	0.022	0.469	0.821

Notes. ASS - Structural Assurances, CALC - Calculative-based beliefs, EXP - Expressiveness, MAV - Market Mavenism, PA - Perceptual Affinity, PD - Personal Distress, PU - Perceived Usefulness, TRU - Importance of Trust.

Table II.2-10: Multigroup analysis of personal trust-related conditions

	Personal trust-related conditions					
	Importance of trust		**Calculative-based perceptions**		**Structural assurances**	
Dependent Variable: Choice	Path-diff (high trust – low trust)	Path-diff (very high trust – very low trust)	Path-diff (high calc. – low calc.)	Path-diff (very high calc. – very low calc.)	Path-diff (high str. ass. – low str. ass.)	Path-diff (very high str. ass. – very low str. ass.)
Provider type ("traditional bank")	0.029	0.084	0.041*	0.061	0.029	0.080
Scope of services ("both digital and branch/store")	**−0.060*****	−0.006	−0.041*	−0.133**	−0.012	0.119*
Customer service experience ("high")	**−0.063*****	−0.075	**−0.074*****	0.017	−0.051**	0.030
Digital innovation ("standard app")	0.018	−0.008	0.023	−0.094	0.009	−0.064
Professional expertise ("human customer advisor")	**−0.137*****	**−0.257*****	**−0.165*****	**−0.261*****	**−0.069*****	−0.135**
Group shares (respondents)	119:926	25:405	152:954	18:428	238:871	24:356

Notes. Significance level: ***** $p < 0.001$**, ** $p < 0.01$, * $p < 0.05$.

Table II.2-11: Multigroup analysis of social conditions

	Social conditions					
	Expressiveness		Market mavenism		Situational normality	
Dependent Variable: Choice	**Path-diff (high expr. – low expr.)**	**Path-diff (very high expr. – very low expr.)**	**Path-diff (high mav. – low mav.)**	**Path-diff (very high mav. – very low mav.)**	**Path-diff (high sit norm. – low sit norm.)**	**Path-diff (very high sit. norm. – very low sit. norm.)**
Provider type (“traditional bank”)	**0.063*****	**0.134*****	**0.055*****	**0.146*****	−0.027	−0.052
Scope of services (“both digital and branch/store”)	**0.119*****	**0.206*****	**0.120*****	**0.154*****	−0.022	**−0.050*****
Customer service experience (“high”)	**0.058*****	0.088*	0.011	−0.022	**0.095*****	**0.174*****
Digital innovation (“standard app”)	0.045**	0.054	0.042**	0.042	0.007	0.001
Professional expertise (“human customer advisor”)	0.043**	0.057	0.043**	0.064*	0.011	−0.025
Group shares (respondents)	896:222	461:41	803:329	400:64	523:496	99:93

Note. Significance level: *** $\boldsymbol{p < 0.001}$, ** $p < 0.01$, * $p < 0.05$.

Table II.2-12: Multigroup analysis of attitudinal conditions

	Attitudinal conditions			
	Perceived usefulness		Perceptual affinity	
Dependent Variable: Choice	**Path diff (high pu. – low pu.)**	**Path-diff (very high pu. – very low pu.)**	**Path-diff (high pa. – low pa.)**	**Path-diff (very high pa. – very low pa.)**
Provider type (“traditional bank”)	**0.079*****	0.122	0.011	0.037
Scope of services (“both digital and branch/store”)	−0.031	0.015	−0.005	−0.027
Customer service experience (“high”)	**−0.172*****	−0.076	0.036*	0.106*
Digital innovation (“standard app”)	−0.030	−0.092	**0.050*****	−0.002
Professional expertise (“human customer advisor”)	**−0.110*****	−0.086	−0.024	−0.115**
Group shares (respondents)	105:1059	10:544	339:750	40:167

Note. Significance level: *** $\boldsymbol{p < 0.001}$, ** $p < 0.01$, * $p < 0.05$.

Table II.2-13: Multigroup analysis of controls

	Controls									
	Loyalty		**Degree**		**Gender**		**Age**		**Personal Distress**	
Dependent Variable: Choice	**Path-diff (high loy. – low loy.)**	**Path-diff (very high loy. – very low loy.)**	**Path-diff (university degree – other)**	**Path-diff (men – women)**	**Path-diff (30-39y – 18-29y)**	**Path-diff (40-49y – 18-29y)**	**Path-diff (50-59y – 18-29y)**	**Path-diff (over 59y – 18-29y)**	**Path-diff (high dis. – low dis.)**	**Path-diff (very high dis. – very low dis.)**
Provider type (“traditional bank”)	**−0.095*****	**−0.145*****	−0.024	−0.008	0.004	0.019	0.039	**0.106*****	0.017	0.025
Scope of services (“both digital and branch/store”)	**−0.125*****	**−0.187*****	**−0.073*****	**−0.047*****	−0.035	−0.033	0.000	−0.012	0.002	−0.061
Customer service experience (“high”)	**0.057*****	**0.172*****	**0.107*****	0.004	**0.094*****	0.067**	**0.089*****	0.060*	**0.074*****	**0.130*****
Digital innovation (“standard app”)	−0.013	0.037	0.026*	−0.013	0.044*	0.044	0.021	0.051	−0.041*	−0.103**
Professional expertise (“human customer advisor”)	**−0.067*****	−0.079	0.037**	−0.024	−0.041*	−0.068**	−0.044*	−0.046	0.019	**0.110*****
Group shares (respondents)	203:754	31:311	503:694	672:524	201:383	201:217	201:271	201:125	869:230	383:41

Note. Significance level: ***** $p < 0.001$**, ** $p < 0.01$, * $p < 0.05$.

II.3 A configurational analysis of smart product-service systems and value proposition types in B2C industries

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Abstract: With the rise of the Internet of Things, plain physical products are equipped with sensors, actors, computational power, storage capacity, and communication technology, transforming them into smart products. Within a smart product-service system (smart PSS), smart products enable smart services by acting as a central integrator of activities and resources of both the service consumer and the service provider. The rise of such service systems in the business-to-consumer (B2C) sector forces companies to rethink their business models. Scientific contributions focusing on the business model perspective of smart PSS are still rare and often domain-specific. Against this background, we analyze the impact of different configurations of smart PSS properties on achieving different value proposition types in B2C. Our approach is twofold. Firstly, we use a total of 56 use cases for taxonomy development and evaluation. Secondly, we apply qualitative comparative analysis (QCA) based on the collected data to identify empirically consistent smart PSS configurations leading to different value proposition types. The outcome serves both scholars and practitioners as a tool for analyzing the compatibility of different empirical smart PSS configurations and their belonging business model patterns.

1 Introduction

The ongoing digitalization has led to tremendous changes and optimizations in businesses in any industry as well as in private households. A major contributor in both areas is the so-called Internet of Things (IoT), which establishes the interconnection between everyday objects and the digital world. As the IoT is growing, more and more of these everyday objects are equipped with sensors, actors, computational power, storage capacity, and communication technology. According to Gartner, 25 billion smart products will be connected in 2021, leading to the generation of an immense volume of data (Omale 2018). More precisely, smart products enable the co-creation of value by acting as the central integrator of the resources and activities of both service consumers and providers. The collected data and its analysis, as well as the decision-making and action-taking capabilities of smart products, offer tremendous opportunities to create an entirely new class of services. In academic literature, such services are commonly referred to as smart services (Anke 2019; Beverungen et al. 2019; Dreyer et al. 2019; Wiegard and Breitner 2019). Furthermore, the terms smart service system (Beverungen et al. 2019; Laubis et al. 2019) and smart product-service system (Mittag et al. 2018; Paukstadt et al. 2020; Strobel et al. 2019) are used to emphasize that a smart product does not operate on its own, but should be part of a service system of different configurations of people, resources and other technologies in order to create a valuable service. In the following, we use the term smart product-service system (smart PSS) to refer to the described phenomenon.

Smart PSS have been part of an active discourse in academic literature in recent years. They have been classified from a smart product perspective (López et al. 2011; Püschel et al. 2016) as well as a more holistic smart service perspective (Paukstadt et al. 2020). Furthermore, the role of smart products within the interactions between service providers and service consumers has been conceptualized (Beverungen et al. 2019). This also applies to the interactions between other smart products, the consumer and the provider (Kees et al. 2015; Oberländer et al. 2018) as well as the changing consumer experience with smart products (Hoffman and Novak 2018). However, the business model perspective of smart PSS has rarely been discussed by scholars (Dreyer et al. 2019), apart from a general framework that provides an overview of the components of IoT-related business models (Dijkman et al. 2015) and a domain-specific taxonomy of smart energy PSS (Paukstadt, Gollhardt et al. 2019). In particular, the different ways of creating value with smart PSS and capturing it with business model strategies represent a key research challenge (Veit et al. 2014). Smart PSS properties are interconnected in different ways, however, these interdependencies have not yet been investigated in a systemic way, for instance, how they combine to produce different business model outcomes. A contribution focusing on the composition of smart PSS and their respective business models would enable a better understanding for both scholars and practitioners of how business value is captured by smart PSS.

Against this background, we identify different configurational types of smart PSS and their relationship with different business model patterns in B2C industries. Hence, we connect and analyze data from a holistic taxonomy of smart PSS in B2C (e.g., smart home), incorporating the currently underrepresented business model perspective. For this, we follow a two-step approach: Firstly, we use 56 B2C real-life use cases for taxonomy development and evaluation. Secondly, we apply qualitative comparative analysis (QCA) to identify empirically consistent smart PSS configurations for different value proposition types in servitization. Drawing on configuration theory, we extend the literature towards typologies of smart PSS in B2C, not just describing and categorizing but also explaining how smart PSS lead to different value proposition types.

The paper is organized as follows: In the next section, we present the theoretical background of smart PSS, their belonging business models, and configurational theory. In section three, we explain our chosen research methodology for taxonomy development and QCA. In section four, we describe and evaluate our developed taxonomy as well as present the results of the configurational analysis with smart PSS configurations to achieve different value proposition types. In the last section, we discuss and conclude our research.

2 Background

2.1 Smart product service systems

In our conceptualization, we draw on the notion of smart PSS as combinations of smart products and services to offer value propositions to customers. Beverungen et al. (2019) define properties of smart products as follows:

- Unique Identification in order to make the product addressable by other products or information systems.
- Localizing in the sense that products “know” their location and can be localized and traced by other products and information systems.
- Connectivity so that products can be connected and share data and functionality via standard communication protocols.
- Sensors to obtain data from their surroundings including users and other smart products.
- Storage and computation to store collected data and compute them to adapt their actions and act autonomously.
- Actuators enable smart products to manipulate their physical reality in their proximity.
- Interfaces deployed for human-machine interactions.
- Invisible computer as the ability to blend naturally into the environment without bothering a user’s consciousness with its presence.

Based on combinations of these properties, smart products enable smart services. In smart services, specialized competencies are applied through actions, processes, and activities enabled by smart products (Beverungen et al. 2019). Smart services range from basic visualization of data collected by the smart product to the prediction of product maintenance tasks and their subsequent execution by humans to the autonomous actions of smart products. Smart products do not act on their own to create smart services but also use the resources and activities of the service consumer and the service provider. Literature refers to this as 'smart product service systems' (Mittag et al. 2018; Paukstadt et al. 2020; Valencia et al. 2015). In this paper, we focus on smart PSS in B2C with regard to their smart product-centered marketing and sale approaches and their business models.

Smart PSS are already today the central service counterpart of B2C customers in diverse B2C industries such as retailing (Pousttchi and Hufenbach 2014). Moreover, smart PSS increasingly become a dominating part of industries such as banking and insurance, for instance, in voice banking or with telematics tariffs (Pousttchi and Dehnert 2018; Pousttchi and Gleiss 2019). Smart PSS providers such as Amazon, Apple, or Google not only generate revenue by selling their products but also aim to generate revenues at the customer interface, for instance, as intermediators in platform ecosystems.

2.2 Value propositions

The term business model is used to describe how an organization creates and captures value (Osterwalder and Pigneur 2012). Business models also serve as tools to depict, evaluate, and innovate business logics (Veit et al. 2014). Value propositions represent the chosen mix of actors, resources, allocation and behaviour of companies, which are offering smart PSS to B2C customers. To achieve different value propositions, smart PSS change existing product and service designs. The value base may be the smart product itself or the smart service based on the product (Alt, Demirkan et al. 2019). A reason for these adaptions is, for instance, the analytical capability of smart PSS that enables the use of collected data for a better understanding of consumer preferences and product usage. By using the connectivity components of smart products, the service performance can, in turn, be improved using over-the-air updates. This results in service offerings that may enhance consumer value. Furthermore, smart products can connect with other products or information systems, often from different manufacturers, leading to more effective services with increased consumer value. For instance, the smart light Philips Hue can not only be controlled using the included Hue smartphone app but also more conveniently with smart products featuring the voice assistants Alexa, Siri or Google assistant. These value propositions ensure recurring revenues through product sales, services, or intermediation. Regarding revenue models, new ways of capturing value emerge that may replace or extend the former simple product sales with recurrent revenues, for instance, enabled by subscription-based payments (Hui 2014).

2.3 Configurational theory

There are diverse ways in which smart PSS along with their properties can be developed and emerge. Hence, complexity, which is characterized by "a particular combination of multiplicities and autonomies that defy explanation" (Barile and Polese 2010, p. 30), is an important issue for the development of smart PSS and their respective business models.

Configurational theory is a useful concept for the analysis of complexity. Configurational theory draws on the notion of equifinality. Equifinality means that, based on different structures, various configurational paths can lead to the same outcome. In particular, the analysis of these paths and the characteristics of different drivers leading to the same outcome is of special interest in a configurational analysis. In this regard, configurational theory not only analyses net effects of individual drivers (variables) but also the interplay between different drivers (sets of variables) for a specific outcome (Kohtamäki et al. 2019). This distinguishes the configurational approach from classical statistical approaches such as regression analysis. We draw on a configurational research approach to examine the interdependent relationships between structures (i.e., smart PSS characteristics) and outcomes (i.e., value proposition types). Regarding structure, smart products and services are the value base of smart PSS (Alt, Demirkan et al. 2019; Oliva and Kallenberg 2003). Smart PSS providers, for instance, may include boundary resources from third-party developers to extend their smart service offerings (Ghazawneh and Henfridsson 2013). The specific drivers in these categories must be identified, which, through their complex interplay, produce several value proposition types as outcomes. Hence, in this paper, we combine both product-service and business model views to empirically derive typologies of smart PSS in B2C.

3 Methodology

Our methodological approach was twofold. Firstly, we relied on established taxonomies for smart PSS in B2C, which we extended for the specific purpose of our configurational analysis. Secondly, we applied qualitative comparative analysis to identify consistent smart PSS configurations for different value proposition types.

Firstly, we followed the taxonomy development approach by Nickerson et al. (2013). The taxonomy development was based on prior literature, provider websites, user manuals, and the startup database 'TechCrunch.' The corresponding data was collected in autumn 2019. The first step of taxonomy development was to determine a meta-characteristic, representing the most comprehensive characteristic. From this, all other characteristics of the research topic are derived, in our case: *Determine business model-specific characteristics of smart PSS in B2C industries*. In the second step, we defined ending conditions to specify when to stop iterating. Instances of the characteristics must not be mutually exclusive in order to include reasonable, non-exclusive instances. After completing both initial steps, we combined an empirical-to-conceptual approach, identifying the characteristics and instances of the taxonomy by using a subset of the to-be-classified objects and a conceptual-to-empirical approach, conceptualizing characteristics without examining actual objects. After each iteration, we checked if the ending conditions were met and decided which of the two approaches to choose for the next iteration. In total, we conducted four iterations. We worked conceptually during the first iteration and consulted the literature (Webster and Watson 2002). In this regard, we identified different taxonomies of smart products and services (Paukstadt, Gollhardt et al. 2019; Paukstadt, Strobel and Eicker 2019; Püschel et al. 2016). After screening and analyzing these taxonomies, we ended up with a taxonomy that contained some duplications. Furthermore, examining a small subset of 10 use cases made clear that the taxonomy was not yet comprehensive enough for our analysis. We applied another 10 and 15 use cases to our interim taxonomy in the second and third iteration. We added four own characteristics from our case observations, excluded duplications, and condensed the number of characteristics. In the fourth iteration, we added characteristics and instances of the outcome variable (i.e., value proposition types) from the literature (Weking et al. 2020) and our 56 cases. Finally, we coded each case with the final taxonomy.

Secondly, we applied configurational theory using qualitative comparative analysis (QCA) as a representative of set-theoretic methods (Fiss 2007; Schneider and Wagemann 2013). Set-theoretic methods build on configurational theory to analyze case studies. The QCA method can be used to analyze how combinations of boolean variables lead to an outcome variable (Ragin 2008, pp. 13 ff.). The method is suitable to examine causal structures with both core (necessary) and peripheral (sufficient) conditions to achieve an outcome. QCA is also an appropriate method for typology development (Fiss 2011). We took upon this approach to derive typological types of smart PSS. We used our instantiated smart PSS taxonomy for 56 qualitative-empirically coded cases. We relied on in-depth guidelines on QCA (cf. Schneider and Wagemann 2013, pp. 275 ff.), which are available in the literature, as well as on the fsQCA 3.0 software package. We did a truth table analysis, which includes all logically possible combinations of the elements. Each row corresponds to one smart PSS case (along with its characteristics) related to different value proposition types as the outcome variables of interest. Our analysis is based on crisp sets that distinguishes outcome variables between "0" and "1." In case a certain smart PSS fulfilled a certain type of value proposition, it was given a "1," otherwise "0." Finally, the fsQCA software was used to analyze the final set of configurations, including a parsimonious solution indicating the core (necessary) conditions to achieve the outcome as well as intermediate solutions incorporating both necessary and peripheral (sufficient) conditions to achieve the outcome. With the help of consistency measures, we analyzed how reliable each solution was. As a reference point, the literature recommends considering solutions with consistency values above 0.80 (Ragin 2009). We followed this recommendation.

Regarding value proposition types, we only took smart services into account that were available in the market. The smart service also had to be offered by the same company that also developed the underlying smart product or its subsidiaries. The 56 B2C cases cover a broad range of the IoT domains proposed by Borgia (2014), such as smart home, smart energy, smart health, smart mobility, as well as individual wellbeing. The cases are based on previous publications (Oberländer et al. 2018; Paukstadt et al. 2020; Paukstadt, Gollhardt et al. 2019; Porter and Heppelmann 2014; Püschel et al. 2016) as well as on the additional online research we conducted to cover the state of the art in practice.

4 Configurational analysis

4.1 Taxonomy description

In the following section, we present the entities of the taxonomy for the subsequent configurational analysis. Product and service are the core and peripheral properties of smart PSS. Subsequently, we introduce the identified set of relevant types of value propositions. We made some adjustments with regard to the designations of a taxonomy. Rather than using the term dimension, we use characteristic, and instead of characteristics, we refer to instances (Pousttchi and Hufenbach 2009).

4.1.1 Smart PSS characteristics

In the following, we describe the core and peripheral characteristics of smart PSS in B2C. Table II.3-1 outlines their definition, instances and shows examples from the data.

Table II.3-1: Characteristics of Smart PSS in B2C

Characteristic	Definition	Instances	Examples
Autonomous acting capability (Püschel et al. 2016)	- ability to act autonomously without any involvement of humans on neither the consumer nor the provider-side – based on the data collected using sensors, the analytics applied on that data, processing and storage components	- yes, no	- 'iRobot Roomba S9+' autonomously cleans rooms - 'The Pod' regulates the temperature of the bed during the night based on the current temperature of the consumer
Sensing capability (Püschel et al. 2016)	- ability to collect usage- and context data based on built-in sensors	- lean, rich	- Kitchen scale 'Drop' uses sensors to measure the amount of material on the scale (lean) - 'Apple HomePod' adjusts sounds to different rooms (rich)
Interoperability (Porter and Heppelmann 2015; Püschel et al. 2016)	- ability to incorporate or be incorporated in broader systems of interconnected smart PSS	- proprietary, - open, - standalone	- proprietary 'HomePod' only working with other smart products from Apple - open APIs like 'Amazon's Echo Dot' - stand-alone smart bike 'VanMoof Smart S'
Coupling control (own)	- ability to couple and control other smart PSS as service counterparts	- yes, no	- voice assistant 'Amazon Echo' controls smart lights 'Philips Hue'
Ecosystem (Dijkman et al. 2015; Valencia et al. 2015)	- ability to enable recurrent interactions and continuous involvement of the user with the product after the sales process	- new content or apps, - 3rd party developers, - consumers as developers, - none	- new ebooks to a 'Kindle' or new apps for 'Fitbit OS' (new content or apps) - different light settings for 'Philips Hue' or new abilities of smart toy 'Anki Cozmo' (consumers as developers)
Interaction between actors (Wünderlich et al. 2013)	- type of interaction that prevails	- consumer active, - provider active, - interactive, - device active	- 'Philips Lifeline GoSafe 2' requires actions from both sides (interactive) - 'Plume Labs Flow' displays the self-collected data in an app (device-active)
User mapping (own)	- ability to uniquely identify users based on their distinct properties	- yes, no	- fitness tracker 'Fitbit' distinguishes between users by data (heart rate, blood pressure or sleep rhythms)
Data capability (own)	- ability to collect valuable consumer or service data	- location, - communication, - health, - transaction, - behavior, - other	- wearables like smartwatches, fitness trackers or disease-treating products collecting health data (e.g., pulse, movement intensity, skin temperature, or the sleep rhythm)
Analytical capability (Wedel and Kannan 2016)	- analytical capabilities to apply obtained knowledge and to improve user experience	- descriptive, - diagnostic, - predictive, - prescriptive	- 'Medtronic Minimed 670G' predicts blood sugar levels, automatically identifies the correct amount of insulin required, and injects it autonomously (prescriptive)
Output medium (Püschel et al. 2016)	- ability to display the service output through its own interfaces or via an intermediary medium	- own, - intermediary	- 'Google Pixel' with an audible signal, a vibration, a text or voice message via in-built display or microphone

Smart PSS with *autonomous acting capability* are able to act autonomously without any involvement of humans on neither the consumer nor the provider side. We indicate whether a smart PSS operates on behalf of a human without any interference or external intermediaries. Wherever this is the case, however, a simple setup process of the intelligent agent (i.e., smart product) has to be done initially by humans, where, for instance, the vacuuming schedule, the desired temperature or the reminder date(s) and time(s) are set. The actual realization following these settings is still done autonomously. We demarcate such small setup processes from smart PSS with a lack of autonomous acting capabilities such as the smart tennis racket ‘Babolat Play’ or the smart sunglasses ‘Snapchat Spectacles 2’, which need constant human actions in order to create a service output. Since autonomy is a core capability of smart PSS, we included autonomous acting as a variable in the further configurational analysis.

Smart PSS with *sensing capability* collect usage- and context data based on built-in sensors. Püschel et al. (2016) propose classifying this capability by using either lean or rich. A rich sensing capability means that a smart PSS obtains more abundant data using complex sensors like, for instance, the ‘Apple HomePod,’ which can determine its room position and adjust the emitted sound waves to create an optimal sound experience. On the other hand, data collected by smart PSS with simple sensors classifies as a lean sensing capability. For instance, the smart switch ‘Logitech Pop Home Switch’ can sensor a few touch sequences like tapping it once or twice or holding the tap for a few seconds. We included rich sensing as a variable in the further configurational analysis (Beverungen et al. 2019).

Smart PSS *interoperability* enables components of connected smart PSS to enhance value (Porter and Heppelmann 2014; Püschel et al. 2016). The concept of recurrent interaction levels (Valencia et al. 2015) aims to increase consumer usage of smart PSS in the long term by extending functions. Smart PSS, which are only designed to work with smart products from the same provider, like ‘Apple’s HomePod,’ are considered proprietary (i.e., integrated). Other smart PSS have opened their APIs so that third-party developers can build interoperable smart PSS compatible with them (e.g., voice assistants like ‘Amazon’s Echo Dot’ or ‘Google’s Home Mini’). Hence, a ‘Google Home Mini’ owner can, for example, control the smart oven ‘June’ as well as the installed ‘Philips Hue’ lights using his voice. Another example for such interoperability is the smart lock by ‘Kevo’, which communicates the arrival of the owner to ‘Google’s Nest Thermostat’, which in turn adjusts the temperature of the house accordingly. Some smart PSS like the ‘Babolat Play’ tennis racket or the ‘VanMoof Smart S’ are not compatible with other smart PSS and thus are classified as standalone. Since openness covers an important aspect of smart PSS, we included this variable in the further configurational analysis.

Smart PSS are also a channel to access the benefits of other smart products. There are many options for a smart product to exercise control over the way its owner uses it in the surrounding ecosystem. A 'coupling' of different smart PSS leads to a value network of interacting smart products to enable even more innovative and attractive smart services (Strobel et al. 2019). The *coupling control* capability describes whether a smart product can serve as a remote control platform ('master') for several other physical smart products ('slaves'). In this regard, smart PSS with coupling control capabilities may integrate the benefits of other smart PSS, third-party developers, or content creators and thereby remain the primary interface in customer interaction. The voice interface of Amazon Echo, for instance, is able to control Philips Hue smart lamps but not vice versa. Those smart PSS maintaining control over the customer interface may increase market power and success in the long run (Parker and van Alstyne 2018). The respective providers build market momentum by absorbing and bundling technical features. This resembles an important aspect of 'platform coring' (Gawer 2009). Thus, we included this variable in the further configurational analysis.

Smart PSS also change the nature of how users are involved with services. *Ecosystems* enable recurrent interactions and continuous involvement with the product after-sales, which is not possible with plain physical products. Valencia et al. (2015) suggest three ecosystem options for service providers: First, service providers can update the smart PSS with new content or apps, meaning they provide new content to a smart product, like new ebooks to a 'Kindle' or new apps to the operating system of a smart product, such as 'Fitbit OS.' Second, opening the system to other third-party developers such as other companies or professionals to develop new apps or content for the provider ecosystem further enhances the chance of a more frequent recurrent interaction with the consumer. Third, service providers may provide the opportunity to co-create the service offering with consumers. Since third-party developers are important boundary resources for smart PSS, we included ecosystem capability as a variable in the further configurational analysis.

Smart PSS also differ in the mode of *interaction between actors*. Wünderlich et al. (2013) distinguish between consumer active, provider active, interactive, and device active. A consumer active smart PSS requires a high level of interaction by the consumer and a low level on the provider side. Provider active, in contrast, features a high level of proactive involvement by the service provider. Smart PSS requiring actions from both sides are classified as interactive, for instance, the personal alert 'Philips Lifeline GoSafe 2'. Device active smart PSS, such as 'Plume Labs Flow,' are primarily simple data collectors that display the collected data in an app or adjust settings automatically like the smart thermostats 'Nest' and 'Ecobee.' Since customer active interaction covers the state-of-the-art in B2C, we included this variable in the further configurational analysis.

We further noticed differences in other categories that may impact business model outcomes. Consequently, we included 'own' characteristics based on our findings and prior research since some of these aspects were missing in previous papers on smart PSS. This relates especially to the competitiveness in B2C ecosystems with the characteristics of coupling control, user mapping, and data capabilities. Smart PSS like Amazon Echo, Google Home Mini, or the smart bed Eightsleep, for instance, can assign data directly on the user level, while others cannot do so.

Smart PSS might identify users based on their distinct properties. We refer to this phenomenon as *user mapping*. This 'own' characteristic was included since direct user mapping helps service providers relate the collected personalized data to a single customer and, consequently, customer profiles can be built more easily. We consider a user account linked to the app of a smart PSS as insufficient to enable one-to-one user mapping. Different family members and friends can easily use many products. Thus, these products do not provide actual data related to a single user (e.g., smart bike 'VanMoof S'). We included one-to-one user mapping in the further configurational analysis.

In smart PSS, data enhances insights about service consumers and reveals their preferences. We refer to the collection of data as *data capability*. We included this 'own' characteristic since previous research uncovered data as crucial for business model success (Pousttchi and Hufenbach 2014; Wedel and Kannan 2016). The instances were included under the premise: the richer the collected data, the better it can be used to build a comprehensive customer profile to improve the service creation, which eventually leads to further value proposition types. In combination with analytics, data collection enables more personalized services with a greater benefit for the consumer. We distinguish five typical data types a smart PSS can obtain: location, communication, health, transactional and behavioral data, as well as 'other.' An example for other data types is social data. The collected data should, at best, be cross-sectional to enable specific applications such as intermediation. Due to its various instances, we did not incorporate data ownership as a variable in our configurational analysis.

Analytical capability is key to figuring out why service consumers make decisions and why they behave in a certain way (Hunke et al. 2019). Hence, service providers can use the knowledge obtained by analytics to enhance their smart PSS in general and improve the individual user experience. Prior research divides the analytical capabilities of a smart PSS into four advancing types (Wedel and Kannan 2016). Descriptive refers to displaying data in aggregated reports or accumulated visualizations. The diagnostic property diagnoses why certain things such as a product failure happened. Moreover, detecting impending events by inferential statistics can be characterized as predictive. Furthermore, the prescriptive attribute deals with identifying measures to improve outcomes or correct problems. For instance, the 'Medtronic Minimed 670G' is able to predict when the blood sugar level is falling and automatically identifies the correct amount of insulin required as compensation and even injects it autonomously. Since predictive analytics covers the state-of-the-art of smart PSS in B2C, we included this variable in the further configurational analysis.

A smart PSS is also able to use an *output medium* for service outputs like, for instance, an audible signal, a vibration, a text, or a voice message through its own interfaces, such as a proprietary in-built display or microphone, or on an intermediary medium like a smartphone or tablet via the supplied mobile application (Püschel et al. 2016). This mainly has a potential impact on interaction quality with customers. Thus, we included own output as a variable in the further configurational analysis.

The results of our validated smart PSS taxonomy are depicted in Figure II.3-1 with the absolute and relative ratios as percentages in brackets. The grey fields indicate the variables used for subsequent configurational analysis.

Characteristics	Instances					
Autonomous acting capability	Yes (64%)	No (36%)				
Sensing capability	Lean (43%)	Rich (57%)				
Interoperability	Proprietary (13%)	Open (45%)	Stand-alone (43%)			
Coupling control	Yes (39%)	No (61%)				
Ecosystem	New content or apps (21%) [25%]	3rd party developers (24%) [29%]	Consumer as developers (12%) [14%]	None (44%) [54%]		
Interaction	Consumer active (71%)	Interactive (4%)	Provider active (0%)	Device active (25%)		
User mapping	Yes (31%)	No (69%)				
Data capability	Location (21%) [34%]	Communication (16%) [27%]	Health (10%) [16%]	Transaction (12%) [20%]	Behavior (25%) [41%]	Other (16%) [27%]
Analytical capability	Descriptive (44%) [82%]	Diagnostic (20%) [36%]	Predictive (20%) [36%]	Prescriptive (6%) [11%]	None (10%) [18%]	
Output medium	Own (62%) [88%]	Intermediary (38%) [54%]				

Note. Grey color indicates input variables for configurational analysis.

Figure II.3-1: Taxonomy evaluation for smart PSS in B2C

4.1.2 Value proposition types

We identified several relevant value propositions for smart PSS in B2C based on our theoretical knowledge and empirical case data. For our taxonomy development, we followed the taxonomy of business model patterns by Weking et al. (2020). In our B2C use cases, we observed three ways to enhance physical products with smart PSS: Either the smart product was complemented by a smart service, bundled with other smart products, or a smart service was complemented with other smart services. These phenomena mainly indicated the prevalence of 'complementary' value proposition types in smart PSS. We deliberately focus on economic business model patterns (i.e., with regard to a firm's revenue model). Finally, we identified a set of 10 value proposition types. Other value proposition types in the literature appeared to be rather vague and did not indicate a strong connection to the smart PSS' properties (e.g., 'experience,' 'premium,' or 'breakthrough markets'). We further classified the identified value propositions into three main areas (Alt, Demirkan et al. 2019): product-centric, service-centric, and intermediation-centric. We coded these categories for each case of our taxonomy and incorporated them as outcome variables into our configurational analysis. In the following, we introduce the final set of value proposition types.

Regarding *product-centric* value propositions, the *product sales type* (59%) [70%] refers to smart PSS without a premium service option. These providers offer smart products, in some cases enriched by additional non-monetarized smart services, and thus do not follow a specific complementary type. When companies offer many related but different smart products as bundles, such as in starter packs, they follow the *bundle elements together type* (14%) [16%]. Besides that, smart products can complement other smart or non-smart products following a *cross-selling* approach (27%) [32%]. Philips, for instance, offers its smart light ‘e27 color’ with the ‘hue bridge’ and a motion sensor in order to turn on the light when motion is detected.

Regarding *service-centric* value propositions, a company follows the solution provider type (79%) [20%] when it partners up with allies to provide a full range of services in one domain while attempting to own the primary customer relationship. Providers of voice assistants, for example, design their products in a way that can be used as a central smart home control point for many other products from the same or third-party providers. Additionally, the *remote usage and monitoring* type (21%) [5%] provides services to prevent errors and monitor usage. The *object self-service* type (0%, i.e., not yet implemented) describes smart PSS with the ability to place orders on the internet independently. Another newly emerged type is the *digital add-on* that describes a smart product with software restricting the full capability of the product. Certain capabilities can be unlocked for an agreed amount of time when paying a fee. The *value added reseller type* buys an undifferentiated existing smart product and complements it with value-added services before reselling it to consumers. Moreover, smart products can complement sales services by enabling consumers to purchase items or services directly. As the percentages in brackets indicate, we did not find an implementation of these types.

Regarding *intermediation-centric* value propositions, the *product as point of sales* type (60%) [38%] indicates intermediary roles of a smart PSS provider. Moreover, the *advertising* type (40%) [25%] uses the data generated by smart PSS to create new or enhance existing user profiles for advertisers.

The evaluation suggests that new value assessment approaches, especially for subscription-based models promising recurring revenues, have not yet fully arrived in the B2C markets for smart PSS. Many smart PSS business models were in fact still based on ordinary asset sale revenue streams that did not differ from those of their predecessors, the plain, non-smart products.

4.2 Truth table analysis

In this section, we present the results of the configurational analysis in QCA. Truth table analysis identified consistent combinations of smart PSS that produce the outcome of a value proposition type. For each smart PSS, we referred to our codings indicating the presence ("1") or absence ("0") of a type. QCA allows determining parsimonious solution sets with 'core' conditions and intermediate solution sets with additional 'peripheral' conditions. Core conditions indicate necessary conditions, and peripheral conditions indicate sufficient conditions to achieve the outcome. Two measures are used to validate the solutions: consistency and coverage. Solution consistency measures the degree to which configurations consistently result in an outcome. We checked whether it is well above the recommended level of "0.80" for all our solutions. To evaluate the consistency of a particular configuration, counterfactual analysis in QCA includes all smart PSS that lead to the presence or absence of the investigated value proposition type. Solutions with lower consistency values are discarded. Raw coverage indicates which share of the outcome is explained by a certain alternative path; unique coverage indicates which share of the outcome is exclusively explained by a certain alternative path. For the reduction algorithm, we used minimum consistency values of "0.80" (Ragin 2009) and a minimum frequency of "1", except for the category 'product sales (only)'. This category encompasses only those smart PSS that do not have any complementary value proposition types. To condense results, each configuration in this category had to include at least two cases.

Figure II.3-2 to Figure II.3-6 graphically depict the results using the QCA notation system (Ragin and Fiss 2008). Each solution block in these figures represents one configuration of conditions and corresponds to one recipe of the intermediate solution. Large (small) full circles indicate the presence of core (peripheral) conditions. Large (small) crossed-out circles indicate the absence of core (peripheral) conditions.

Next, we present all solutions of product-, service-, and intermediation-centric value propositions.

4.2.1 Configurations of product-centric value propositions

The first solution set entails configurations for the *product sales* type, characterized by rather simple smart PSS. These smart PSS operate without coupling control, ecosystem, and prediction functionalities. The first solution shows smart PSS with considerable sensing and acting capabilities provided via open interfaces. This includes more complex appliances such as smart cleaners or smart locks. The second solution describes smart PSS that do not dispose of their own output medium. This includes technically rather simple household appliances (e.g., smart kitchen scales). The third solution shows smart PSS with considerable acting capabilities and one-to-one user mapping for personalized customer interaction. This includes smart safety devices or smart clothes.

The second solution set shows configurations for the *bundle elements together* type, characterized by a necessary connection to ecosystems as well as customers actively using these smart PSS via their own output medium. These smart PSS do not dispose of advanced analytical capabilities like the first solution set. The first solution shows autonomously acting and rich sensing devices with a particularly strong user connection (e.g., remote toys). The second solution includes rich sensor devices with a strong ecosystem and an emphasis on customer contact (e.g., e-readers). The third solution comprises smart PSS that primarily act as extension elements (e.g., smart lights). Their lack of sensors requires bundling over ecosystems. All these configurations show at least some extendibility.

The third solution set shows configurations for the *cross-selling* type that is not characterized by a generic pattern. This type contains many smart PSS that pursue both cross-selling and bundling objectives. Solutions 1, 2, and 4 are very similar to configurations of the bundling type. Several products fall into both categories. The differences result from some other products included in the cross-selling type. The third solution is the most diverging one. These smart PSS have opened their APIs and dispose of advanced analytical capabilities, however, they do not include third-party developers or depend on customer active interactions. Typical examples are smart energy boxes.

The results of smart PSS configurations of product-centric value propositions are depicted in Figure II.3-2 to Figure II.3-4.

Product-centric VP	Product sales (freq ≥ 2)		
	1	**2**	**3**
Autonomous Acting	•	⊗	●
Rich Sensing	●		⨂
Openness	●	⊗	⊗
Coupling Control	⊗	⊗	⊗
Ecosystem (3rd Party)	⊗	⊗	⊗
Consumer active	⨂		
User Mapping	⊗	⊗	●
Prediction	⊗	⊗	⊗
Own Output		⨂	
Consistency	1.00	1.00	1.00
Raw Coverage	0.10	0.14	0.14
Unique Coverage	0.10	0.14	0.14
Overall Solution Cons.	1.00		
Overall Solution Cov.	0.38		
Example	Irobot Roomba S9+	DropScale	Lattis Elipse

Note. ● present core condition, ⨂ absent core condition, • present peripheral condition, ⊗ absent peripheral condition.

Figure II.3-2: Smart PSS configurations to achieve product-sales only

Product-centric VP	Bundle elements together		
	1	**2**	**3**
Autonomous Acting	●		⨂
Rich Sensing	●	●	⊗
Openness		•	•
Coupling Control		●	
Ecosystem (3rd Party)	●	●	●
Consumer active	•	•	•
User Mapping	●		⊗
Prediction	⨂	⨂	⊗
Own Output	●	•	•
Consistency	1.00	1.00	1.00
Raw Coverage	0.11	0.11	0.11
Unique Coverage	0.11	0.11	0.11
Overall Solution Cons.	1.00		
Overall Solution Cov.	0.33		
Example	Anki Cozmo	Amazon Kindle Oasis 3	Phillips Hue Light

Note. ● present core condition, ⨂ absent core condition, • present peripheral condition, ⊗ absent peripheral condition.

Figure II.3-3: Smart PSS configurations to achieve bundling

Product-centric VP	Cross-selling (products)				
	1	**2**	**3**	**4a**	**4b**
Autonomous Acting	⨂	⨂	●	●	●
Rich Sensing		●	⨂	●	●
Openness	●	●	⬤	⨂	⨂
Coupling Control	⊗		⬤	⊗	
Ecosystem (3rd Party)	⬤	●	⨂	⬤	⬤
Consumer active	●	●	⨂	●	●
User Mapping				⬤	⬤
Prediction			⬤		●
Own Output	●	●		●	●
Consistency	1.00	1.00	1.00	1.00	1.00
Raw Coverage	0.06	0.06	0.06	0.06	0.11
Unique Coverage	0.06	0.06	0.06	0.06	0.11
Overall Solution Cons.	1.00				
Overall Solution Cov.	0.34				
Example	Phillips Hue Light	Amazon Kindle Oasis 3	Curb Energy Box	Anki Cozmo	Fitbit Versa Watch

Note. ⬤ present core condition, ⨂ absent core condition, ● present peripheral condition, ⊗ absent peripheral condition.

Figure II.3-4: Smart PSS configurations to achieve cross-selling

4.2.2 Configurations of service-centric value propositions

The first solution set entails configurations for the *solution provider* type, which are characterized by autonomous acting, rich sensing, and platform openness along with a connection to third-party developer ecosystems. Moreover, an own output medium complements these smart PSS. Despite the many shared characteristics of these solution providers, there are noticeable differences between the two solutions. The first solution comprises smart PSS that do not offer advanced analytical capabilities. This includes smart home appliances such as cams or doorbells, among others. Their interfaces are opened for broader ecosystems and aim to collect (additional) customer data to enable smart services. The second solution, on the other hand, includes smart PSS with predictive capabilities at the user level (e.g., voice assistants). Coupling control indicates that these appliances maintain the primary customer relationship compared to smart PSS in the first solution.

The second solution set comprises of one particular configuration for the *remote usage and monitoring* type, characterized by autonomous acting potentials and rich sensing technologies, customer-active interactions, predictive data analytics, and an own output medium. This indicates a high technical demand to cover this value proposition type. Thus, only a few cases in our sample followed this type (e.g., smart vehicles). Further configurations seem possible in the future. There are no consistent solutions for the value proposition types of objects self-service, digital add-on, and value-added reseller based on the cases in our sample. The results of smart PSS configurations of service-centric value propositions are depicted in Figure II.3-5.

Service-centric VP	Solution provider			Remote usage and monitoring
	1a	**1b**	**2**	**1**
Autonomous Acting	⬤	⬤	●	⬤
Rich Sensing	●	●	●	⬤
Openness	⬤	⬤	⬤	⨂
Coupling Control	●		⬤	⊗
Ecosystem (3rd Party)	⬤	⬤	⬤	●
Consumer active		●	⬤	⬤
User Mapping	⊗	⊗	⬤	⨂
Prediction	⨂	⨂	●	⬤
Own Output	●	●	●	⬤
Consistency	1.00	1.00	1.00	1.00
Raw Coverage	0.09	0.09	0.54	0.33
Unique Coverage	0.09	0.09	0.54	0.33
Overall Solution Cons.	1.00			1.00
Overall Solution Cov.	0.72			0.33
Example	Nest Cam Indoor	Nest Hello Doorbell	Google Home Mini	Tesla Model X

Note. ⬤ present core condition, ⨂ absent core condition, ● present peripheral condition, ⊗ absent peripheral condition.

Figure II.3-5: Smart PSS configurations to achieve solution provider and remote usage and monitoring

4.2.3 Configurations of intermediation-centric value propositions

The first solution set entails configurations for the *product as point of sales* type, characterized by coupling control and ecosystem integration. Coupling control is a prerequisite for the occupation of the customer interface and is crucial for intermediation purposes. In addition, these smart PSS dispose of platform capabilities connected to external ecosystems. We identified four different types of smart PSS in this solution set. Smart PSS in the first solution are primarily characterized by autonomous acting, customer-active interaction, and advanced analytics. These interfaces do not have their own output medium but autonomously react to predicted customer needs. This includes, for instance, an automated ordering of products by smart refrigerators. In contrast, smart PSS in the second solution are primarily characterized by their sensing capabilities and platform connection. These devices are data collectors (e.g., Google Nestcam), the business logic such as advanced analytics is realized on the platform (e.g., Google Assistant). Smart PSS in the third solution operate either proprietary or standalone as they do not open their platform. Consequently, the provider occupies the customer interface itself, for instance, the cockpit of a smart vehicle as a point of sales. The fourth solution comprises smart PSS that fulfill all necessary characteristics for recommendation marketing (like solution 3), however, they might have opened their platform. This configuration includes smartphones, smartwatches, and smart home devices. Those smart PSS are part of an integrated ecosystem that controls different customer touchpoints and collects different data types. The aim is to obtain a holistic view of consumers to place personalized offerings.

The second solution set shows configurations for the advertising type, characterized by an own output medium to place advertisements. Acting and sensing capabilities are somewhat included in these smart PSS to capture customer perceptions. In particular, two solution types can be distinguished. Smart PSS in the first solution do not have advanced customer interaction and regard advertising as an additional revenue source besides product sales (e.g., smart household appliances). Smart PSS in the second solution consider advertising more as their core business. This is realized by opening the platform and controlling the customer interface. Thus, the type is largely similar to solution 4 of the product as point of sales type. The smart PSS configurations of intermediation-centric value propositions are depicted in Figure II.3-6.

Intermediation-centric VP	Product as point of sales					Advertising	
	1	**2a**	**2b**	**3**	**4**	**1**	**2**
Autonomous Acting	●			•	•	•	•
Rich Sensing		●	●	•	•	•	●
Openness	⨂		•	⨂		⨂	●
Coupling Control	●	●	●	●	●		•
Ecosystem (3rd Party)	•	●	●	●	●	⊗	●
Consumer active	●		•		•	⨂	•
User Mapping	⨂			●	●	⨂	
Prediction	●	⨂	⨂	●	●		
Own Output	⨂	•	•	•	•	●	•
Consistency	1.00	1.00	1.00	1.00	0.88	1.00	0.88
Raw Coverage	0.08	0.08	0.08	0.25	0.58	0.14	0.52
Unique Coverage	0.08	0.08	0.08	0.08	0.41	0.14	0.28
Overall Solution Cons.	0.92					0.92	
Overall Solution Cov.	0.92					0.85	
Example	LG Insta View	Nest Cam Indoor	Amazon Kindle Oasis 3	Tesla Model X	Amazon Echo 3rd	Nest Thermos-tat	Ecobee Switch+

Note. ● present core condition, ⨂ absent core condition, • present peripheral condition, ⊗ absent peripheral condition.

Figure II.3-6: Smart PSS configurations to achieve product as point of sales and advertising

Overall, we see an evolution from the stand-alone smart PSS for sales purposes, the complementary bundling and cross-selling smart PSS, over the external ecosystem solution providers and remote usage and monitoring smart PSS to the intermediary and controlling product as point of sales and advertising smart PSS.

5 Conclusion

This study analyzed smart PSS properties and their impact on value propositions. To achieve this, we developed a taxonomy of smart PSS in B2C and applied configurational analysis for typology development.

Our research findings indicate how individual smart PSS are used by providers economically with regard to underlying business and revenue models. Conversely, the current state of the art in practice shows that specific product characteristics are necessary to achieve more advanced value proposition types. The taxonomy allows the descriptive comparison of the properties, while the typological archetypes have a categorizing function, showing which properties are necessary to improve a business model to remain competitive.

We found smart PSS configurations across the different value propositions ranging from simple to more complex sensors and actuators towards complex service solutions connecting entire ecosystems. In this regard, the analysis showed two important findings. First, simple, smart PSS focusing on the smart product core are not suitable to follow advanced business model goals. Second, platform ecosystems and data analytics are necessary capabilities for advanced business model goals but also ecosystem control through products (coupling control) is a vital aspect to consider.

The business model of many smart PSS is focused on product sales, whereas more sophisticated smart PSS generate revenues by intermediation. Here, a central question is what type of smart PSS will become the main interface to the B2C customer in different industries in the future. The dominating providers will expand their customer outreach through integrating and controlling other smart PSS via open APIs or acquisitions. In contrast, others that do open their products but do not have control over the customer interface might turn out to be only data suppliers. This also poses a threat to the business models of traditional industries. Especially, banks and insurances made intermediation-centric smart PSS available to their convenience-driven customers and built complete services on them (e.g., smart and voice banking or telematics insurance tariffs). This could also be a possible evolution in the automotive industry.

Our study makes two important contributions to research: First, typologies beyond purely descriptive analyses are derived for smart PSS in B2C using a configurational theory approach. Second, smart PSS capabilities determine what types of value propositions can be achieved beyond core product features.

Despite its strengths and contributions, this study also has limitations that provide opportunities for further work. The results of the QCA analyses were derived from the qualitative coding methods, based on the taxonomy definitions of the characteristics. Concerning the consistency values, the results met the required quality criteria of QCA analyses (Ragin 2009). In subsequent studies, fuzzy sets could be used in the coding instead of crisp sets for finer gradations. In this study, we have taken the current market situation into account. Further configurations beyond those depicted in the paper are conceivable in the future. The results should be confirmed or extended in follow-up studies as we currently find only a low number (i.e., frequency) of smart PSS in B2C industries. Design-science research could investigate smart PSS characteristics based on our findings. Our methodology and the empirical results point to the critical characteristics for developing business models. Based on this, it is possible to consider how these can be translated into concrete designs. Industries such as banking and insurance might also recognize which limitations or dependencies exist in relation to existing usage of smart PSS, their business models, and end-customer contact.

We also had a clear focus on revenue sources of value proposition types, whereas there might be other sources of value to consider from the customer perspective. Besides that, we have used qualitative case data and not included concrete measures of business model success (e.g., sales or usage figures, profits, or market valuation). Future research could also examine more in-depth how smart PSS are able to obtain coupling control on the product and service level. A comparison of B2C and B2B smart PSS would be another possible next step for future research.

Ⅲ Effects

III.1 Sustaining the current or pursuing the new: Incumbent digital transformation strategies in the financial service industry − A configurational perspective on firm performance

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Abstract: Digital Transformation (DT) is a major challenge for traditional companies. Despite the term, DT is relatively new; its substance is not: A whole stream of research has examined the relationship between DT and firm performance with contradictory findings. Most of these studies have chosen a linear correlational approach, however, did not analyze the holistic interplay of DT dimensions, leading to firm performance. This applies especially to the mature financial services industry and the future perspectives of traditional financial service providers (FSP). Hence, it remains an open question for both research and practice what DT configurations have a positive impact on firm performance. Against this background, the aim of this exploratory study is to examine how DT dimensions are systemically connected to firm performance of incumbent FSP. Drawing on a qualitative-empirical research approach with case data from 83 FSP, we identify digital configurations along different levels of firm performance. Our findings suggest an evolution of digital configurations of FSP, leading to five empirical standard types from which only one managed to establish a profound basis of DT.

1 Introduction

Management scholars have examined the difficulties of industry incumbents to innovate their business (Eklund and Kapoor 2019). Especially the financial services (FS) industry is undergoing a radical transformation. The previously stable market shows unprecedented competitive dynamics, regulatory changes, and non-/near-banks as asymmetric competitors in the day and age of digital technologies. Practitioners speak of a disruptive change that could decrease the importance of traditional financial service providers (FSP), exemplified by a recent practitioner study (McKinsey 2019b) that tackles future industry perspectives regarding profitability measures.

Our article focuses on DT of incumbent FSP with the characteristics of high market power, revenue streams from traditional services, and the presence of physical branches (Chiorazzo et al. 2018). Incumbent banks and insurance companies play an important role in society and for sustainable development, as they exert several important economic functions, such as the promotion of saving and wealth formation in the population and the credit supply to the economy. Given their long tradition, FSP have a particular focus on their B2C retail businesses with four major product types: Payment, financing, investment, and insurance (cf. Alt and Puschmann 2016, pp. 12 f.), roughly resulting into two major subsectors: Banking and insurance. While banking implies the transfer, accumulation, and increase of savings and the provision of capital, insurance involves mainly the transfer and management of risks.

Traditionally, FS are barely interesting products, making differentiation difficult. Digitalization, however, makes customer orientation a central aspect for competition (Alt and Puschmann 2012; Bons et al. 2012; Nüesch et al. 2015). New digitally empowered competitors position themselves with a range of standardized digital and easy-to-handle products. While switching costs decline, customers can choose among the offers of both traditional and novel FSP for their accounts, payments, loans, mortgages, investments, or insurance products, questioning their former strong, trust-based relationship to their FSP (Pousttchi and Dehnert 2018). In addition to new digital offerings, interaction via digital channels becomes a decisive competitive factor. Pousttchi et al. (2015) found that the traditional, direct communication scenarios could lose significant proportions against impersonal and indirect communication scenarios. The tendency towards digital services puts traditional FSP in an uncomfortable position: While the competitive effect of their dense branch networks weakens, cost pressure skyrockets. This development is also reflected in firm performance (PERF), which is reflected in key figures, such as profitability. Digital transformation may be a key driver to increase profitability by reducing costs and increasing revenues.

A whole stream of research has examined the relationship between digitalization and PERF (Aral and Weill 2007; Bharadwaj 2000; Chae et al. 2014; Chen et al. 2009; Koellinger 2008; Mithas et al. 2011; Rai et al. 2006). The findings are somewhat contradictory. Bharadwaj (2000), for instance, indicates that firms with a high information technology (IT) capability outperform the control sample of firms on a variety of profit and cost-based performance measures, whereas Chae et al. (2014) found no significant link between IT capability and PERF. Aral and Weill (2007), for instance, found that firms' total IT investment is not associated per se with PERF, however, investments in specific IT assets consistent with their strategic purpose can explain performance differences. More recent research, however, supports the notion of DT being a mediator between IT investments and PERF (Nwankpa and Roumani 2016). In particular, DT was found to have a large and positive long-term effect on FSP PERF (Scott et al. 2017), productivity (Bertoni and Croce 2011) and organizational agility (Ravichandran 2018). DeYoung et al. (2007) also found a positive relationship between DT and community bank profitability.

One recurring finding is that specific configurations seem to be essential for PERF (Ketchen et al. 1997; Ray et al. 2005). In particular, prior studies on FSP showed that contiguous resource management is vital for superior PERF (Sirmon and Hitt 2009), however, none of these studies have yet analyzed the interplay of DT dimensions and its relationships to firm performance. Against this background, we tackle the following research question: *'Which digital configurations in financial services are systemically connected to superior firm performance, and which are not?'* To tackle this research question, we adopt a qualitative-empirical research approach to examine if and how structural elements of DT in FS are systemically connected to PERF and, accordingly, which FSP standard types have developed along different levels of PERF.

Our coherent research design consists of three steps. Firstly, we develop a research model of the relevant DT dimensions to specify the research scope and lay the foundation for our further research. Secondly, we conduct a literature review with a deductive, concept-oriented approach to obtain a comprehensive overview of the current state of research on DT in the FS industry. Thirdly, we collect case studies from the international FS market to examine how a FSP's configuration of DT is connected to PERF. In particular, we use fuzzy-set qualitative comparative analysis (fsQCA) as an innovative approach in management and IS research (e.g., Fiss 2011; Park and Mithas 2020; Werani et al. 2016) to identify standard types of consistent digital configurations in the FS industry.

The rest of the paper is organized as follows: In the next section, we provide the background, i.e., the research model and our setting along with a comprehensive literature review on DT in FS. In the third section, we conduct the configurational analysis. In the fourth section, we present the results of the configurational analysis and five standard types. In the fifth section, we discuss our findings regarding the identified FSP evolution as well as their future perspectives. We close with a conclusion and outlook.

2 Theoretical background

In a first step, we develop a research model that underpins our research design in two ways: On the one hand, it precisely circumscribes the area and scope of DT in FS. On the other hand, it structures both the review of the literature and the configurational analysis. After this, we analyze the state of the art in research of DT in FS, collecting relevant literature, following the guidelines from Webster and Watson (2002). This helps us to gain a deeper understanding of DT for FSP and the potential impact of each dimension on PERF. A keyword search was conducted in relevant scientific databases (i.e., AISel, IEEE Xplore, ACM DL, EBSCOhost, ScienceDirect, SpringerLink, Proquest, Informs, Wiley) in mid-2019 to identify relevant literature for the following expressions: ("digital*" OR "digitiz*") AND ("financial service" OR "bank*" OR "insur*") within relevant research strands (i.e., IS, Business Informatics, Economics, FS, Banking, Insurance), and, subsequently, classified against our research model in a concept-oriented approach. The focus was on industry-specific DT articles in IS, management, and industry-specific journals, listed in VHB-JOURQUAL3 as "B" or higher. Due to the novelty of the research field of DT, the search period started from 2010 onwards but was extended in the case of promising citations during the backward and forward search. This resulted in over 350 relevant sources for both industry sectors, from which only a subset of the 92 most representative research articles has finally been included in the paper. Hence, these papers were selected as they give an indicative picture of the different research strands in DT of FS for the building blocks of our research model.

2.1 The financial services industry

Banks and insurance companies play a central role in modern economies as typical providers of financial services (e.g., Hellenkamp 2015, pp. 7 ff.; Nguyen and Romeike 2013, pp. 9 ff.). There are several functional similarities which both industry sectors share. Firstly, this entails the *risk transformation function*. While banks reconcile the different risk propensities of debtors and investors in the credit and investment function, the insurance business model consists of risk identification, calculation, and balancing in underwriting processes. Secondly, the *maturity transformation function* allows banks to reconcile the different maturity interests of debtors and creditors, whereas specific insurance companies conduct savings and deposit businesses as well, such as life insurers. Thirdly, the *customer service function* distributes complex financial products by means of customer advisory services. Hence, both sectors are characterized by the management of customer accounts: On the one hand, the banking checking account, on the other hand, the insurance file. An important basis for these three main pillars is the *information transformation function*, i.e., the timely processing of financial market data in banking or the data-driven underwriting and premium pricing processes in insurance. Moreover, banks also perform *lot size transformation* activities, which are more comparable to reinsurer businesses, and provide *payment transaction functions*. These activities lead to comparable deposit and disbursement models of banks and insurance companies, which finally impact the annual net income and firm profitability (i.e., PERF). The competitive threat posed by declining revenues and high fixed costs, which challenge incumbent firms to secure their future economic existence, are particularly evident here. Regarding this, we systematize the concrete impact of DT on FSP across three dimensions in the following.

2.2 Digital transformation in financial services

Digital transformation affects the FS industry as digital technologies change business in three characteristic dimensions: Value creation, value proposition, and customer interaction (Pousttchi et al. 2019; Pousttchi 2020). The *value creation model (VCM)* captures the impact of DT on how FS products and services are created (Pousttchi 2020). This entails the underlying processes to perform the different business functions, such as risk, maturity, or information transformation. Achieving both efficiency and effectiveness advantages requires a process-oriented reengineering of the firm (Hammer and Champy 1993, pp. 34 ff.); the corresponding business processes require a different form of management (Picot et al. 2003, pp. 77 ff.). The *value proposition model (VPM)* includes the impact of DT on what FS products and services are created, i.e., the improvement of existing products and services, the offering of new or even novel products and services, and changes in revenue models (Pousttchi 2020; Skålén et al. 2015; Teece 2010). This entails the concrete outcomes of the different business functions provided to different customer segments. FSP may conduct profitability and performance analysis and use data to develop new products and services. The *customer interaction model (CIM)* includes the impact on the nature and content of customer interaction in financial services, i.e., "the cross-channel and holistic design of the customer relationship and the inclusion of automated communication and modern forms of data analysis" (Pousttchi 2020). This entails the concrete interaction with customers in the customer service function, such as for sales, service and marketing purposes.

Other factors from the fields of *technological* and *strategic choices* are systematically connected to these three dimensions. From a resource perspective, FSP require sufficient IT resources to conduct the business functions appropriately (e.g., standardized or customized hardware, applications, databases, and data warehouses). This entails the operation of the *IT core systems (CORE)* and cross-functional support of all activities. Regarding the information transformation function, *data analytics (DATA)* is a major technological driver and hence another suitable building block for FSP technological prowess (Sun et al. 2019). This includes data-driven decision-making from customer-contracting, to providing warning signals to financial market traders about position risk, to detecting customer and inside fraud, and improving compliance and reducing model risks (e.g., Yang et al. 2017). *Digital strategies (STRA)* are another important driver for organizational change in incumbent FSP, with increasingly converging business and IT strategies (Bharadwaj et al. 2013; Constantiou and Kallinikos 2015; Grover and Kohli 2013; Matt et al. 2015; Seddon et al. 2017). In the area of strategy-making, strategic technological partnerships entail a number of possibilities to enhance the business model (Al-Debei and Avison 2010; Osterwalder and Pigneur 2010). FSP sourcing decisions may affect the organizational distribution and competitive positioning towards new Fintech service providers. In this regard, *cooperation (COOP)* indicates to which extent incumbents have expanded their value network to third-party providers in times of open banking regulations.

There are further conceptualizations of DT available in the literature (see Vial 2019 for a review) which mostly coincide with our DT building blocks for concrete tangible DT outcomes but also include additional qualitative aspects, such as agility or organizational culture, which would have been difficult to assess in our study and, hence, were not in the scope of our analysis.

The themes identified from the literature are introduced for each DT building block in the following.

2.2.1 Value creation model

The *value creation model* entails operations with a transaction processing downstream of product and sales activities such as risk transformation, transaction management as well as asset and liability management. There are different research strands on DT in FS in this area. Some scholars examined methods to measure the efficiency of FS processes (Frei and Harker 1999), others highlight specific barriers to digitalizing bank processes (Graupner et al. 2015; Graupner and Maedche 2015). Another stream of research dealt with structural characteristics of incumbent FSP (Zhu et al. 2004). Insurance-focused literature analyses mainly to what extent digital technologies can improve the internal core processes. Claims processes, for instance, can benefit highly from business platforms or spill-over effects from collaborating networks (Menon 2015). Further contributions concentrate on process automation (e.g., Braunwarth et al. 2010; Cooper et al. 2017) and flexibility gains (e.g., Afflerbach et al. 2014; Braunwarth and Ullrich 2010). In sum, prior research shows that digital business processes can foster firm productivity along the entire value chain in FS (Bertoni and Croce 2011; Eling and Lehmann 2018).

Since *IT core systems* are essential to perform tasks and processes of a FSP, serving as the IT backbone of the transactional business, another important question is how transformed the incumbent core systems are already. In this area, FSP typically operate 'legacy' systems, which are often older than 30 years. Accordingly, core system renewal is a major research area (Alt and Puschmann 2016, p. 160; Mocker et al. 2015; Puschmann et al. 2012). Scholars, for instance, studied migration strategies for renewing core applications in banks and risk management systems of insurers (e.g., Wolle 2014). Another research stream is discussing application areas of blockchain technology, which is still in its early stages in practice (Avital et al. 2016; Nofer et al. 2017; Notheisen et al. 2017). Prior research has verified the impact of IT-driven innovation on PERF in particular for FS: Beccalli (2007a) found a heterogeneous impact of different types of IT investments on bank performance, with especially IT outsourcing being positively related to PERF, whereas Harris and Katz (1991) discovered a positive link between IT investments and insurers' performance.

Prior research in the area of *data analytics* covered the management and applications of data-driven innovation (Sun et al. 2019). Possible implementation issues are important to consider (Audzeyeva and Hudson 2016), especially regarding data analytics for marketing purposes (Martens et al. 2016). Insurance-related literature explores and discusses the potential of advanced data analytics methods greatly to foster the actuarial competencies of insurers. Many contributions focus on the implementation of usage-based insurances or pay-as-you-drive models through sensors, actors, and real-time analytics (e.g., Marabelli et al. 2017; Vaia et al. 2012; Weidner and Transchel 2015). However, new data sources and analysis methods can bring new opportunities for risk calculation and underwriting or forecasting (e.g., Biffis and Blake 2013; Boyer et al. 2012), for instance, by using maintenance records to predict accidents (Bair et al. 2012). Further prospects derive from new possibilities for individual pricing and fraud detection (Crainich 2017). Performance-enhancing effects have been found for customer analysis and knowledge processing (Coltman et al. 2011; Setia et al. 2013; Tomczyk et al. 2016). In particular, prior research found that data analytics can, in fact, increase customer knowledge and, based on new service offerings, also the profitability of FSP (Alt and Reinhold 2012; Fang et al. 2016; Tomczyk et al. 2016).

In the area of *digital strategies*, scholars examined the presence of digital agendas (Bohnert et al. 2019), diversified intermediaries (Peng et al. 2017) and the impact of digital strategies on service productivity and service innovation (Aspara et al. 2018), all of which are positive factors on PERF. Potential paths towards digital strategies in FS are analyzed in the literature as well (Chanias 2017; Chanias et al. 2019).

2.2.2 Value proposition model

The *value proposition model* includes the business areas of product development, business direction and innovation management for originating and testing new products, services, and business models. Scholars identified novel types of digital products and services in FS in the area of *value proposition*, such as digital finance, investment, money, payment, financial advisory, and digital insurance (Gomber et al. 2017). Social customer relationship management (Du et al. 2019) and crowdlending (Blohm et al. 2016), for instance, are promising digital banking services. Insurance-related contributions cover mainly the benefits of usage-based insurances (Vaia et al. 2012) or cyber-risk insurances (Eling and Schnell 2016). Gordon et al. (2003) present a framework for cyber-risk insurances, while Zhao et al. (2013) explore useful alternatives. Other product innovations include insurances for SLA violations (Morshedlou and Meybodi 2018), reputational damages through social media, flaws from cloud computing services, semi-autonomous cars, or new product types, such as micro and add-on insurances (Fleisch et al. 2015) or integrated services (Mocker and Ross 2013). Concrete product implementations, such as robo advisors, have been examined in the literature as well (Jung, Dorner, Glaser and Morana 2018; Jung, Dorner, Weinhardt and Pusmaz 2018). Prior research found a positive relationship between digital service portfolio and service performance (Setia et al. 2013). Hernando and Nieto (2007) showed that in Spanish banks the introduction of online banking was positively related to profitability. Regarding new digital revenue sources, only a few scientific contributions can be identified in the banking literature. Insurance-oriented literature reveals a similar picture: Basically, usage-based insurance products (Vaia et al. 2012) and digital distribution channels (Klotzki et al. 2017) are analyzed as drivers to generate digital revenues. In sum, this indicates the potential crucial role of digital product portfolios, however, research on the impact of revenue models on PERF is still rare.

2.2.3 Customer interaction model

The *customer interaction model* in FS includes sales and customer services as well as marketing initiatives. In this area, multi-sided platforms set up novel recommendation and marketing systems to become the monopolized first touchpoint of the customer (Pousttchi and Dehnert 2018; Pousttchi and Gleiss 2019). With these new Fintech entrants, new challenges for customer interaction of FSP emerged. In this regard, digital channels are an important research stream (Cortiñas et al. 2010; Geng et al. 2015; Klumpes and Schuermann 2011), especially on new opportunities to interact with customers (e.g., Klotzki et al. 2017; Pousttchi and Dehnert 2018), and choosing the right channel for a specific service is a complex endeavor (e.g., Perissinotto 2003). The implementation of omnichannel management, taking changing user behavior into account, is even more complex (e.g., Honka and Chintagunta 2016). More generally, Yusuf Dauda and Lee (2015) explored customer preferences in banking, whereas Dai and Salam (2014) identified service convenience as a significant factor for long-term relationships between customers and FSP. Several studies have analyzed the customer acceptance of new digital channels (Ackermann and Wangenheim 2014; Choudhury and Karahanna 2008; Polo and Sese 2016). The adoption of mobile services in banking (Bons et al. 2012; Ha et al. 2012; Laukkanen 2016; Sharma 2019; Zaffar et al. 2019) or insurance (Heinze and Matt 2018; Lee and Cheng 2007; Prasopoulou 2017) has especially been highly investigated in research. Other customer characteristics have also been examined, such as financial knowledge and risk preferences (Königsheim et al. 2017). Further light is shed on the importance of customer satisfaction, loyalty and retention (e.g., Hammerschmidt et al. 2016; Keiningham et al. 2015). Other contributions focus on the role of co-creation and self-service technologies (e.g., Moeller et al. 2013; Yu et al. 2013), which might lead to a reduction of service costs for FSP (Kumar and Telang 2012). Regarding the impact on PERF, Campbell and Frei (2010) examine the effects of digital customer interaction on short-term customer profitability and long-term customer retention. Their findings indicate that new digital services may lead to lower short-term customer profitability, however, the usage is also associated with higher customer retention rates over multi-year horizons, and leading to higher market shares.

The major research emphasis in the area of *cooperation* is on networking models of FSP. One particular research stream deals with digital platforms: Ondrus et al. (2015) analyze the effects of platform openness, Drummer et al. (2017) explore possibilities of credit marketplaces, and Kazan et al. (2018) find categorization criteria based on value architectures. Further contributions identified challenges and opportunities of open platform models (Gozman et al. 2018). Other analyses examine ecosystem moves from competition towards coopetition between banks and Fintech (Drasch et al. 2018; Schmidt et al. 2018) or insurances and Insurtech, respectively (Stoeckli et al. 2018). Broader contributions examine insurance companies' cooperation with IT service providers to streamline processes and reduce costs (Ejodame and Oshri 2018; Mani and Barua 2015; Willcocks and Lacity 1999; Zimmermann et al. 2018). Furthermore, the importance of intermediaries has been explored widely, particularly for insurance companies (Karaca-Mandic et al. 2018; Peng et al. 2017; Pousttchi and Gleiss 2019). Most of these contributions, however, did not account for the particular impact on PERF.

2.3 Configurational theory

Prior research has examined all of the aforementioned DT building blocks in a rather isolated manner. The findings indicate a particular influence of several dimensions, however, have not analyzed their particular interplay with regard to PERF. In this regard, the study of *organizational configurations* is a rather innovative research approach (Lee et al. 2004; Liu et al. 2017; Park et al. 2017; Park and Mithas 2020). Organizational configurations are *"any multidimensional constellation of conceptually distinct* *characteristics that commonly occur together"* (Meyer et al. 1993, p. 1175). The underlying theory suggests that organizations are best understood in their interconnected structures. In contrast to traditional regression analysis, configurational analysis focuses on the causes of effects not on the net effects of causes. While statistical approaches are symmetric, holding other dependent variables constant, configurational analysis allows to identify asymmetric configurations to achieve an outcome (Fiss 2011). The concept of *equifinality* considers at least two or more organizational configurations as separate paths to achieve PERF (Fiss 2007).

Firm performance serves us as an indicator of *competitive advantage* (Peteraf and Barney 2003; Porter and Millar 1985; Schilke 2014), measuring how well a firm can meet its goals and objectives compared with its primary competitors (Miller and Cardinal 1994). Our analysis focuses on the financial perspective of PERF with profitability measures as a well-accepted indicator in management (e.g., Hughes et al. 2019) and IS (e.g., Chae et al. 2014). In case of low PERF over longer periods, for instance, the raison d'être of a FSP may be at stake, while superior PERF is generally characterized by higher profitability, growth, and market value (Cho and Pucik 2005).

The *resource based view* suggests that firm-specific resources are the primary determinants of PERF (e.g., Nwankpa and Roumani 2016). Thus, we argue that DT configurations are systemically connected to PERF, since more digital FSP may, after an initial adoption phase, generate more profits through increasing revenues and decreasing costs. Drawing on the concept of equifinality, we account for multiple causal relationships linking DT and PERF (Fiss 2011). Some FSP might focus on digitalizing their value-creating processes and infrastructures, some might concentrate on developing new value propositions, and others may prioritize strengthening their value network and introduce digital channels for customer interaction first (Sebastian et al. 2017). Each approach presents a different way of assembling DT logic, potentially connected to different PERF. In this regard, the results of the literature analysis highlight multiple potential influences from the DT building blocks on PERF which are connected in a systemic, but non-linear way. Our research follows an inductive approach to analyze these connections.

Control variables in fsQCA are usually not incorporated into the analysis as we do not estimate independent effects of causal variables but focus on combinations of causally relevant conditions (Fiss 2011). As such, we identified three potential contingency factors for PERF in the literature: Firm size, regulation, and interest rate situation (e.g., Forman 2005). Firstly, there are studies on firm size in FS that underline its impact on the choice of bank strategies (e.g., Tallon 2010). One of these studies showed that smaller banks may benefit more than larger ones from the adoption of digital technologies (Scott et al. 2017). Secondly, regulation sets the political frame for FSP in DT (Knackstedt et al. 2013) and different regulations might affect PERF. Finally, the interest rate situation affects existing revenue models (Altavilla et al. 2018; Hayo et al. 2019) and, thus, may drive and limit DT. In the context of FS, however, we found only a few research articles supporting these factors in DT. There are, for instance, no scientific contributions regarding the relationship between interest rates, DT building blocks and PERF. Hence, following the two-step QCA approach (Schneider 2019), we conducted prior necessary condition analyses by obtaining current data based on market estimates on the global FS regulation and interest rate situation from industry experts (Citibank 2018; Organisation for Economic Co-operation and Development 2019) and assigning these to the companies in the best possible way. This was difficult for two reasons: Firstly, the majority of the companies in our sample are large international corporations, therefore, we based our assessments mostly on the domestic markets. Secondly, our study focuses largely on highly regulated and homogeneous low interest markets, such as Europe or the US, leading to only a little variance between local interest rates. Our preliminary test of the contingency variables as necessary conditions for PERF showed that, despite an existing correlation between regulation as well as interest rate and PERF, no substantial causal effect is to be expected on PERF. We decided not to include external factors other than firm size into our main analysis due to the restrictions in the number of variables to incorporate, as an in-depth contingency analysis was not the aim of this paper. The fsQCA typically follows an iterative process (Greckhamer et al. 2018) unless the focus is on theory-testing (Park et al. 2020). Hence, we included these variables in additional robustness checks.

Figure III.1-1 shows the research model for configurational analysis with its seven DT building blocks.

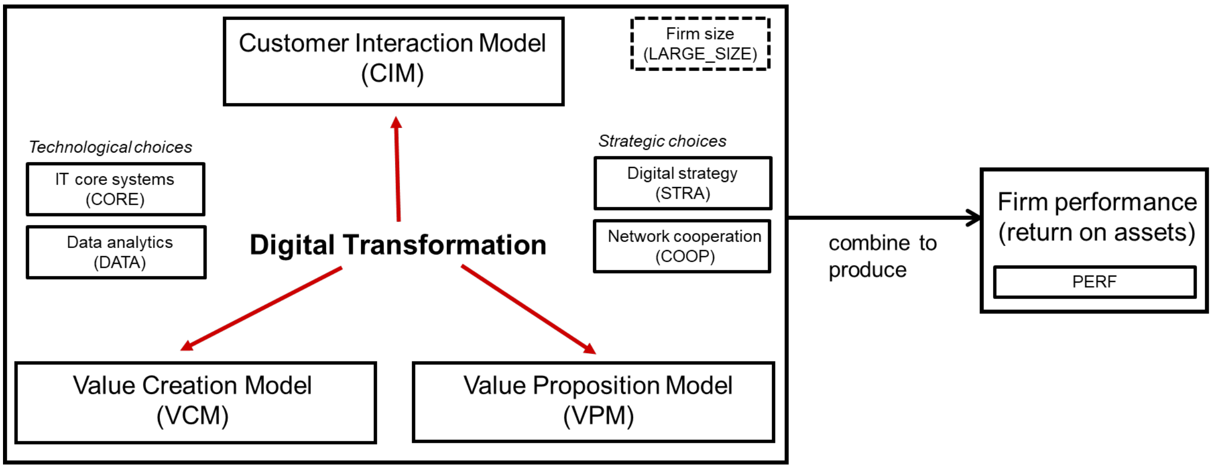

Figure III.1-1: Research model

3 Research approach and analysis

While our literature review confirmed a potentially positive impact of all building blocks of our research model on PERF, the focus of this study is on the interplay of the DT building blocks, as these are interconnected in different ways. Regarding this, *configurational analysis* allows us to incorporate larger numbers of cases and identify the combinatorial nature of organizational configurations associated with an outcome in a holistic way (Fiss 2011; Park et al. 2017). Prior research into configurational methodologies revealed a mismatch between configurational theory and particular methods, such as cluster analysis (Fiss 2007). We use fuzzy-set qualitative comparative analysis (fsQCA) as a representative of set-theoretic methods to avoid this pitfall (Fiss 2011; Schneider and Wagemann 2013). Set-theoretic methods build on configurational theory in their conceptualization of cases as combinations of Boolean variables in the analysis (Ragin 2008, pp. 13 ff.). The fsQCA method is particularly suitable for qualitative data analysis to identify configurations that can be used for theoretical abstraction in the context of typology formation. In this sense, the fsQCA reflects the causal structures with both core (necessary) and peripheral (sufficient) conditions to achieve an outcome (e.g., firm profitability). The fsQCA allows one to include ordinal and continuous measures from 0 to 1 to describe the outcome variable more precisely and to stay with the Boolean algebraic logic (e.g., Fiss 2007; Ragin 2008; Schneider and Wagemann 2013). In the following, we use the fsQCA 3.0 software package to analyze digital configurations of FSP that lead to the outcome of PERF.

3.1 Data collection

To run its analysis, fsQCA requires researchers to operationalize items and calibrate the membership of cases in dimensions and outcome variables. Fuzzy sets represent memberships nummerically on a ordinal or metric scale (Legewie 2017). An item shows how strongly a FSP adopts a particular digital building block, e.g., by coding qualitative data or aggregating responses on items from a survey. We have to justify our choices regarding the presence or absence of conditions with our available theoretical knowledge on the empirical FSP cases (Legewie 2017). At this, our approach follows guidelines on qualitative data use in fsQCA (e.g., Greckhamer et al. 2018; Nishant and Ravishankar 2020). It consists of three steps: (1) operationalization of the research model, (2) coding of cases, and (3) calibration of the data. In the following, the research sample is described and each step is shortly introduced.

3.1.1 Research sample

Our dataset comes from a diverse set of incumbent FSP. The outcome of interest PERF was used to identify a purposeful sample of suitable cases (Greckhamer et al. 2018). The qualitative data collection took place in mid-year 2019. Our theoretical sampling was done inductively with a focus on different FSP types, firm size, and regions. To avoid limited diversity, we especially looked for companies from different PERF categories. Our goal was to reflect the international state of the art in DT, but also to include regional banks in the sample. To identify a representative set of major international FSP, we went through reviews, lists, and international banking awards (e.g., Euromoney, Asian Banker Award). We further identified important minor (i.e., regionally operating) FSP in Europe and the US in press and practitioner releases. An important criterion was the availability and practicability of firm-specific information for the purpose of our analysis. Since there is only sparingly available public data on smaller FSP, especially regarding IT core system status, data analytics, and digital strategy, we conducted additional telephone interviews and a management survey with DT executives from 22 German community banks. These banks operate on a regional level and draw on similar corporate structures, whereas they differ in their size and location (city, periphery, and rural area) as well as in their digital maturity. Our final sample includes 59 banks and 24 insurance companies from mostly Europe (55), the US (12) as well as the rest of the world (16) such as Asia, Africa, and Australia.

3.1.2 Operationalization

In the first step, we developed measurement items based on the findings of our literature review for every building block of our research model. We examined what observations and other types of qualitative data translates into what range of values on a single DT building block. Helpful sources were theoretical knowledge, scales from relevant survey items (e.g., Aral and Weill 2007; Chae et al. 2014) as well as empirical findings from other studies. If we detected ambiguities in connection to a specific dimension, we revisited our operationalization, which provides the necessary means for a systematic and transparent assignment of items scores across all DT building blocks (Legewie 2017). We subsequently discussed the operationalization, based on 5-point scales as anchor points, with a handful of FS practitioners who gave us helpful remarks.

For the VCM, we look at the digital implementation of contracting processes in major product areas from the perspective of customers, for instance, accounts, loans, and savings in banking, leading from many non-digital interfaces to end-to-end digitalization. We further examine the products and business models of each FSP for the VPM regarding the degree of digital revenues, ranging from traditional-only to data-driven credit and telematics tariffs. Regarding the CIM, we consider the channels of each FSP, ranging from the provision of traditional branch to a complete set of digital channels including video consultations or AI-based chatbots. Regarding IT core system status, we examine the digital maturity of the core transaction system of each FSP, ranging from untransformed legacy systems to transformed cores. We further look for the presence of tactical or strategic data analytics applications. We analyze whether FSP are in concrete agreement with Fintech, either as a platform sponsor or partner, regarding network cooperation. We finally examined the extent and time frame of digital strategy for each FSP. For PERF, we rely on recent numbers on return on assets (RoA), which is a commonly used indicator in both management (e.g., Fiss 2011) and IS research (e.g., Bharadwaj 2000). The RoA lays out how profitable a company is in terms of its net income relative to its total assets, thus, how well a company utilizes its assets (Hagel et al. 2013). RoA is a particularly appropriate measure for incumbent FSP, as these firms operate as monoliths with extensive assets (e.g., branch networks) and, thus, high operating costs. We also include the actual numbers of employees for each FSP as a typical figure for firm size.

3.1.3 Coding

The second step turns each dimension and seeks to determine scores while coding. For each dimension we developed a list of codes to identify the respective building block(s) of DT and subsequently its maturity for each firm. Regarding the annual reports, we also coded information on business processes, workflows, or innovations, such as in the area of operations. The building block VCM, for instance, includes processes, systems (including industry-specific characteristics and supplier brands), work environment, employee competencies, workplace, and operations. Based on the coded case's relevant data and the developed scale, each coder assigned a score. Concrete references on the re-engineering of processes or the standardization of IT systems were indications of a high maturity of the VCM, which, however, also had to be reflected in the concrete functionality to the customer, such as on the website or via an app, at which each coder had an in-depth look. The observation to be able to “make purchases and sales of securities, sign-ups and repurchases by funds, and conduct arbitrage online,” for instance, translates to the high degree of digital processing in the VCM. Similarly, the scale has been grounded on behalf of the literature and through the analysis of the cases for each building block. The information in annual reports and press releases was further used to assess each FSP’s digital strategy, IT core system status and data analytics. For instance, time and content of statements, such as: “business uplift from 'Think Forward' digital strategy” translate to the extent of digital strategy-making involved, and likewise for the other DT building blocks. The coding procedure was done by the research team with two scientific assistants, independently.

Interrater reliability is measured using Krippendorff's alpha with values between 0 ("random") and 1 ("perfect match"). In our case, alpha was 0.835 for the coding in our dataset, which is well above the recommended threshold of 0.8 (Krippendorff 2004). Thus, the interrater reliability is good, which may be mostly attributed to the clear definition of the measurement items during the operationalization. The research team subsequently had in-depth discussions on all areas with more pronounced differences in coding, which further enhances the reliability of the coding procedure. We complemented the coded case data on DT with independent actual financial data for the outcome variable of PERF, which also avoids common method bias (Podsakoff et al. 2003). We used single values of RoA which we accessed via recent annual reports and from market data platforms. Accordingly, we rely on numbers of firm size.

3.1.4 Calibration

In the third step, we calibrate the income and outcome variables into set-membership scores. The use of fuzzy scores with fsQCA forces us to employ theoretical and substantive knowledge in the creation of the measure (Fiss 2007). In this sense, calibration defines the extent to which a given case has membership in the set of, for example, a certain level of PERF. There are three qualitative anchors implemented in fsQCA: Full membership, a crossover point of maximum ambiguity and full nonmembership (Ragin 2008, pp. 85 ff.). These three anchors have to be determined by our contextual knowledge (Fiss 2007; Park et al. 2017; Ragin 2008, pp. 33 ff.). The original interval-scale data are converted into fuzzy membership scores by calibration of fuzzy sets that range from "0" to "1" (Ragin 2009). Thus, the final fuzzy set can be seen as a continuous variable that has been purposefully calibrated to indicate the degree of membership (Ragin 2008, pp. 124 ff.). In that sense, fsQCA assigns all cases with values below the lower boundary to "0" (full nonmembership) and all cases above the upper boundary to "1" (full membership).

We especially have to consider how to calibrate the outcome variable PERF measuring firm profitability (RoA). In fsQCA, it is possible to analyze the configurations for the presence and the absence of an outcome separately (Greckhamer et al. 2018). In order to determine the sustainability of the competitive advantage based on the differences between companies that have a difficult or a more solid market position, we have chosen a conservative approach to RoA calibration. We use a RoA value of "0.8" as the upper boundary for the analysis, "0.2" as the crossover point and "0" as the lower boundary. The crossover value of 0.2 allows for both a rational distinction between the low-end (inferior) and better performing (superior) FSP (PERF, 0.8, 0.2, 0). By using this low outcome threshold, we can examine low-performing digital configurations indicating a long-term financial risk that may endanger the raison d'être of the FSP. We do this by negating the calibrated outcome (~PERF), which outputs digital configurations of inferior FSP that cannot achieve an RoA of "0.2" at the lower end of the market.

The list of calibrated sets with their anchor points is described in appendix A. The set labels for each DT building block represent a *high level of maturity* in case a condition is present for the sake of simplicity.

3.2 Configurational analysis with fsQCA

After calibration, in the next step, we apply truth table analysis in fsQCA that identifies consistent combinations of the DT building blocks producing the outcome variables (Ragin 2008, p. 34). A truth table includes all logically possible combinations of the elements, and each row corresponds to one combination. We included the seven *DT building blocks* and *LARGE_SIZE* as input variables leading to PERF, with profitability as the outcome variable. The truth tables are depicted in appendix B.

The truth table algorithm calculates a consistency score that explains how reliably a combination results in the outcome. This consistency value is defined as the subset membership score between two sets (Ragin 2009) and can be seen as an indicator of the quality of the results, comparable to significance levels in regression analysis. We set the recommended value "0.8" as a cutoff for raw consistency. Thus, only combinations with a raw consistency of at least "0.8" go into further reduction algorithms. We set minimum PRI consistency value "0.5" to avoid fatal inconsistencies but also allow for broader coverage (Greckhamer et al. 2018), in additional robustness checks we set this threshold to "0.75."

In the next step, we define a frequency cutoff as the minimum number of cases in each combination to be considered further. When the total number of cases is manageable, i.e., less than 100 cases, frequency cutoffs of 1 are appropriate (Ragin 2009). As we could gain familiarity with each case during the interrater coding process, this mitigates the coding errors that would motivate the use of a higher threshold. Based on the threshold "0.8" for raw consistency, the performance column shows a value of "1" for all combinations with a raw consistency above 0.8, otherwise "0." The reduction procedure then finds smaller sets of configurations.

After the reduction, we identify necessary and/or sufficient conditions for the outcome of interest. This is also referred to as *core* and *peripheral conditions*, which are two core aspects of causality (Fiss 2011; Ragin 2008, pp. 34 f., 2009). Three solutions are derived by fsQCA for each analysis: A "complex" solution (no logical remainders used), a "parsimonious" solution (all logical remainders used) and an "intermediate" solution (selected logical remainders used). For the latter, we use our theoretical knowledge based on the literature to define whether a DT building block is present or absent, to achieve the respective level of PERF. If this remains unclear, the logical remainders are not defined and not incorporated into the analysis. For low PERF, this entails the theoretical assumption that the three DT dimensions and the building blocks of IT core systems, data analytics, and digital strategy are *absent*, the rest were defined as present or absent. For superior PERF, this includes the theoretical assumption that the three dimensions and a dedicated digital strategy are *present*, the rest were defined as present or absent.

4 FSP Configurations in digital transformation

In this section, we present the results in the form of multiple configurations that produce PERF from which we derive standard types of FSP.

4.1 Sufficient solutions

We next describe the causal recipes sufficient for different performance levels based on the fsQCA notation (Ragin and Fiss 2008). Table III.1-1 presents the fsQCA results in the Boolean expression for parsimonious and intermediate solutions: * means logical operator AND, + means logical OR, and ~ means negation, → denotes the logical implication operator. The set-subset relationships between core and peripheral conditions are of special interest in set-theoretic analysis. Core conditions in fsQCA are examined by the parsimonious solution, whereas peripheral conditions refer to the respective intermediate solutions for achieving a certain level of PERF.

Exemplarily, regarding superior performance, our findings indicate a parsimonious solution with three causal recipes (configurations), meaning three different combinations of the DT building blocks produce superior performance (see Table III.1-1): **COOP*~STRA** + **~VCM*~STRA*~LARGE_SIZE** + **VPM** → PERF. This can be interpreted as the combination of present value network cooperation and absent digital strategy or the combination of absent digital processes, absent digital strategy and absent large firm size or a present digital value proposition. Following the notion of Park et al. (2017) and Park and Mithas (2020), the elements in the parsimonious solution are embedded in the intermediate solution as a bold font. The elements of the parsimonious solution described are *core conditions* that have a strong causal relationship with the outcome. The other elements in the intermediate solution are *peripheral conditions* that have a weaker relationship with the outcome. They complement core conditions for achieving PERF.

We explain the fsQCA notation in more detail in appendix C.

Table III.1-1: Configurations of elements sufficient for different levels of performance

Outcome	Parsimonious solution	Intermediate solution
Low performance	**CIM*~COOP** + **~VPM*STRA** → ~PERF	~CORE*~DATA*~VPM* **CIM*~COOP** *~LARGE_SIZE + ~VCM*~CORE*~VPM* **CIM*~COOP** *~STRA*~LARGE_SIZE + ~VCM*~CORE*~DATA*~VPM* **CIM*~COOP** *~STRA + ~VCM*~CORE*~DATA* **~VPM** *CIM* **STRA** *~LARGE_SIZE → ~PERF
Superior performance	**COOP*~STRA** + **~VCM*~STRA*~LARGESIZE** + **VPM** → PERF	CIM*COOP*~STRA + **COOP*~STRA** *LARGE_SIZE + **~VCM** *~COOP* **~STRA*~LARGE_SIZE** + VCM*DATA* **VPM** *CIM*COOP + **VPM** *CIM*COOP*~LARGE_SIZE + CORE*DATA* **VPM** *CIM*COOP → PERF

*Notes. *: AND, +: OR, ~: NOT, →: implicates.*

4.2 Configurations

In this section, we describe the configurations identified along two different levels of PERF. Firstly, we analyze configurations of low performing FSP at the low end of the market. We do this simply by analyzing those configurations that are consistent for the absence of the outcome of performance. This is done using a negation of the outcome variable (~PERF, with RoA < 0.2). That means, all FSP which cannot achieve superior performance get "full membership" and are, thus, low performers. As Figure III.1-2 shows, we found four configurations with two main solutions that FSP adopt which achieve low performance. The raw coverage of 0.55 indicates that the DT conditions included explain a considerable share of the outcome variable PERF.

The first main solution, comprising A1, A2 depicts FSP with digital customer interaction but without Fintech cooperation. These FSP, at least partly, managed to innovate their customer interaction but failed to digitalize their value proposition as well as huge parts of their value creation, especially regarding IT core systems. The second main solution comprising B is constituted by FSP with a digital strategy but lacks a digital value proposition with digital products and revenues. These companies managed to digitalize their customer interaction regarding digital channels, however, the VCM and especially the VPM are still rather untransformed – with non-digital processes, non-digital IT core systems, and not yet existing advanced data analytics. Configuration A1 has the largest unique coverage, in the equifinal solution set for low performance, which indicates that A1 is the empirically most relevant configuration of low (inferior) performers. Configuration A1 includes 11 FSP with a membership score above 0.5, and A2 and A3 each have 1 FSP. Configuration B includes 3 FSP.

Configurations for Achieving	**Low Performance**			
	Solution			
	A1	**A2**	**A3**	**B**
Firm Size		⊗		
Digital Strategy		⊗	⊗	●
Value Network Cooperation	⨂	⨂	⨂	
IT Core System Status	⊗	⊗	⊗	⊗
Data Analytics Use	⊗		⊗	⊗
Value Creation Model		⊗	⊗	⊗
Value Proposition Model	⊗	⊗	⊗	⨂
Customer Interaction Model	●	●	●	•
Consistency	0.89	0.92	0.94	0.80
Raw Coverage	0.42	0.21	0.24	0.37
Unique Coverage	0.14	0.00	0.03	0.10
Overall Solution Consistency	0.81			
Overall Solution Coverage	0.55			

Note. ● present core condition, ⨂ absent core condition, • present peripheral condition, ⊗ absent peripheral condition.

Figure III.1-2: Digital configurations of FSP for achieving low firm performance (PERF)

Secondly, we examine the configurations for superior performing FSP with higher profitability levels. As Figure III.1-3 shows, we found six configurations for FSP which achieve *superior performance* (PERF, with RoA > 0.2) with three main solutions. The overall solution consistency is 0.89, which is far above the recommended cutoff value (0.80). The raw coverage of 0.68 indicates a broad explanation of PERF by the DT conditions included.

The first main solution, comprising C1 and C2, depicts both larger and smaller FSP with a strong focus on Fintech cooperation but without an actual digital strategy. The second main solution, comprising D, describes smaller FSP that are based on non-digital processes and, thus, do not yet define a digital strategy or any value network cooperation. The third main solution, comprising E1, E2, and E3, depicts FSP with digital value propositions and digital customer interaction. They build upon value network cooperation and, at least partly, managed to innovate their IT core systems and data analytics applications. The consistency value of all the six solutions is well above the recommended cutoff (0.8). Configuration E1 has the largest unique coverage in the equifinal solution set for superior performance, which indicates that E1 is the empirically most relevant configuration of the superior performers. Configuration C1 includes 4 FSP with a membership score above 0.5 and C2 includes 2 FSP, respectively. Configuration D only includes 2 FSP. Configuration E1 comprises 11 FSP, E2 19 FSP and E3 8 FSP, respectively.

Configurations for Achieving	**Superior Performance**					
	Solution					
	C1	**C2**	**D**	**E1**	**E2**	**E3**
Firm Size		•	⨂		⊗	
Digital Strategy	⨂	⨂	⨂			
Value Network Cooperation	●	●	⊗	•	•	•
IT Core System Status						•
Data Analytics Use				•		•
Value Creation Model			⨂	•		
Value Proposition Model				●	●	●
Customer Interaction Model	•			•	•	•
Consistency	0.91	0.97	0.82	0.93	0.89	0.98
Raw Coverage	0.31	0.24	0.09	0.46	0.35	0.43
Unique Coverage	0.01	0.03	0.03	0.04	0.03	0.03
Overall Solution Consistency	0.89					
Overall Solution Coverage	0.68					

Note. ● present core condition, ⨂ absent core condition, • present peripheral condition, ⊗ absent peripheral condition.

Figure III.1-3: Digital configurations of FSP for achieving superior PERF

4.3 Standard types

The results of configurational analysis can be interpreted in such a way that the fsQCA software identifies several solution sets that represent ideal types. These ideal types display standard types as outcomes of the case-based typology derivation (Fiss 2007, 2011). Each of the real type FSP refers more to one of these standard types than to another. We return to the data through case-level analyses to interpret the fsQCA findings and facilitate theory building (Greckhamer et al. 2018). In the following, we analyze the DT configuration of each standard type in detail with special regard to a typical example from the cases. Due to their important role and the differences identified with regard to the DT strategies adopted, the three subtypes of standard type E are described in greater detail.

Table III.1-2 depicts each of the standard type in detail. We have used the pseudonyms Alpha and Beta to maintain the anonymity of the representative FSP for standard type A and B, respectively.

4.3.1 Standard Type A - Facader (Alpha)

The community bank Alpha is a typical representative of standard type A. Alpha started DT a few years ago with an external project, leading to a first catalogue of DT measures, but still does not have a comprehensive digital strategy. Up to now, the institute mainly relied on DT of the CIM, for instance, the development of an online customer portal, the underlying campaign management, or the provision of additional digital channels. Many digital customer channels are already offered (e.g., chat, video, screen sharing) but have not yet been fully integrated. The institute does not cooperate with Fintech, except for the payment area; it relies more on the IT standards set by its umbrella organization. Regarding its VPM, only few digital products, such as P2P payments, were already introduced. Regarding its VCM, the company considers itself to be rather backward-oriented and relies on the group's IT service provider. The umbrella organization has, for instance, introduced a center for the evaluation of digital process maturity in which Alpha takes part. The introduction of new processes aims primarily at increasing operational efficiency internally, such as in the area of digital signatures. The introduction of an incremental update of the IT core system is planned, which will introduce new customer-configurable advisory solutions such as construction financing and further improve interaction with customers via digital channels, especially sales and back office processes. Externally, Alpha provides solely consulting services with tablets using mobile communication technologies, such as Wi-Fi. Advanced data applications are currently not apparent at Alpha.

The standard type A constitutes a frequently occurring type of FSP with a strong focus on customer interaction. In addition to Alpha, other community banks especially run the risk of remaining in this group. However, for standard type A, not only banks but also insurance companies correspond to this type. Like Alpha, NICL India lays a strong focus on customer interaction, for example, via dedicated online customer portals, social media channels, or 24/7 accessibility on live chat. The low performing FSP of this group might be even in more trouble in future as they are not well prepared regarding digital business models.

Table III.1-2: FSP standard types

Type / Dim.	A Facader	B Transitioner	C Cooperator	D Preserver	E Innovator
SIZE	small and medium community banks, insurance companies	small and medium community banks, large banks	esp. medium and large insurance companies	small insurance companies, small private banks	esp. large banks and insurance companies
STRA	no dedicated digital strategy	dedicated digital strategy	no dedicated digital strategy	no dedicated digital strategy	digital as an inherent long-term part of corporate strategy
COOP	no strategic cooperation with Fintech	no strategic cooperation with Fintech	strong Fintech ecosystem	no strategic cooperation with Fintech	strong Fintech ecosystem
CORE	untransformed legacy core	incremental update of legacy core	incremental update of legacy core	incremental update of legacy core	incremental update of legacy core or transformed new cloud core
DATA	not recognizable	tactical applications (e.g., rule-based customer sales)	tactical applications (e.g., small data risk underwriting)	not recognizable	strategic applications (e.g., product development or fraud detection)
VCM	low maturity (non-digital processes, many interfaces)	medium maturity (individual categories, such as digital mailbox services)	medium maturity (individual categories, such as digital claim processing)	low maturity (non-digital processes, many interfaces)	medium or high maturity (e.g., digital loans, AI-based process automation)
VPM	low maturity (existing products, online tariffs)	low maturity (existing products, online tariffs)	medium maturity (e.g., digital apps, new tariffs)	low maturity (existing products and tariffs)	high maturity (e.g., data-driven tariffs, software licensing, personal finance, robo advisory)
CIM	high maturity (digital channels, e.g., video banking)	high maturity (additional digital channels, e.g., WhatsApp)	high maturity (digital channels and appointments)	medium maturity (mobile app)	high maturity (e.g., biometrics, AI chatbots, third party integration of channels)

As these FSP have not yet implemented digital processes and improved their IT core systems and barely incorporate digital innovations in their VPM, those companies rely on digitalizing their interface towards the customer. These FSP digitalize their front end but not their back end, giving the outward impression that they are highly digitized but, in fact, are not. Customers experience this especially, for instance, through many non-digital processes and long processing times. Thus, we call this type a "facader."

4.3.2 Standard Type B - Transitioner (Beta)

The community bank Beta is a typical representative of the standard type B. Beta has newly developed a dedicated STRA with external partners and participates in strategic projects of the umbrella organization, such as identity services. An incremental update of the old core banking system has already been introduced, cloud core migrations are planned. Regarding the CIM, Beta relies on new consulting settings, such as customer-configurable services and new advisory settings with tablets as well as the connection to further customer channels, such as WhatsApp. Beta was also focusing on the development of a mobile application for the young customer group and, together with its partners, is developing additional interfaces to connect business partners. Regarding the VPM, Beta started to invest in new developments in the product area, for example, in new app functions, such as P2P payments. The core processes at Beta are more digitalized than at Alpha, but there are still many process interfaces and the channels are not integrated from the customer's point of view. As with Alpha, process digitalization at

Beta is primarily internally focused, such as a paperless branch, digital file, or digital mailbox. Currently, Beta does not rely on strategic Fintech cooperation, except for payment, but shows a greater willingness than Alpha to do so in the future. Data silos could be reduced through a new release of the IT core. In the area of data analytics, Beta has implemented a rule-based customer sales engine ("next best product") but is not using any advanced techniques yet.

The standard type B constitutes a transition type regarding DT. In addition to Beta, there are other banks which follow this DT logic and, thus, constitute this group. Like Type A FSP, these low performing FSP might struggle in the future if they do not manage their ongoing transition towards a more digitalized business model. Like type A, these FSP have implemented digital channels for customer interaction to a greater extent but are still lagging concerning digitalizing their VCM and VPM. These FSP started adopting dedicated digital strategies but have not yet managed to transform their VPM. Hence, the implementation is evolutionary and based on an old technology back end. Thus, we call this type "transitioner."

4.3.3 Standard Type C - Cooperator (Allianz)

Allianz is a typical representative of standard type C. The transformation of Allianz was first set out in the recently adopted corporate strategy, which is one of the important company initiatives leading to a newly established technology committee. In contrast to FSP type A and B, the entry into new digital business fields is achieved mostly by drawing on strategic technology cooperation. Allianz has formed many technological alliances through partnerships, for example, with the Chinese company Baidu or the mobility provider Drivy, to increase digital competitiveness. The company also relies on Fintech and Insurtech partnerships in the area of data analytics. Allianz X is a fund and incubator for start-ups to access innovative business models. Similar to Alpha and Beta, the transformation so far has been focused on digital channels and web-based interactive tools for improved interaction with customers. Customers currently have access to online contracts, apps for motor vehicles (claims payment), and a digital customer portal (online, app). A digital factory deals with the redesign of the customer journey, and meanwhile, appointments with brokers can be arranged digitally. However, Allianz has not yet fully digitalized its VPM, only provides an app-based digital claim processing, but aims to radically simplify its insurance products, such as homeowners' and liability insurances, in future. Some products can already be configured online, but most products require intensive personal advice and cannot be concluded online. In addition to its technological partnerships, Allianz builds on its existing infrastructure, with individual IT systems slowly being replaced, especially the IT core systems, to become faster and more agile. To improve this, the harmonization of IT systems and VCM processes is being pushed ahead across the company, such as underwriting systems and data centers.

This standard type applies to several international insurance companies such as Generali, Roland, and Prudential. The standard type C constitutes a frequently occurring type of FSP that puts an emphasis on cooperation with Fintech, especially to incorporate new forms of value proposition and customer interaction. Those companies have a focus on customer interaction but only dispose of initially digitalized value creation and products or services; they try to compensate for this through strategic cooperation. Thus, we call this type "cooperator."

4.3.4 Standard Type D - Preserver (Emmental)

A typical representative of standard type D is the insurance company Emmental, which is a small customer cooperative for property and liability insurance. It has made a name for itself in B2B sectors, such as agriculture, in addition to its private customer business. The company regards the insurance business as a relationship business, following the claim: “We are there for our customers personally.” Consequently, the company focuses on personal advisory services. As the focus remains on personal contact scenarios, in its CIM and VPM, Emmental provides only essential digital channels and digital products. The paper-bound process of claims recording, for instance, can already be done via a mobile app. In this case, the electronic claims report and the fee invoice are imported electronically, compensation agreements can be entered directly via mobile app, and corresponding payments can be initiated digitally. Emmental also does not explicitly have a dedicated digital strategy. To this end, the corresponding IT core systems have been revised, however, advanced data applications are not used.

The standard type D constitutes a less frequently occurring type of FSP. These FSP rely mainly on non-digital customer relationships (e.g., in branches or agencies). Due to intense customer relationships, these FSP preserve their non-digital heritage, and do only provide essential digital services such as mobile apps. This type of FSP applies to smaller insurance companies that have not established a digital strategy but operate in a non-digital way. This standard type might also be applicable to smaller private banks although the sample did not incorporate this type of FSP. Thus, we call this type “preserver.”

4.3.5 Standard Type E - Innovator (Ping An)

Ping An is a typical representative of a type E1 FSP. This type pursues a strategically farsighted DT approach on platform ecosystems and data. As a bancassurance offering car policies, life insurance, mortgage loans, credit cards, and bank accounts, Ping An features a strong digital focus on finance based on three core technologies: AI, blockchain and cloud computing, to support several ecosystems: FS, health care, auto services, real estate services and smart city services (Kyriasoglou and Palan 2019). Similar to Amazon, Ping An sells its software and analysis tools to other financial providers and generates its own revenues through its digital value proposition (VPM). Ping An develops new business models outside the boundaries of the traditional banking and insurance business (e.g., China’s largest used car platform Autohome or the health portal Good Doctor, Kyriasoglou and Palan 2019). These digital services form the basis for future digital revenues. Compared to type C insurance companies, Ping An is very digitalized along all three DT dimensions: Policy sellers, for example, are selected using data analyses, voice robots replace call center employees, and claims processing is already fully digital (VCM). However, direct non-digital customer touchpoints still exist (CIM). Ping An also relies heavily on networking partnerships (COOP): With a strong emphasis on platform ecosystems, Ping An connects several European B2B customers via APIs, providing its technology to other banks and insurances (Kyriasoglou and Palan 2019). Through its software licensing business, Ping An also gains access to the data of other international insurance companies and banks. The company builds individual platforms, develops new digital products and integrates digital channels using artificial intelligence (DATA). Accidents, for example, can be analyzed by means of recorded images from a mobile app connected to an extensive spare parts database (Kyriasoglou and Palan 2019). Data required for credit assessment is provided by facial recognition, for example, and prospective credit applicants conduct interviews for the credit granting directly via mobile app (Kyriasoglou and Palan 2019). Ping An is able to analyze and segment customers and dynamically adjust product recommendations and prices based on its big data platform.

Incumbents of type E2, small and medium banks, such as EmiratesNBD, international community banks, such as Umpqua, as well as insurance companies, such as HukCoburg, emphasize digital value propositions with first comprehensive data driven tariffs (VPM), a strong ecosystem integration, and special industry applications. Emirates NBD, for instance, extends its product portfolio to include social aspects (i.e., social banking) and offers interfaces in non-banking areas (e.g., fitness accounts). Other FSP such as Wells Fargo provide their products fully digitally via mobile apps. What these FSP still lack is a fully digitalized IT core system.

Incumbents of type E3, medium and large banks, such as DBS, China Merchants Bank or Sberbank, as well as insurance companies, such as Achmea, already operate full digital divisions. DBS, for instance, sets a strong focus on its operational IT backend for greater automation and scalability, which distinguishes it from FSP of other standard types. Sberbank, on the other hand, relies on a re-engineered centralized service platform. In the VCM, standardized business processes and integration strategies enable flexible service provision, such as digital services which allow customers access to banking services without necessary branch visits. DBS renewed its IT core systems, a new cloud-based core banking system for more scalable operations, and provides, on this basis, strategic data applications, such as AI-based product recommendations and fraud detection (Skinner 2020, ch. 3). China Merchants Bank, for instance, relies on a data platform for big-data analyses to recommend its products to customer segments.

In summary, the standard type E constitutes a frequently occurring type of FSP with a strong focus on digital VPM. It is a common type of FSP that *proactively* faces DT. Insurance companies, such as Ping An, or IAG Australia, as well as banks, such as DBS, Emirates NBD, or China Merchants Bank, belong to FSP type E. These FSP belong to the better financial performers. These FSP mostly pertain over higher digital process maturity and data capabilities than all prior standard types, in some cases, having already completed the transformation of their IT backbone. What firms of this type have in common, is their long-term orientation on DT, indicated by its crucial inherent role in corporate strategy-making and organizational culture. This gives these companies a decisive time advantage over companies from the previous types, which also leads to a reduction in costs and greater possibilities in the area of digital products and services. Thus, we call this type “innovator.”

4.3.6 Future Standard Type - Full-digital FSP

What all prior cases have in common is that the DT of the VCM and related technological back end has not yet been completed – either from an underlying processual, IT system, or a data technological perspective. Fintech such as N26, Revolut, or Oscar, however, operate on modern “full-digital” core systems. On the incumbent side, the standard type F has not yet been fully established in the market (we did not find a consistent solution), however, our prior findings clearly show it on the horizon. This type constitutes FSP that innovate their digital IT backbone, eliminating legacy systems to build full digital services on this (like Fintech or Insurtech companies who operate straight-forward digital cores). In the VCM, standardized business processes and integration strategies enable flexible service provision, such as DBS Digibank, a full-digital service which allows customers access to banking services without having to visit a branch. Santander has launched its fully-digital Openbank, with full-digital services available through a single website and mobile app, and automated investment through robo-advisory.

In future, this type will resemble FSP operating on a fully digital backbone. Most of these full-digital FS services provide banking services separately from the parent organization (e.g., Goldman Sachs Marcus), and some of these initiatives also failed on the market (e.g., RBS Bó). The FSP of future type F may represent either a digital spin-off from an incumbent organization (such as described) or an evolution of one of the previous FSP types (especially the innovators). Thus, we call this type "full-digital FSP." This type masters all building blocks holistically but may still provide traditional advisory services upon request to specific customer segments (e.g., via pop-up stores).

4.4 Robustness checks

One important aspect of fsQCA studies is to ensure that the essential findings, i.e., the configurations identified, do not change greatly through a variation of the input factors, such as the sets of variables, calibrations, or settings included (Greckhamer et al. 2018; Schneider and Wagemann 2013). One way to check this is to perform robustness checks in which individual parameters are systematically varied (cf. Greckhamer et al. 2018). Our additional analyses encompass five models with a) a higher PRI consistency value of 0.75, b) a bank/insurance distinction variable, c) additional contingency factors, but only the three central DT dimensions, IT and data systems (due to restrictions in the number of variables), d) different crossover values for PERF and e) different calibration values of the outcome PERF. The details of these specific analyses are described in appendix D.

While these analyses provide additional interesting insights into the structures of the relationships, in sum, the interpretation of the results remained substantively unchanged. Type B and D FSP (the transitioners and the preservers) were already at the boundary of consistency thresholds in our main analysis, so, they should be considered with caution. However, we stick to these standard types since our additional case analyses revealed strong differences in the DT approach between these FSP and the other types, especially for small and medium-sized companies. Our analyses provide evidence particularly on the dichotomy between type A facaders and type E innovators that is backed by many cases, revealing an impressive contrast in terms of the sustainable competitive advantage between companies that will struggle to survive in the short to medium term (i.e., the facaders) and those that are better prepared to meet the competitive challenges and generate new revenues (i.e., the innovators). This underlines the fact that in our sample, with the conditions for FS mentioned above, DT could primarily be understood as a lever to maintain the sustainable competitive advantage of a firm (i.e., the long-term survivability of the companies), however, since companies are in the midst of their DT process, today's digital maturity is not necessarily a factor for differentiating the high or even very high performers according to our analyses.

5 Discussion

Prior research has exemplified competitive dynamics induced by IT for several industries other than FS (e.g., Segars and Grover 1995). We observed the evolution of DT in FS across two different PERF levels. We argued that five standard types exist in the market, each of them consisting of FSP following the same DT logic. With regard to our research question, our findings indicate that DT configurations are related to certain levels of PERF, with two types of less developed DT configurations being related to low PERF and, one type of more advanced DT configurations being related to superior PERF. With the help of our qualitative-empirical research approach, we were able to show that the relationship between DT and PERF is non-linear, since there are also consistent types of FSP which, with low levels of DT, still produce useful market results. Our analysis also showed that no consistent DT configurations have been identified that lead to (very) high PERF.

Although the evolution across different types does not necessarily reflect the evolution of each single FSP over time, it shows the industry evolution of achieving increasing levels of digital maturity. Figure III.1-4 illustrates the relationship between the identified standard types, their digital maturity, and competitive advantage.

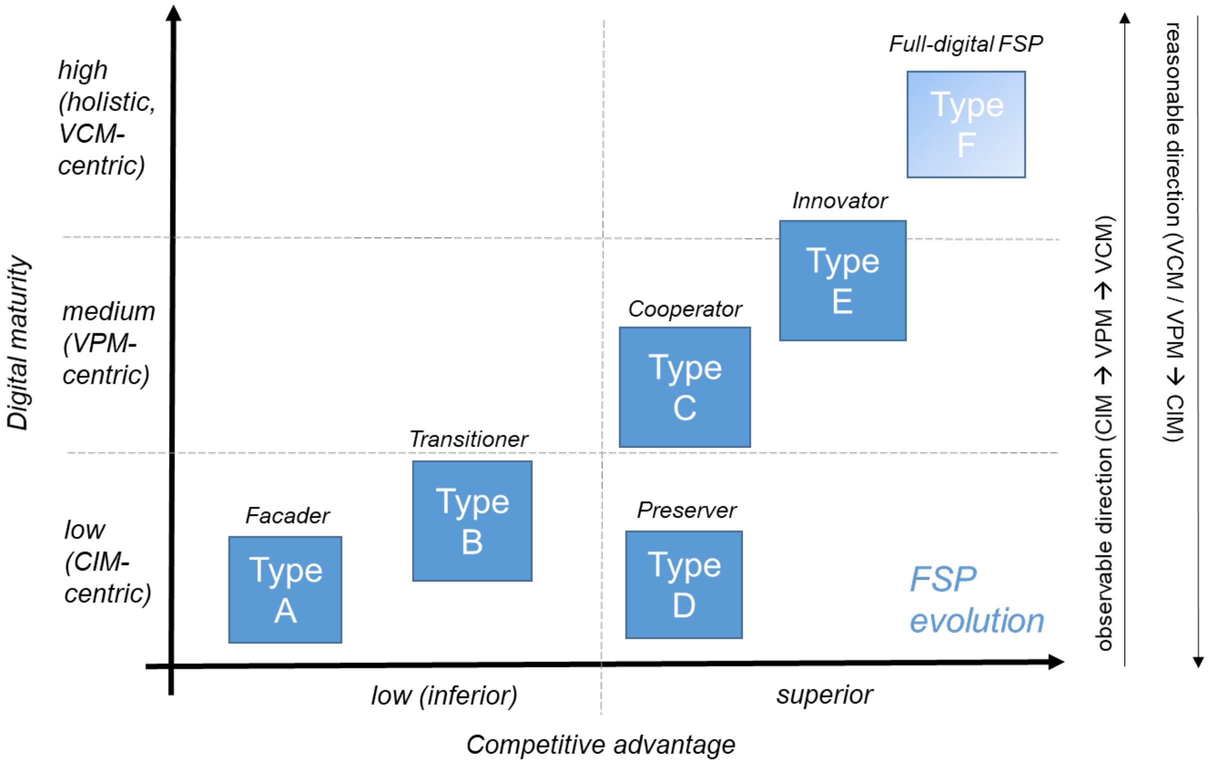

Figure III.1-4: FSP evolution

Our findings point out that most incumbents approach DT incrementally or even defensively, only some incumbents take DT as their core business in all three dimensions holistically. Our results show that low-performing FSP (type A, B) follow CIM-centered transformation strategies but, to a large extent, neglected their VCM and VPM. Type A *facaders* rely on “quick wins” by offering digital interaction channels (CIM) on the basis of existing dysfunctional organizational structures (VCM). Type B *transitioners*, at least, established a STRA, although they have not yet managed to change their portfolio of services. Some FSP focus solely on strategic partnerships to deliver customers' digital services (type C). Type C *cooperators* use cooperation as a lifeline to offer their customers an innovative range of digital products and channels, despite their dysfunctional VCM. Lastly, some of the higher performing FSP focus on transformation of their VPM and have started to digitalize their VCM (type E). Type E *innovators* see innovation of the business model as their core task, although an end-to-end digitalization of their VCM is still partly neglected. A type F *full-digital FSP* will build its operating model around a digital core. Some FSP, the *preservers*, are remarkable exceptions to this scheme due to their special firm structures and personal relationships with customers (type D). Whether type D *preservers* can sustain superior PERF in the long run will depend strongly on their customers' behavior such as face-to-face consultations for high net worth individual, complemented by digital services.

Figure III.1-4 also indicates that the observable direction of FSP evolution goes from CIM over VPM towards VCM; but, from a theoretical standpoint, a move in the other direction would be more reasonable. Our findings showed that a pure front end approach (CIM first) goes hand in hand with path dependencies in the infrastructure that make comprehensive DT impracticable in the long term. A back end approach (VCM first) or even better a holistic DT approach might deliver a more comprehensive and structured approach to business model innovation in the case of FS. In this regard, our results for the FS industry are in line with findings from other industries (Kuk and Janssen 2013).

There are two propositions that can be drawn from our findings.

Firstly, we propose that facade digitalization, which describes a type of digital strategy with a high maturity in customer interaction (CIM) but a low maturity of the value creation and value proposition building blocks (VCM and VPM, respectively), will lead to low PERF and mitigate a firm's future perspectives substantially, especially for small FSP. The absence of digital business models is particularly evident here, due to outdated processes and technological backwardness as well as the absence of strategic technological partnerships (e.g., platform ecosystems). (P1)

Secondly, we propose that holistic digital configurations, which entail established digital strategy-making along with a high maturity of the three DT building blocks at the core (VCM, VPM, and CIM), advanced digital technology use and the presence of strategic technological partnerships (e.g., platform ecosystems), will lead to superior PERF and sustainable competitive advantage. The presence of digitally transformed value propositions is particularly crucial in this regard. (P2)

Accordingly, we provide evidence that DT is a nonlinear process that favors holistic approaches (Park and Mithas 2020) but in the current transitional phase, also gives backward firms the chance to keep track. This is an opportunity, especially for type C FSP, to climb the ladder of digital maturity. Smaller FSP, such as community banks in low interest areas, are particularly at risk, as a sufficient financial cushion turned out to be a necessary condition for achieving a high IT core system status. This underlines the path dependencies to overcome, primarily by switching to more cost-effective and flexible cloud services. In this regard, firm size serves as a cushion in difficult FS environments, such as a low interest rate situation or regulation, however, DT is not a condemnation of firm size. A number of regional banks were represented in the three standard types A, B, and E, just as there are some large FSP among the facaders. Traditional banking and insurance strategies will remain important drivers for PERF but no guarantee for high PERF in the future, especially since FSP are in the midst of their transformation to fully leverage the effects of the digital value propositions on their revenue models. Another interesting finding was that digitalization has become an inherent long-term part of corporate strategy for the innovators, so that a dedicated digital strategy as a declaration of intent has become obsolete. Our study also reveals some remarkable differences between the two FS industries, as insurance companies may currently still achieve an acceptable PERF despite rather low levels of DT, whereas the banks in our sample typically do not do so. In particular, those FSP who do not manage to evolve at least to standard type C might struggle to maintain their competitive advantages, especially in the light of persistent low interest rates and high customer expectations.

It is questionable how the FSP evolution can be explained and what future perspectives of FSP will look like. Our findings highlight the role of *long-term* digital orientation, which was not always the case. One plausible reason is the market valuation orientation of firms. Another reason could be the *asset specificity* of firms. Prior research found that the greater an incumbent's asset specificity to an old operating model (such as branch-based FS) and the greater the level of competition they face, the lower their firms' valuations are when investing in the new model relative to when investing in the existing model (Eklund and Kapoor 2019). The literature further suggests that firms adjust their future digital investments to their market situation (Duflo 2012). As such, digital strategy exerts an increasingly convergent effect under higher industry concentration and higher industry growth. Most of the incumbent FSP, especially in Europe and the US, operate in saturated markets. Thus, the aim of these FSP in B2C business is not market growth at first but rather securing their market shares in face of new competitors and industry concentration which limited their willingness to invest in DT for a long time. We also found that direct competitors tend to move in tandem, such as type A, type C, or type E, forming a strategic group (Fiegenbaum and Thomas 1995). In future, the pressure for low-performing FSP to digitalize will further increase as the branch network continues to become less differentiating, but the operating costs cannot be reduced to the same extent (Pousttchi 2020). Fintech competition will also increase, such that Google, Apple, Facebook, or Amazon might extend their engagement in the FS industry. At this, our analysis also shows the warning implication that FSP which do not manage to evolve at least to standard type C will struggle to gain competitive advantages in the long run.

Hence, it is reasonable that survival of FSP will depend on the FSP evolution path depicted in Figure III.1-4. Those FSP who succeed and pass these stages towards truly digital operations will stay in the market, others will disappear (at least in their present form). The most threatened FSP, standard type A and B, such as community banks, are struggling the most with the necessary efforts to renew themselves. FSP who aim to achieve at least the performance of standard type C will either innovate their business with Fintech cooperation or (better) build their own digital business regarding value proposition and value creation. Type C shows that pursuing a new model firstly via *alliances* (e.g., Fintech cooperation) might indicate a strategy that helps to mitigate the necessary adjustment costs of transformation. It is reasonable that low-performing banks and insurance companies will make further use of platform ecosystems in the form of *open banking* and *insurance*, as well as *infrastructure sharing* in the area of IT core systems becomes a major issue. The most evolved FSP (standard type F) will have a sophisticated digital VCM, VPM, and CIM in its holistic DT approach, successfully innovated their IT core system and pursue advanced data analytics.

6 Conclusion

In this study, our aim was to analyze the evolution and perspectives of FS in DT. Based on our research model, we first conducted a comprehensive literature review to identify the state of the art in research. Subsequently, we applied the fsQCA to examine the relationships between DT configurations and firm performance, and finally derived five empirical FSP standard types.

Our findings indicate an evolution of DT in the financial sector. Traditional FSP may adopt one of three general approaches:

- Focusing on digital customer interaction via apps and other digital services while leaving the underlying ground fundamentally untouched;
- developing their CIM while focusing on the digital proposition model using agile methods and aiming for low-hanging fruit but addressing the CORE only to a limited degree; or
- going the hard way, re-engineering their processes and developing a digital core as a basis for a sophisticated digital value proposition and customer interaction – while still being able to offer non-digital services if necessary (e.g., for face-to-face advisory and/or high-value customers).

Our findings have shown that the last approach is the most sustainable one. For research, our study provides three key contributions. Firstly, we synthesize the existing literature on DT of FS with a comprehensive approach. Secondly, we explain the complex dynamics of DT in FS with an innovative configurational approach. At this, we identified the phenomena of *facade digitalization*, which describes a prevarication or misrepresentation of the actual digital competitiveness of FSP which may also apply to firms in other industries. Thirdly, we make a methodological contribution by applying fsQCA to investigate the complex relationship between DT and PERF by means of configurations.

There are several limitations to be considered when using the results. We did not measure actual customer behavior but digital configurations (e.g., not digital channel use but digital channel availability). Further on, our data is based on qualitative coding and restricted to the information on the FSP available within the sample. The coded characteristics, measured on one-dimensional scales, are, in reality, multidimensional constructs. Our results have shown the relationship between DT configurations and PERF. The causality is ambiguous, since financial scope, which is based on the financial success of the companies, can also be cited as a necessary condition for achieving certain DT goals. There are a few FSP that are not financially successful but have already started to digitalize (e.g., Deutsche Bank). However, these firms do not form their own consistent standard type – our results are, therefore, not to be understood as typical correlational analysis but have their strength in the nonlinear set-theoretic approach for the analysis of causal mechanisms. In addition, our analysis of small and medium-sized FSP was limited to the western markets. However, at the time of the analysis, we did not identify any inconspicuous digital business models from smaller FSP in other regions (e.g., Asian banker awards). A future research option is utilizing metrics for PERF that measure the market valuation of companies, such as Tobin's Q. Future research should further examine the industry evolution based on longitudinal data sets over time. Regarding our main findings, it is to be expected that the gap between low and superior performers will tend to widen if the revenue models of the digital value propositions take full effect.

For practice, our findings clearly suggest that a proactive DT is a decisive factor for FSP PERF. The FSP standard types with their digital configurations allow one to categorize market participants and assess their future perspectives.

Appendix

A Calibration - Sets and anchor points

Table III.1-3: Calibration of sets

Variable	In (“1”)	Crossover (“0.5”)	Out (“0”)
LARGE_SIZE	> 50,000 employees	10,000 employees	< 1,001 employees
STRA	dedicated digital strategy (at least three years in place)	(to some extent) part of corporate strategy	not available
COOP	strategic cooperation with Fintech or Insurtech	- (crisp set)	no strategic cooperation with Fintech or Insurtech
CORE	transformed new integrated core	in transformation (modernized core)	not transformed old core
DATA	transformed new strategic big data applications	in transformation (tactical small data applications)	not transformed data collection and use
VCM	transformed digital processes, mostly without non-digital interfaces	in transformation (standard cases digitally possible, advanced cases require human intervention)	not transformed non-digital processes, with many non-digital interfaces
VPM	transformed products and revenues, i.e., data-driven credit and telematics tariffs	in transformation (e-commerce business products and tariffs)	not transformed products and revenues, i.e., existing products and tariffs
CIM	transformed interaction, i.e., chatbots, voice assistants, or video consultation	in transformation (digital channels available: website, online portal, mobile app)	not transformed interaction, i.e., branch, hotline
PERF	RoA ≥ 0.8	RoA = 0.2	RoA ≤ 0
~PERF	RoA ≤ 0	RoA = 0.2	RoA ≥ 0.8
HIGH_PERF	RoA ≥ 1.5	RoA = 0.8	RoA ≤ 0
VERY_HIGH_PERF	RoA ≥ 5.0	RoA = 1.5	RoA ≤ 0
FAV_Regulation	high	medium	low
FAV_Interest	> 4 percent	2 percent	< 0 percent

If we refer to the variable names of the sets for the DT building blocks, their presence always implies a high level of maturity.

B Truth tables

Table III.1-4: Low performing FSP

SIZE	STRA	COOP	CORE	DATA	VCM	VPM	CIM	number	~PERF	raw consist.	PRI consist.
0	1	0	0	0	1	0	1	2	1	0.93	0.80
1	0	0	0	0	0	0	1	1	1	0.92	0.80
0	1	0	0	0	0	0	1	2	1	0.92	0.77
0	0	0	0	1	0	0	1	1	0	0.89	0.38
0	0	0	0	0	1	0	1	2	1	0.86	0.66
0	1	1	0	0	0	0	1	1	1	0.81	0.52
0	0	0	0	0	0	0	0	1	0	0.79	0.34
0	1	1	0	0	0	1	1	1	0	0.78	0.36
0	0	1	0	0	0	0	1	1	0	0.77	0.40
1	0	1	0	0	0	0	0	1	0	0.60	0.04
0	1	1	0	1	1	1	1	1	0	0.53	0.10
0	0	1	1	0	1	1	1	1	0	0.53	0.01
1	1	1	1	1	0	1	1	1	0	0.50	0.00
1	1	1	0	1	1	1	1	1	0	0.47	0.10
1	1	1	1	1	1	1	1	1	0	0.39	0.03

Table III.1-5: Superior performing FSP

SIZE	STRA	COOP	CORE	DATA	VCM	VPM	CIM	number	PERF	raw consist.	PRI consist.
1	1	1	1	1	0	1	1	1	1	1.00	1.00
0	0	1	1	0	1	1	1	1	1	1.00	0.99
1	1	1	1	1	1	1	1	1	1	0.98	0.97
1	0	1	0	0	0	0	0	1	1	0.97	0.94
0	1	1	0	1	1	1	1	1	1	0.95	0.90
1	1	1	0	1	1	1	1	1	1	0.94	0.90
0	0	0	0	1	0	0	1	1	1	0.92	0.57
0	0	0	0	0	0	0	0	1	1	0.89	0.66
0	1	1	0	0	0	1	1	1	1	0.87	0.62
0	0	1	0	0	0	0	1	1	1	0.85	0.60
0	1	1	0	0	0	0	1	1	0	0.80	0.48
0	0	0	0	0	1	0	1	2	0	0.73	0.34
0	1	0	0	0	0	0	1	2	0	0.71	0.19
0	1	0	0	0	1	0	1	2	0	0.71	0.20
1	0	0	0	0	0	0	1	1	0	0.70	0.20

C fsQCA notation

Figure III.1-2 and Figure III.1-3 depict the results of Table III.1-1 graphically using the notation system by Ragin and Fiss (2008), with the available templates by Fiss (2011). We number the configurations in our figures based on core conditions to indicate first- and second-order equifinality (Fiss 2011; Park et al. 2017). We label the configurations A1 and A2 in Figure III.1-2, for instance, because they share the same set of core conditions. Each solution block in these figures represents one configuration of conditions and corresponds to one recipe of the intermediate solution. Large circles indicate core elements, and small circles indicate peripheral elements. Full circles indicate the presence of a condition, and crossed-out circles indicate its absence. This means that dark circle elements are an enabler for the outcome and crossed-out elements may inhibit an FSP from achieving the outcome. The absence (X circle) in digital strategy in Figure III.1-2, for example, means that full membership in digital strategy does not exist in the configuration (i.e., inhibiting role of digital strategy), and the presence of value cooperation (dark circle) means that full membership for technology cooperation exists (i.e., enabling role of cooperation), which leads to superior performance. The presence of customer interaction model underlines the digital customer interaction model as an enabling peripheral element of this configuration. Blank spaces, such as in A1 for LARGE_SIZE, indicate a "don't-care situation," for example, whether LARGE_SIZE is present or absent. In addition, each figure shows two types of measures for validating the solutions: Consistency and coverage. Overall solution consistency measures the degree to which all configurations together consistently result in an outcome. The overall consistency for superior performance in Figure III.1-3 was 0.89, which is well above the recommended minimum level of 0.80 (Ragin 2008, p. 185). The FSP can achieve performance with different digital configurations, but individual configurations differ in their empirical importance and effectiveness. Thus, coverage shows the empirical relevance and effectiveness of the solution for the outcome (Ragin 2008, p. 204). Raw coverage indicates which share of the outcome is explained by a certain alternative path (comparable to R^2 in regression analysis); unique coverage indicates which share of the outcome is exclusively explained by a certain alternative path (Ragin 2009). Unique coverage is depicted for each solution in Figure III.1-2 and Figure III.1-3.

D Robustness checks

Regarding a), higher PRI consistency values typically reduce empirical coverage. Hence, standard type A, the CIM-focused facader, turned out to be the most empirically relevant type of low performing FSP. We found solutions for the superior performers that confirm type C (i.e., large companies with strong ecosystems) and type E (i.e., companies with strong digital value propositions). The analysis also highlights subtypes of E as potential independent standard types (i.e., the process digitalizers, the business model digitalizers and the technological leaders in IT core systems and data analytics) and reveals the rather low empirical representation of standard type D FSP (the preserver).

Regarding b), we made an explicit bank to insurance comparison. As our results confirmed, large insurance companies tend to be less strategically digitalized than large banks (cf. primarily type C, in exceptional cases also type A) but are more likely to achieve higher levels of PERF. However, there are also more digitally advanced insurance companies that fall into type E (e.g., AXA).

Regarding c), the consistency analyses incorporating the additional sets FAV_Regulation (Citibank 2018, p. 16) and FAV_Interest (OECD 2019) also confirmed the phenomenon of facade digitalization (absent VCM, present CIM) for the low performers in a difficult market environment; as well as the crucial role of digital value propositions for the highly digitalized innovators (type E, especially under difficult interest and regulatory conditions) among the superior performers and shone additional light on the role of sheer company size for type C.

Regarding d), the main results could be largely confirmed for the slightly higher PERF crossover value of 0.4. We found two types of CIM-centric FSP that rely on digital customer interaction but lack digital processes or value propositions, with some companies among them that want to “go for digital.” The superior PERF types remained largely unchanged.

Regarding e), we found no configuration for high PERF (1.5, 0.8, 0) or very high PERF (5.0, 1.5, 0) that entails a parsimonious solution, hence, there was no stable configuration. Remarkably, companies in a favorable regulatory and interest rate environment were the only ones with a very high PERF (e.g., Sberbank)

III.2 Analyzing the contradictory impact of digitalization on the performance of German savings banks − Evidence from annual reports utilizing a text mining approach

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Working paper

Abstract: Digitalization has arrived with a bang in the daily business of banks. However, determining its impact is still a relevant research question that has not yet been conclusively answered. There has been a stream of studies on the impact of information technology on firm and bank performance, with different results. In particular, there is a lack of studies regarding the impact of digitalization on small and medium-sized savings banks. While banking is often mentioned as one of the most digital industries by its nature, it is questionable how especially small-to-medium-sized savings banks have been impacted by the challenges posed by digitalization. Against this background, this paper uncovers the contradictory impact of digitalization on firm performance in savings banks. Innovative text mining techniques are applied to annual reports and combined with industry data to develop a unique and comprehensive data set on digitalization in German savings banks from 2009 to 2017, which is subsequently analyzed with econometric regression methods. Our findings indicate that digitalization led to a workforce reduction. However, although bank efficiency improved due to unobserved structural reasons, individual digital transformation measures in the customer interaction model were identified as negatively related to bank efficiency after the analysis incorporated time fixed effects. The business model dimension was positively related to bank efficiency, measured as the business volume per employee. Our findings further indicate a negative impact of digitalization on savings bank profitability from a marginal perspective, even after multi-year time lags. One probable reason could be indicated by the negative performance effect of switching towards digital customer interaction without new products and revenue models that could increase profits. Our cross-sectional analyses highlight that savings banks became less successful when shifting towards digital customer interaction, while the process and business model transformation did not significantly impact their profitability. The findings underscore the phenomenon of facade digitalization in small and medium-sized banks. Based on the results, we suggest a more holistic digital transformation approach, ensuring that the process and business model dimensions are not neglected to strengthen the transition towards digital customer interaction.

1 Introduction

Digitalization encompasses the increasing penetration of society with digital technologies and does not skimp on industry sectors such as banking (Legner et al. 2017). Digital transformation (DT) describes the process of companies incorporating a wide range of digital technologies into their business as a strategic response to digitalization (Vial 2019). It implies changes in value creation and organizational structures, which must be aligned with financial aspects (Matt et al. 2015). As DT brings in new processes, products, and forms of customer interaction (Pousttchi 2020), we can distinguish an internal process-oriented, a product-related, and an external customer-related dimension. Across these dimensions, DT and firm performance are intuitively closely connected. However, it is evident that the DT requires a lot of effort from companies, and it is not clear whether and when these measures will pay off (Hess et al. 2016; Matt et al. 2015; Sebastian et al. 2017). In this regard, metrics can be different, such as traditional profit analysis, profitability indicators, market value, or even the posed demand for new metrics (Rahmati et al. 2020; Verhoef et al. 2021).

There have been some studies on the relationship between DT and firm performance, with different results. In addition to several correlational-based studies (e.g., Jabr and Zheng 2020), with some of them directed towards specific technologies such as Big Data (e.g., Müller et al. 2018), there has also been a stream of research drawing on configurational analysis (Park and Mithas 2020). While some of these studies indicate a clear positive impact, others do not, and configurational analyses even derive the potential driving forces behind those different results (e.g., Dehnert 2020b). Hence, the impact of digitalization on organizations is still a relevant and open research question, and further research is necessary to provide additional empirical evidence.

One sector particularly affected by DT is the *financial service industry*, with banks as an important representative. The economic role of *savings banks* in the economy and the fact that their future depends on digitalization provides reasons to conduct a study on the impact of DT in this sector. In particular, the *German savings bank group* provides a unique research setting that entails approximately 400 legally independent companies that belong to the same umbrella organization. Due to the homogeneity of the corporate structures, there is less interference from the firm- and industry-level effects. At the same time, each savings bank acts autonomously in its strategic business decisions.

Against this background, this paper draws on a novel panel data set from 320 institutions of the savings bank group for a time frame from 2009 to 2017. We extracted data on digitalization and DT initiatives from annual reports utilizing an innovative text mining approach. We then conducted analyses with state-of-the-art econometric methods. The paper's outcome is a series of findings regarding the impact of DT on a variety of performance metrics for bank efficiency and bank profitability. Thus, the paper provides insights into the contradictory effects of DT on firm performance.

The paper is structured as follows: In the next section, we analyze prior research on the impact of DT on firm performance, systematize important factors of DT for savings banks, and derive our research hypotheses. In the third section, we explain our data collection, operationalization, and econometric analyses. In the fourth section, we present the results of our analyses for the individual hypotheses. In the fifth section, we discuss our findings. The last section summarizes our contributions, derives implications for research and practice, and gives an overview of the study's limitations.

2 Theoretical Background

2.1 Digital transformation and firm performance

Historically, there have been numerous studies on the influence of information technology (IT) on firm performance. Several prior IS and management studies have dealt with the question of how *IT investments* have had an impact on the profitability of companies so far. While a number of studies showed a positive effect (Bharadwaj 2000; Mithas et al. 2011, 2012), others did not identify any performance advantages for IT-intensive companies (Chae et al. 2014; Joensuu-Salo et al. 2018). As far as the effects of IT have solely been concerned, various meta-analyses indicate that the differences in performance are partly attributable to the specifics of the industry and the dependent variables under study (Kohli and Devaraj 2003; Sabherwal and Jeyaraj 2015). In this regard, Aral and Weill (2007) point to a virtuous circle in the relationship between IT investments and firm performance, meaning that IT investments must be well planned to affect firm performance positively. In addition, newer research results have manifested the J-curve, stating that digital innovations undergo a time lag until the positive effects manifest in the business figures of traditional organizations via intangibles like business processes (Brynjolfsson et al. 2021).

Digital strategies of companies offer a new field of application for IT (Bharadwaj et al. 2013; Duflo 2012; Grover and Kohli 2013). There are different target values for studies on firm performance, such as productivity (e.g., workforce per business volume), profit (e.g., net income), profitability (e.g., return on assets: RoA), or market value (e.g., Tobin's Q). While the latter provides exciting insights into the potentials of business models regarding future market opportunities, it is interesting to study the productivity and profitability effects of DT for companies to assess the immediate economic impact on their businesses.

There are very few studies related to traditional profitability measures, while most of the studies analyze the impact of DT on the market value (e.g., Tobin's Q). One possible explanation could be that the impact of DT on traditional profitability measures is far less clear and points to the profitability paradox (Beccalli 2007b, p. 65). One recent study relying on Tobin's Q indicates that the internal and external orientation of companies in DT provides a possible direction for further research (Jabr and Zheng 2020). According to these findings, companies that are more strongly internally digitalized benefit more from further DT and can orient themselves more strongly towards the market and customers. Therefore, a marginal utility analysis on DT appears valuable regarding various productivity and profitability figures for savings banks.

There are also several *banking-specific studies* on the impact of DT on firm performance. Beccalli (2007a), for example, in an early study, found little impact of IT investments on profitability but a positive effect from external IT resources and a negative effect from internal resources. Scott et al. (2017), who studied the introduction of the digital technology SWIFT, found that it took a decade to observe a significant positive effect on firm performance. Further studies provide evidence that investments in DT can positively affect bank profitability (DeYoung et al. 2007; Giaretta and Chesini 2018), while other scholars have found that difficulties can decrease bank efficiency and profitability (Kriebel and Debener 2020). Bohnert et al. (2019) have shown a positive effect of holistic DT measures on the market valuation of insurance companies. These findings suggest that how the DT is carried out plays an important role and that counterintuitive or even time-delayed effects could emanate. The complex interplay indicates that an increased level of DT does not necessarily have to be accompanied by higher profits and profitability. In sum, the connection between DT and firm performance in its various facets is still quite unclear, especially for the banking industry. In the following, we elaborate on how different DT dimensions could influence the performance of savings banks and derive a set of research hypotheses.

2.2 Research model and hypothesis development

There are various building blocks of DT, which scholars have extensively reviewed more recently (Vial 2019). Following Vial, DT creates changes in the value creation paths of firms, which implies structural changes across the organization, such as new types of business models, new forms of network cooperation, and changing customer interaction via digital channels. The impact of DT can be categorized along three dimensions (Pousttchi 2020): The *value creation model (VCM)* capturing the impact of DT on the necessary processes and organizational structures to create FS products and services (Davenport 1993; Overby 2008; Pousttchi 2020); the *value proposition model (VPM)* referring to the improvement of existing and creation of new products and services as well as related business and revenue models (Pousttchi 2020; Skålén et al. 2015; Teece 2010); and the *customer interaction model (CIM)* including the impact on the nature and content of customer interaction and value cooperations, such as for sales, service, and marketing (Pousttchi 2020; Pousttchi and Gleiss 2019). These dimensions are also attributable to banking, as previous research shows (Dehnert 2020b). Consequently, different effects of DT can be expected along these three dimensions.

Regarding the *VCM*, prior research shows that digitalized business processes can increase firm productivity across the banking value chain (Bertoni and Croce 2011; Eling and Lehmann 2018). The measures in the VCM include automation of processes (e.g., Braunwarth et al. 2010; Cooper et al. 2017) and improved flexibility (e.g., Afflerbach et al. 2014; Braunwarth and Ullrich 2010), as well as service productivity (Aspara et al. 2018). Regarding the *VPM*, research uncovered a positive relationship between online banking services and firm profitability (Hernando and Nieto 2007), as well as between digital products and performance (Setia et al. 2013). Regarding the *CIM*, prior results indicate that new digital services may decrease short-term customer profitability (Campbell and Frei 2004). However, digital channels are also associated with higher customer retention rates over multiple years and increasing market shares.

A set of hypotheses can be derived from these various DT dimensions. A set of hypotheses can be derived from these various DT dimensions. Based on the structural changes induced, especially in the VCM, we assume that the workforce shrinks and the *bank efficiency* will increase with increasing levels of DT, i.e., more business volume will be performed per employee. The credit volume per employee could also increase, i.e., the remaining employees may do more business than before. Credit volumes could decline, which means that as digitalization increases, the savings banks will do less business than before because competition becomes stronger. In contrast, customer deposits may have risen as banks enjoy a safe harbor of money reputation, and access to checking accounts is more effortless. In sum, *we hypothesize that DT has a positive effect on the bank efficiency of employees considering the marginal utility of each DT measure (H1).*

Furthermore, various potential effects are conceivable from DT on *firm profitability* (Neumeier et al. 2017): New and improved processes in the VCM may improve process flexibility, automation could increase productivity, while new products and value propositions in the VPM could reduce costs while increasing efficiency but also provide opportunities for new revenues and increasing returns, and finally, a digital CIM could improve relevance among customers but also decrease revenues from existing customers. The question here is whether the investments and structural changes will also positively impact the financial figures. Previous research has shown that digital customer interaction is associated with costs that initially exceed the additional revenues (Campbell and Frei 2010). *We assume that digitalization and individual measures in the DT dimensions impact the annual profit positively (H2a).* We suppose that DT may negatively affect firm profitability, initially indicating a profitability paradox (Beccalli 2007b, pp. 64 f.; Kriebel and Debener 2020). Thus, *we hypothesize that the DT of the savings banks harms the profitability (return on assets) considering the marginal utility of DT, which may turn into a positive effect after a time delay (H2b).*

Given our assumption that DT is not immediately positively related to bank profitability by individual measures or investments per se, *we further hypothesize that the presence of measures in specific dimensions, i.e., the VCM, VPM, and CIM, contribute to higher bank performance (H3).*

2.3 Research setting: Digital transformation of the German savings banks group

The German savings banks provide the research setting for this study. Savings banks are affected by DT in a similar way to the whole financial services industry. The stable market shows unprecedented competitive dynamics, regulatory changes, and Fintech challengers as competitors (McKinsey 2019b). Digitalization makes customer orientation a central aspect of the competition (Alt and Puschmann 2012; Bons et al. 2012; Nüesch et al. 2015). Additionally, savings banks are particularly affected by low interest rates due to the substantial deposits share. Given the structural similarities and the economic independence among the nearly 400 financial institutions, which allows an analysis *ceteris paribus*, it is questionable whether the DT strategies chosen by the savings bank group show the hypothesized effects on firm performance.

What distinguishes savings banks from other banks is that their owners are local authorities, and their business is limited to a regional territory. Their statutory goal is to satisfy their customers' local credit needs and provide investment opportunities to broad sections of the population. The economic significance of the savings banks group is indicated by a fairly high market share of 18 percent of the overall German banking business volume in 2019 (Deutsche Bundesbank 2020b). As incumbents, they exert high market power, with revenue streams coming from traditional services and the presence of stationary branches (Chiorazzo et al. 2018). While the number of branches decreases, savings banks still have the broadest branch network in Germany (Deutsche Bundesbank 2020b). Their high branch density may be an advantage for savings banks to be directly available for customers on-site but is a substantial cost driver in times of declining frequencies of personal customer advisory (Pousttchi 2020).

These developments point to competing concerns that savings banks are currently facing, like many other incumbent banks. On the one hand, there is the urge to preserve their traditional business, while, on the other hand, there is a strong desire to become more digital (Dehnert 2020a). Regarding the three dimensions of DT, each independent institution takes different measures, with a large share of standardized products and services. In the *VCM*, new processes and upgrades in core banking systems ("OSPlus_neo") are being introduced in many savings banks. This goes hand in hand with specific changes in system operation (e.g., data centers). Document digitization, "the Internet Branch 6.0," and upgrading the branch network technology are also being driven forward at different speeds by the institutions. In the *VPM*, several savings bank group solutions are used on a highly individual basis. The savings bank introduced the first single-sign-on system for third-party systems with “Yes.” The “Kwitt” payment solution is the German market leader in mobile peer-to-peer payment solutions. The “e-safe” provides personal storage space for data as well as legitimation and trust services. Several savings banks have also cooperated with local partners. In the *CIM*, savings banks increasingly use digital channels for customer interaction, such as mobile apps (“Internet Filiale”).

3 Methodology

3.1 Dataset

Assessing DT measures in firms is not a trivial task. Following its definition, there are many facets to be considered. Our approach is based on innovative text mining analysis of annual reports becoming more popular recently (e.g., Bohnert et al. 2019). Annual reports reflect relevant firm-specific business topics and, hence, essential projects that contributed to financial results, with DT being one important business aspect. We rely on *LexisNexis*, which includes the yearly annual reports from the German *Bundesanzeiger* and use consolidated firm data from the annually published *Sparkassenfachbuch* as data sources. Whereas the former was used to assess DT in the annual reports, the latter included additional annual data on the outcome and control variables, such as bank strategy.

Our main analysis examines a six-year time frame from 2012 to 2017, with digital technologies such as mobile apps already being present and others, such as mobile payment and digital platforms, on the rise. We analyzed 320 from the 385 existent savings banks (in 2018), as not all annual reports were available. To reduce missing data per institution, we only included those savings banks with at least five annual reports available in the six-year time frame. As a result, we collected 1,835 records for the six-year time frame leading to overall data completeness on DT measures of 96 percent. Eighty-five savings banks had published five annual reports, 235 complete annual reports. This approach avoided having no annual reports for two years in a row and imputing missing data. Additionally, we used a longer time frame for coding our variable to examine different time-lag specifications. We collected additional data on DT measures from three previous years (2009 onwards) to analyze the lagged DT variables, which finally provided us with data on DT over a solid nine-year time frame.

Accordingly, we searched for keywords in the banking context to extract whether a report dealt with digitalization, to which extent, and in which areas of DT. Savings banks, for instance, report activities surrounding the IT core banking system and associated organizational changes. Regarding this, we created a complex keyword list that indicated specific DT measures. To create the keyword list, we analyzed the banks' websites, included a codebook from our prior research on financial services (Dehnert 2020b) and a toolbox on digital technology use case types (Pousttchi et al. 2019). The complete keyword list can be found in the appendix. Each keyword was transformed into a regular expression that matches different spellings, abbreviations, singular and plural forms, and synonyms. These keywords were then searched for in the reports using Python scripts. The results were checked for misleading matches that are not related to DT. The number of occurrences was assigned to the corresponding institution and business year. The number of keywords per institution and year results in a DT variable. The ten keywords found most often are listed in Table III.2-1.

Table III.2-1: Top 10 keywords

Number	Keyword	total hits
1	IT	5852
2	Software	5762
3	Internet	3546
4	Digital	3364
5	Online	3007
6	Informatics	2890
7	Channel	2746
8	Data center	2392
9	Information Technology	2104
10	Core banking	2020

Numerous fundamental IT topics are on the top 10 keyword list, but only fewer innovative technologies of digitalization and DT. This trend is apparent for the period up to 2017 in the complete list in the appendix. However, further analyses of the year 2018 annual reports have confirmed this overall low maturity level of digital innovation at the savings banks.

We also account for the three DT dimensions specifically for further analysis. Toward that end, we use the DT keywords and observe them in their context. Accordingly, we conceptualized each DT dimension following the definition by Pousttchi (2020). We developed a concise list of keywords to assign the measures to one or more DT dimensions (Bohnert et al. 2019). These were also used as regular expressions. The contextual keywords for the assignments are listed in Table III.2-2.

Table III.2-2: Contextual DT keywords (translated)

Dimension	Keywords
VCM	process, operations, work, automation, staff, employee, team, competency, training
VPM	product, service, offer, business model
CIM	channel, marketing, sales, customer service

In addition, the neighborhood range of the dimension assignment had to be specified. This value was determined by robustness tests following earlier publications (Bohnert et al. 2019). We first started with higher numbers and got higher DT values in the dimensions. Individual counts in our manual spot checks then signaled assignments in different contexts than DT for higher values, so we successively restricted the range of characters using annual report samples. Finally, one hundred characters before and after the initial keyword were determined for searching the annual reports to indicate a potential membership to the DT dimensions. As a compromise, this number corresponds to one sentence of medium length before and after the DT keyword, given the median sentence length of 20 words for public administrative texts (Pieper 1979, p. 50).

3.2 Operationalization

We describe our operationalization in the following section. We begin with our main variables and then focus on the control variables.

3.2.1 Independent DT variables

We derived several DT measures as independent variables for each institution in each business year following our text mining approach. Those independent DT variables were measured in different variations. We used one DT variable to account for the absolute number of keyword occurrences in the annual reports (absolute). We also created another variable as the relative number of keyword occurrences that relates the absolute number to the total word count of each annual report (relative). The relative values are likely more unbiased since there is no skewing effect due to the annual report length. We created these two variables for the digitalization variable DT and all three DT dimensions specifically: VCM, VPM, and CIM. We also created time-lagged variations of the DT variable to consider potential delay effects of DT on firm performance (i.e., -1, -2, and -3 year time lags).

We used binary variables for additional analyses to distinguish whether specific DT measures were present in the institutions. These key figures will typically also describe general descriptions of digitalization effects and not only concrete measures of the institutions. Thus, they represent the general digital orientation of an institute, its awareness, and the acknowledgment of digitalization impacts. We developed a binary variable to account for concrete DT measures in each dimension, i.e., VCM, VPM, and CIM, to analyze comprehensive DT initiatives in savings banks. Furthermore, we examined whether any measures were present in the DT dimensions and used binary variables with one or zero values for the analyses (VCM_{binary}, VPM_{binary}, and CIM_{binary}). These variables are helpful to observe the potential treatment effects of DT between firms in cross-sectional analyses.

3.2.2 Firm performance as a dependent variable

We used three different efficiency and profitability measures to apply panel regression analysis and the variables for business and credit volume and the number of employees. We analyzed workforce *bank efficiency*, calculated as the number of employees divided by the business volume. This performance indicator indicates whether DT improves the ratio of the employee resources used, i.e., savings banks are becoming more efficient through DT and which dimensions are related to this (cf. Botsis et al. 2015, p. 138). Regarding *firm profitability*, we relied on recent numbers on the annual net income and the return on assets (RoA), a commonly used indicator in management (e.g., Fiss 2011) and IS research (e.g., Bharadwaj 2000). The RoA indicates the profitability of a company in terms of its net income relative to its total assets, i.e., how well a bank utilizes its assets (Hagel et al. 2013). Savings banks are monoliths with extensive assets (e.g., branch networks) and, thus, high operating costs but also considerable incomes from customer businesses. It also allows the comparison between companies of different sizes. To calculate the RoA, we take the annual net income from the annual reports (*Jahresüberschuss*), divided by total assets (*Geschäftsvolumen*).

3.2.3 Control variables

We included various control variables to check for other potential influences on firm performance.

It is conceivable that the success of a company depends on its size (Forman 2005). Firstly, we controlled for *firm size*, measured by the business volume and the number of employees. We used the number of employees specifically as a selection criterion for implementing DT in the cross-sectional analyses. In order to increase efficiency, we assumed that companies with a larger workforce and business volume would particularly opt for DT, besides the likely greater financial scope of larger banks for DT investments. Secondly, we controlled for several business development aspects. This includes the impact of *prior year profitability* (RoA_{t-1}). Regarding this, we controlled for reverse causality because firm performance in a specific year may be impacted by prior year performance. Furthermore, this includes the variable *sales*, measured by the annual customer deposits, and the variable *customer accounts*, indicating the number of customer accounts. Thirdly, we controlled for structural changes of *staff* and *branch networks*. Here, strategic business decisions are made that are related to the DT dimensions. In addition, we controlled for *credit volume* and *customer deposit volume*. This entails essential aspects of bank strategy that could impact bank performance. In times of low interest margins, some savings banks might switch more assets from customer deposits to credits than others. The share of credit and customer deposit volume in relationship to total business volume was also calculated in some analyses. Plus, we calculated different growth measures related to the prior year's data.

Furthermore, we included the number of *inhabitants*. Different types of savings banks, i.e., rural, urban, and metropolitan areas, might deal with their branch offerings differently for structural reasons. We calculated *branch density* as the number of branches per inhabitant. However, we only include the population size in the cross-sectional analyses to indicate the savings bank-specific structural differences. The fixed effects panel regressions do not include this variable, as we observe the development within each savings bank over a 6-year period. Greater structural changes in the number of inhabitants are not expected during this period per savings bank region but changes in the number of branches. There were also mergers within the savings banks group, which was mapped by tracing the corresponding data of the institutes back in time, based on the institutional structure of the savings banks group in 2017.

Finally, we included fixed effects variables as recommended in the literature (Brüderl 2010) as our analysis will initially focus on the digitalization impact on the business figures of savings banks over time. A fixed effects analysis uses the individual analyses of the 320 savings banks to determine the mean value of the estimator for our independent DT variable, taking into account the fixed effects across all banks over time. Time-fixed effects reflect factors changing over each year across all savings banks (i.e., year dummy variables). This way, we can rule out biases due to unobservable variables that are constantly changing for all savings banks over time.

3.3 Model specification

We applied an econometric regression analysis following two approaches to examine the relationship between DT and firm performance. The models were calculated in STATA.

Firstly, we applied *fixed effects panel regression models* to analyze the within-firm effects of individual DT measures on firm performance. A fixed effects model examines the effect of DT within each savings bank over time and then calculates the average effect across all entities, which determines the overall effect (cf. Wooldridge 2016, p. 445). This approach accounting for within-firm differences in savings banks has several advantages, such as fewer control variables needed. We look at the effects over time and only need to consider how additional individual effects such as bank strategies have affected the same institution. We did not use an instrumental variable approach for these models following the literature (Brüderl 2010). Instead, time-fixed effects were modeled. In particular, time-fixed effects affect the revenue model of all institutions of the savings bank group equally. The time-fixed effects capture unit-invariant heterogeneity over time, controlling for unobserved heterogeneities. The models capture events that affect all the units of analysis in the same year in precisely the same way. We, therefore, separate the observable DT measures from the unobserved effects in the fixed effects models. Common structural influences of digitalization, such as common trends in customer behavior, as well as the interest rate situation could also be reflected by the unobserved fixed effects.

In order to analyze H1, we derived models that account for the impact of DT on the number of employees, business volume, and bank efficiency.

(1): $\text{Bank efficiency}_{j,t} = \alpha + \beta(\text{DT})_{j,t} + \text{fixed}_t + \mu_{j,t}$

Regarding H2, we developed models that account for firm profitability, and each incorporates one of the different DT variables and several controls reflecting changes in bank strategy. We conducted additional analyses with lagged DT variables to account for possible time variations.

(2): $\text{Bank profitability}_{j,t} = \alpha + \beta(DT)_{j,t} + \gamma(\text{controls})_{j,t} + \text{fixed}_\text{t} + \mu_{j,t}$

We follow the recommended approach from the literature regarding heteroscedasticity in the fixed effects panel regressions (Wooldridge 2016, p. 445). Hence, the fixed effects models employ robust clustered standard errors. One cluster consists of the individual savings bank data for the business years from 2012 to 2017.

Secondly, we applied a *treatment selection regression model* to analyze the between-firm effects for the binary DT treatment variables on firm profitability. Such a model leaves the assumptions of the longitudinal panel data regressions and looks at the data from a cross-sectional perspective. This approach broadens our empirical evidence and enables the analysis of treatment effects of DT across all individual savings banks (Guo and Fraser 2015, p. 143). We used a treatment selection approach to avoid self-selection bias regarding DT (Florens et al. 2008; Wooldridge 2015). The treatment function accounts for the fact that there is self-selection into treatment (i.e., DT) between firms. Firm size served us as the selection variable in the first stage probit model (i.e., the treatment selection function), estimating the likelihood of engaging in DT in the second stage model regressions (Shaver 1998). To control for investments in DT, firm size was measured by business volume and the number of employees. This likely reflects available resources for digitalization and the operational efficiency pursuit of small and medium-sized banks (Tallon 2010). It can be assumed that other organizational characteristics, such as brand, are comparable between the savings banks in their impact on firm performance due to the uniform structures, i.e., a *ceteris paribus* condition. Savings banks with direct banking services were not included in the sample. However, additional control variables, such as *branch density* were included to account for structural differences. We included *GDP growth* that probably affect all savings banks in their profitability (Elekdag et al. 2020). However, we did not have regional economic data. We further incorporated annual measures for *interest margins* for the savings banks group specifically (Deutsche Bundesbank 2020b). Moreover, fixed effects could not be integrated here in the cross-sectional models. Model 3 finally accounts for the impact of the binary DT dimensions on firm profitability.

(3): Bank profitability = $\alpha + \beta(\text{binary} \mid \text{firm size})_j + \gamma(\text{controls})_j + \mu_j$

We relied on binary variables to distinguish whether one data point for an institution is digital in terms of the specific variable and compared the related performance of the digital treatment group with the non-digital control group. Consequently, we derived the average treatment effect of DT across the banks. The models were estimated by a maximum likelihood estimation using robust standard errors.

4 Empirical results

4.1 Descriptive statistics

Firstly, we describe our descriptive statistics. Figure III.2-1 shows the evolution of absolute measures clustered per institution per year (DT, VCM, VPM, CIM). As expected, the average number of mentions of DT measures increases continuously over time. Absolute values rise by the years, reaching a peak in the last observed year, 2017, with a mean of 19 DT occurrences per annual report.

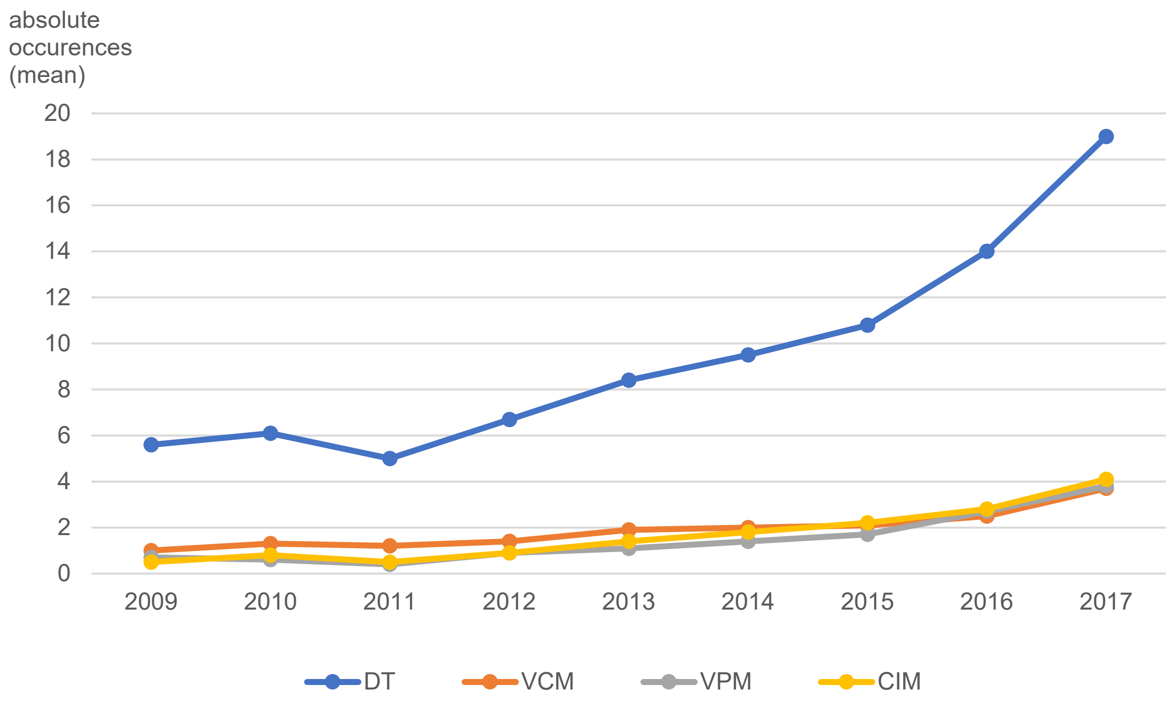

Figure III.2-1: Development of DT variables over time

Table III.2-3 depicts an overview of the descriptive statistics. Regarding firm profitability, the values for RoA suggest a large spread of values. The DT keywords were mentioned around 11 times on average per annual report. We observed clear differences in DT between the lower quartile at 5 and the upper quartile at 15. This was also the case for the DT variable variants. The quartiles, being wide apart, show that DT is not an equal endeavor between the institutions. The savings banks in the upper quartile include twice as many DT keywords as the institutions in the lower quartile. The standard deviation of the DT variables, being equally as large as the mean values, also suggests that there are no uniform strategies regarding DT in savings banks, encouraging our research setting. Table III.2-9 in the appendix provides additional insights into the correlations.

Table III.2-3: Descriptive statistics (main variables)

Variable	Mean	*SD*	1st quartile	Median	3rd quartile
return on assets (percent)	0.16	0.44	0.08	0.13	0.21
net profit (m)	5.20	13.52	0.94	2.36	5.67
business volume (m)	2820.13	3127.59	1034.00	1865.50	3400.50
branches	38.53	30.94	16.00	32.00	50.00
employees	608.91	562.12	249.25	450.50	783.00
DT (absolute)	11.33	10.54	5.00	9.00	15.00

4.2 Fixed effects model: DT variables on firm performance (H1, H2)

4.2.1 Preliminary studies

First, we conducted preliminary studies on the correlation between DT and structural indicators (not tabulated). We distinguished between correlations without time-fixed effects and effects with time-fixed effects as well as analyses including other variables like the number of branches as a proxy for the traditional on-site banking strategy.

We first find, as expected, that digitalization has led to a reduction of the workforce as the *number of employees* without considering time-fixed effects (−1.60, $p < 0.01$). Including time-fixed effects, the effects become smaller but remain negatively correlated (−0.61, $p < 0.05$). This effect remains stable for the relative number of DT keywords and after including the number of branches as an additional variable (−246.41, $p < 0.10$). In the analyses of DT dimensions, we see that this is primarily due to measures in the VCM, where a significant negative relationship becomes evident (−1509.71, $p < 0.05$). Hence, the time-fixed effects share some reduction effect with the individual digitalization measures. The head-count reductions gathered momentum from 2015 onwards and became significant regarding the time-fixed effects in the year 2017. Thus, the specific individual DT measures are related to a workforce reduction. However, unobserved fixed effects absorb some strength of the relationship and might be partly attributable to common yet unobserved structural changes in the digitalization of savings banks.

The *number of branches* was found to be significantly negatively correlated with the absolute number of DT measures without considering the time-fixed effects (−0.114, $p < 0.01$). This individual effect becomes smaller and is no longer significant when considering the unobserved time-fixed effects across all savings banks (−0.026). Here, we find that from 2014 to 2017, strong effects emanate from the time-fixed effects, i.e., unobserved structural conditions could be the primary driver of branch reductions across all institutes and not individual absolute DT measures. Accordingly, the relative individual DT effect is surprisingly positive (but not significant) when the time-fixed effects are considered. A prior study also showed that introducing new digital channels might demand more local presence at first (Campbell and Frei 2010).

The results for *business volume* vary between absolute and relative consideration of the DT measures. We reveal that the business volume is significantly positively associated with the absolute number of DT measures (both with and without time-fixed effects: 9.53, $p < 0.01$, and 4.39, $p < 0.05$, respectively). However, the picture turns for the relative number of DT measures standardized to the annual report length. After including the time-fixed effects, we must assume an adverse effect of individual relative DT measures on the business volume of savings banks. This shrinkage is attributable to the significant impact of DT measures in the VCM ($p < 0.05$). Still, business volume was positively impacted by unobserved time-fixed effects from 2014 to 2017.

The impact of digitalization is also not conclusive regarding *credit volume*. As the absolute DT occurrences increase, so does the credit volume (5.08, $p < 0.01$). In relative terms, however, the correlation is negative again (−1168.62, $p < 0.10$), i.e., the credit volumes have decreased for the savings banks more oriented towards DT, considering the unobserved time-fixed effects as well. The time-fixed effects show an overall positive impact from 2013 to 2017, with increasing credit volumes. We further find a significant negative correlation between the VCM and credit volume (−6725.16, $p < 0.05$). Consequently, measures in the VCM have probably been accompanied by a reduction in credit volumes.

In addition, *customer deposits* have increased for the absolute and relative DT measures, including the time-fixed effects. Here, measures in the VCM positively impact customer deposits (8.21, $p < 0.05$ for the absolute VCM measure; still positive but not significant for the relative VCM measure).

In addition, both absolute and relative measure counts showed a significant decline in *customer accounts*. More digitally oriented institutions lost more customer accounts (measured in thousand) on average than their counterparts (−0.27 for the absolute and −66.99 for the relative DT measure, $p < 0.05$). The causality could be reversed as the savings banks losing more customers could have become more DT-oriented as a result.

4.2.2 Bank efficiency

Now we examine the data for H1 on whether DT impacts bank efficiency. The coefficients can be interpreted meaningfully regarding the direction of the effect of digitalization and DT dimensions on the performance indicators. We also depicted the 95 percent confidence intervals for the DT measures.

By looking at the *business volume per employee*, information can be obtained on the efficiency and employee intensity, with a higher value being more advantageous (cf. Botsis et al. 2015, p. 138). Considering the correlations without incorporating time-fixed effects, we see significant positive correlations with DT for absolute and relative measures ($p < 0.01$ and 0.05, respectively). If we add the fixed effects as recommended in the literature, this effect emanating from the individual DT measures disappears. The unobserved time-fixed effects absorb the positive association. However, when looking at the individual DT dimensions in relative terms, we observe a significant negative effect of the CIM dimension leading to the reduction of the business volume per employee ($p < 0.01$). Savings banks could thus become less productive regarding their total assets as they transform towards digital customer interaction. The same tendency could be observed for the VCM, but this relationship is not significant. In contrast, the DT measures in the VPM transforming the products and the business model exert an efficiency-enhancing effect ($p < 0.01$). Thus, employees became less efficient as a result of the process and channel digitalization, while new products or business models could have likely increased bank efficiency immediately. Table III.2-4 shows the results.

Additional analyses revealed similar DT influences on *credit volume per employee*. The absolute DT measures impact remained consistently positive ($p < 0.05$) even after including time-fixed effects in the equation. On the other hand, the positive impact of relative DT measures ($p < 0.10$) switched towards negative relative DT impact when the time-fixed effects had been considered (not significant). In the fixed effects model, the VCM had a non-significant negative impact on sales efficiency in relative terms. There was a positive relative impact of DT measures in the VPM ($p < 0.01$), as well as a negative impact of the CIM relatively ($p < 0.01$). Likewise, the VCM and the CIM measures tend to reduce customer deposits per employee, while the VPM increases them. Unobserved fixed effects increased the bank efficiency significantly over the years. In sum, the analyses of the fixed effects models uncovered that the relative DT measures did not impact bank efficiency positively. *Hence, we reject H1.*

Table III.2-4: Regression results for fixed effects model (business volume per employee)

Dependent variable	**Business volume per employee (m)**			
Specification	absolute		relative	
DT	0.0008 (−0.0018…0.0035)		−0.185 (−0.883…0.403)	
VCM		−0.005 (−0.014…0.005)		−1.870 (−4.560…0.818)
VPM		0.003 (−0.006…0.129)		**9.035**** (2.191…15.880)
CIM		0.003 (−0.006…0.129)		**−5.742**** (−10.032…−1.451)
2013	0.022†	0.023†	0.023†	0.024†
2014	0.081***	0.082***	0.084***	0.086***
2015	0.239***	0.239***	0.243***	0.243***
2016	0.471***	0.470***	0.478***	0.475***
2017	0.762***	0.762***	0.772***	0.771***
_cons	4.096***	4.101***	4.101***	4.101***
rho	0.918	0.918	0.918	0.919
Observations	1835	1835	1835	1835
***F*-value**	176.17	137.31	176.31	134.54
Prob > *F*	0.000	0.000	0.000	0.000
***R*²**	0.117	0.117	0.113	0.110

Notes. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.10$.

4.2.3 Bank profitability

Secondly, our findings also show a significant negative impact of DT measures on *annual profits* overall. We find that the more digital-prone savings banks generated fewer profits. The direction of the relationship was also confirmed for the relative DT variable but is no longer statistically significant. The insights are similar for the individual dimensions. In absolute terms, we see a negative but statistically not significant influence of process and channel digitalization (VCM, CIM) on annual profits. Quite contrary, the absolute number of VPM measures exerts a statistically significant positive effect on profits. However, the positive relationship could not be confirmed as statistically significant for the relative VPM variable. However, the results still suggest a positive relationship of business model innovation. To interpret the concrete figures: Savings banks lose on average 24,002 EUR in profit with each DT measure but gain 89,988 EUR with each measure in the VPM. On average, the absolute and relative DT measures did not have a positive impact on savings bank profits. Table III.2-5 shows the results.

Concerning our main hypothesis H2, the analyses indicate a profitability problem for savings banks since, from an absolute perspective, increasing digitalization levels were accompanied by a statistically significant decline in RoA. We could infer from the linear panel regression that each absolute DT measure reduced the RoA by around 0.0008 percent on average. Hence, the effect size is very small but statistically significant. For reference, the mean value for return on assets was 0.16 percent and the mean number of DT measures was 11.33 for the total sample. This trend was also confirmed in the relative analysis but was no longer statistically significant. The dimensional analysis points to the CIM as a possible root cause since a statistically significant decline in RoA was associated with increasing absolute measures in DT of the CIM. Each additional CIM measure described in an annual report thus reduced the RoA by around 0.003 percent on average, which is also not a huge effect. This correlation remained stable in the direction but was no longer significant when the measures in the DT dimensions were relatively considered. The VCM dimension, on the other hand, surprisingly did not improve profitability. The VPM dimension has a predominantly positive effect that is also not significant. Profitability has additionally been negatively impacted by unobserved time-fixed effects from 2014 to 2016. This point to an average RoA decline of around 0.02 percent per year. *Hence, we find support for H2a, stating that DT has a negative impact on bank profitability.* Table III.2-6 shows the results.

The identified absolute negative impact of DT on bank profitability could be confirmed in additional analyses for cumulative absolute DT measures. We added up all absolute DT hits in the annual reports over the years for profitability analysis. The results also indicate a negative effect on RoA (not tabulated). The analysis was repeated for a one- to nine-year DT lag of the absolute and relative DT measures to check whether this effect gets reversed over time. However, none of the analyses showed a significant positive impact (not tabulated). *Hence, we reject H2b.*

In addition, we examined the binary effects of the DT measures in fixed effects models. The analysis also showed a negative but insignificant correlation for the DT measures and a significant negative relationship for the CIM ($p < 0.10$). When including time-fixed effects, the correlation for DT and the CIM was still negative but no longer statistically significant.

Table III.2-5: Regression results for fixed effects model (annual profits)

Dependent variable	**Annual profits**			
Specification	**absolute**		**relative**	
DT	**−24002.01**† (−51192.94…3188.91)		−753062.8 (−8725251…7219125)	
VCM		−182379.2 (−425525.3…60766.9)		−7611607 (−5.30*10^7…3.77*10^7)
VPM		**89988.29*** (11592.1…168384.5)		2.25*10^7 (−1.90*10^7…6.40*10^7)
CIM		−20698.5 (−51646.4…110249.4)		−1.42*10^7 (−5.30*10^7…3.77*10^7)
Branches	−141998.3†	−140152†	−142664.5†	−142224.8†
Employees	5947.80*	6260.70*	6587.28*	6554.31
ROA_{t-1}	9.92*10^7	2.11*10^9	−1.02*10^8	2.11*10^9
Business volume (m)	824.43	676.17	871.50	854.38
Credit volume (m)	−269.39	−382.31	−497.42	−527.22
Deposits (m)	−113.72	30.08	−224.90	−179.21
2013	1638900	1681880	1611043	1614183
2014	41942.74	64094.29	−1648.10	3789.73
2015	202441.4	192201.2	141397.4	143463.1
2016	171855.3	117085.2	79056.17	72037.02
2017	283908.8	269982.1	99299.91	98767.33
_cons	2119015	2226693	2064745	2079343
rho	0.287	0.283	0.287	0.287
Observations	1736	1736	1736	1736
***F*-value**	9.98	9.43	11.56	11.76
Prob > *F*	0.000	0.000	0.000	0.000
R^2	0.124	0.118	0.114	0.114

Note. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

Table III.2-6: Regression results for fixed effects model (return on assets)

Dependent variable	**Return on assets**			
Specification	absolute		relative	
DT	**−0.0008*** (−0.0014…−0.0001)		−0.313 (−0.88…0.25)	
VCM		−0.0003 (−0.0044…0.0036)		−0.005 (−0.020…0.105)
VPM		0.001 (−0.001…0.004)		0.027 (−0.032…0.085)
CIM		**−0.003*** (−0.006…−0.0002)		−0.031 (−0.088…0.026)
Branches	−0.0008	−0.0008	−0.0006	−0.0007
Employees	0.00005	0.00006	0.00005	0.00006
ROA_{t-1}	−0.089	−0.089	−0.090	−0.091
Business volume (m)	−0.00006**	−0.00006**	−0.00006**	−0.00005*
Credit volume (m)	0.00003	0.00003	0.00001	0.00002
Deposits (m)	0.00002	0.00002	0.00003	0.00003
2013	−0.004	−0.004	−0.005	−0.004
2014	−0.020***	−0.020***	−0.021***	−0.021***
2015	−0.027***	−0.027***	−0.029***	−0.029***
2016	−0.017*	−0.017*	−0.019*	−0.019*
2017	0.005	0.005	−0.0004	0.001
_cons	0.262***	0.260***	0.003***	0.003***
rho	0.550	0.553	0.582	0.581
Observations	1736	1736	1736	1736
***F*-value**	4.25	3.70	4.27	3.76
Prob > *F*	0.000	0.000	0.000	0.000
R^2	0.013	0.013	0.013	0.013

Note. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

4.3 Treatment selection model: Binary DT variables on firm performance (H3)

To get a complementary statistical picture of the actual relationships, we did not only consider the developments on a longitudinal timeline within each savings bank. We compared the effects of the individual DT measures in the dimensions between all available savings banks. Hence, we conducted an additional cross-sectional analysis where we observed 1736 observations of savings banks.

The results for the treatment selection model suggest that the presence of DT measures across the three dimensions might impact firm profitability differently. We included controls for bank strategy, branch density, and several growth measures. The presence of measures in the VCM dimension shows a positive but insignificant relationship with RoA. The VPM dimension does not impact profitability much and is statistically not significant. For the CIM dimension, we find a significant negative impact on RoA. Hence, in binary terms, the shift to digital customer interaction was accompanied by a decline in profitability considering all covariates from the control variables. While the number of branches is positively correlated with ROA, the shift to digital channels had a negative impact on ROA. *Hence, we reject H3.* Table III.2-7 shows the results.

We further identified a positive impact of a bank's previous year's profit, firm size, the share of loan volume, the share of customer deposits, the number of customer accounts, and branch network density on profitability (RoA). The coefficient for branch network density (per inhabitant) shows that the more closely branched savings banks were more profitable. Accordingly, savings banks could have derived an economic benefit from their local presence. We see that increasing customer deposits squeezed savings bank margins, although the specific interest rate margins had no influence. It is also interesting that economic GDP growth had a significant negative impact on bank profitability. A time-delayed positive effect on the bank business could be expected here. Our analyses showed that the positive effect of economic growth occurs with a one-year time lag but became statistically highly significant with a two-year lag. However, this additional observation had statistically no influence on the negative relationship of the CIM on bank profitability.

Table III.2-7: Regression results for the treatment selection model with binary DT variables

Treatment equation			
Dependent variable	**Return on assets**		
VCM_{binary}	0.007 (−0.02…0.03)		
VPM_{binary}		−0.001 (−0.02…0.01)	
CIM_{binary}			**−0.256***** (−0.32….−0.19)
Business volume	−0.000004*	−0.000004*	−0.000003*
Branches	0.0004	0.0005	0.0004
ROA_{t-1}	0.198***	0.199***	0.119*
Employee growth	0.0004	0.0003	0.0007
Sales growth (deposits)	−0.002***	−0.002***	−0.002**
Sales growth (loans)	0.0007	0.0007	0.001*
Branch growth	0.0006	0.0006	0.0005†
Share of loans	0.073*	0.072*	0.111***
Share of customer deposits	0.099*	0.097†	0.091*
Inhabitants	0.00005	0.00005	0.00006
Branches per inhabitants	0.065*	0.069*	0.071*
Interest margins	−0.071	−0.077	0.027
GDP growth	−0.009†	−0.009†	−0.009†
_cons	0.133	0.152	0.108
Selection equation			
Dependent variable	VCM_{binary}	VPM_{binary}	CIM_{binary}
Business volume	0.00005***	0.00008***	0.00005***
_cons	0.411***	−0.140**	0.007
rho	−0.030	−0.020	0.952
Obs.	1735	1735	1735
Wald test **(*p*-value)**	0.037	0.270	0.000
Log-likelihood test **(*p*-value)**	0.000	0.000	0.000

Note. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

5 Discussion

Our study provided insights into how digitalization impacts savings banks in the time frame from 2012 to 2017. From a methodological perspective, the two analytical approaches used in this study complement each other, whereby we analyzed DT measures as absolute count, relative, and binary. Furthermore, the implementation can make a difference regarding the impact that IT or, more broadly, digitalization has on firm performance (Xin and Choudhary 2019). However, we suppose that implementation problems or failures are not the primary problems in the DT of savings banks. After all, there is a lack of innovative ideas regarding products and business models in the DT of the VPM (see descriptive analyses in the appendix).

Our results show that the savings banks benefited from their traditional business model and have not realized the transition towards a profitable DT since the measures did not positively affect annual profits and RoA. Our main finding is that digitalization negatively impacts the firm profitability of German savings banks, even after a multi-year time lag. Thus, we find support for a profitability paradox in savings banks. Similar findings have been derived when analyzing annual reports of US banks (Kriebel and Debener 2020). In addition, our results coincide with earlier IS studies, where firms leading in IT have been compared to a lagging control group, not indicating a significant performance advantage for the leaders (Chae et al. 2014).

A first, quite understandable reaction is to stick to the traditional business model as long as possible since stationary branches might impact business figures positively. However, new sources of revenue could have been developed in parallel as part of a sustainable, long-term digital strategy. We found the DT measures' potential for product and business model innovation (i.e., the VPM) to increase annual profits. However, the VPM did not strongly impact profitability overall from a statistical perspective. So, the savings banks have not succeeded in implementing digital technologies in their organizations to improve profitability and reflect a true DT.

Both longitudinal and cross-sectional analyses indicate a negative impact of the transformation of the CIM dimension on bank profitability. Thus, we argue that savings banks have not responded adequately to the challenge of digitalization, indicating a higher digital interaction with customers (i.e., the CIM), which is not substantiated within new products and services but reflected in adverse business outcomes (Dehnert 2020b). One reason could be that cross-selling via isolated digital channels is not yet more valuable than traditional face-to-face consultations, especially since omnichannel capabilities have not yet been widely established in the processes of these banks. Banks also need to offer digital products and services that make a difference when interacting with customers more digitally. Our findings suggest the critical role of the VPM dimension to prevent firms from facade digitalization. Furthermore, bank efficiency has tended to decline with increasing VCM measures, showing a productivity paradox when controlling for unobserved time-fixed effects. Hence, the measures in the VCM have not yet had a positive effect on the performance of savings banks. We can only speculate that the CIM could require being combined with the appropriate VCM and VPM transformation measures to increase overall bank profitability (Fang et al. 2021).

Hence, the main obstacle for the incumbent savings banks is not only to consider the cost side but to develop new products that generate new income sources and, ultimately, profits. Customers must also be offered products via digital channels that generate additional revenues (Campbell and Frei 2010). The savings bank business models are still lacking behind their international counterparts, i.e., new products are not yet driving revenues. The platform economy, for instance, did not play a considerable role in the strategies of the savings banks in our study. The descriptive analysis also shows that hardly any new digital technologies have found their way into the annual reports (and business models) of the banks studied up to 2017. Savings banks are thus an excellent example of primarily small and medium-sized incumbents that take a defensive approach to digitalization and DT. Hence, we could not uncover whether DT would contribute to bank performance if digital technologies find their way into processes, products, and business models, so savings banks operate digitally more advanced.

Apart from the processual and technological foundations and organizational structural changes, DT is concerned with intangible investments that require creativity and the intelligent use of human resources to develop the right strategy. Hence, we would expect the investments to pay off relatively quickly if the relevant know-how is available, provided they are made correctly, especially in the VPM. However, our results for the cumulative DT measures and the corresponding time delays indicate that this does not seem to be the case for the savings banks under study. The question that continues to arise is how companies, particularly the smaller ones, manage to get the maximum impact from DT out of limited resources; this stimulates future research.

6 Conclusion

This paper examined the impact of DT on the performance of small and medium-sized firms. We uncovered the contradictory effects of DT on firm performance for a comprehensive multiyear sample of German savings banks drawing on innovative text mining and econometric regression techniques for annual reports. Our paper stimulates the discourse on digitalization for banking, providing insights into the contradictory effects on firm performance in an important industry with a unique data set. In this regard, our paper is one of the few papers that entails small and medium-sized enterprises specifically.

The paper's outcome is threefold: Firstly, we found that, from the marginal perspective, DT has no or even a negative impact on workforce-related bank efficiency figures after controlling for fixed effects. Secondly, we identified a negative DT effect on bank profitability for different digital maturity levels and time lags. Thirdly, we find indications that digital customer interaction could have harmed firm profitability as new revenue sources were likely missing.

Regarding practice, our paper provides new insights into how specific DT strategies impact bank performance. DT could be pursued somewhat defensively and efficiency-driven, negatively affecting bank profitability measures. However, DT could also be followed more proactively and effectiveness-driven (i.e., providing the right digital products and services), probably related to a positive profitability impact. Our paper provides evidence that DT in its initial stages does not contribute to firm profitability figures, which is paradoxical but might be explained by the DT strategies chosen. Savings banks are encouraged to develop profitable digital business models on digitalized banking cores.

Despite its strengths, this work also has limitations. Annual reports served us as a proxy for DT. We cannot rule out simultaneity bias, such as DT was pursued in anticipation of changes in customer demand and profits. Nevertheless, we assume that the annual reports provide a meaningful picture of the DT measures of the savings bank as firms that invest strategically in DT will also report information on this. It is not necessarily more purposeful to look at total monetary investments in DT. We find the concrete outcomes of digitalization in the annual reports, as these seem reportable to the banks. Notably, the semi-automated text mining approach to assess a firm's DT has limitations. It is more difficult to assess the nature of the DT measures, i.e., whether they are attributable to the bank under study (or maybe referring to general trends) and how they are implemented. Therefore, we also looked at the individual dimensions. However, this work cannot replace but rather complements a thorough qualitative assessment of firm activities in DT. Our method likely induces measurement error bias. Thus, the results are not conclusive but show overall effect trends on a solid data basis. We avoided the omitted variable bias by including fixed effects and other bank-strategic variables. Our cross-sectional analysis is too imprecise to identify further regional factors as drivers of digitalization success among the different savings banks across Germany. Additional control variables would have made the statistical analyses even more robust. Banks' equity and investment volume and non-performing loans would have been of interest, especially for the cross-sectional analysis.

Future research might follow our approach with cross-industry data from incumbents and more advanced technologies to examine the impact of DT more broadly. Further research could target more digitally advanced banks and industries but might not neglect the perspective on small and medium-sized enterprises. Regional factors would be helpful to better understand the contingency factors of digitalization, especially in between and within effects analyses. Additional analyses are planned for the future, including more recent and additional data on strategic banking variables such as bank equity and cost-income figures.

Appendix

Table III.2-8: Identified keywords for digital transformation (not translated)

Keyword	count
IT-*	5852
Software	5762
Internet	3546
Digit*	3364
Online	3007
Informatik	2890
Kanal	2746
Rechenzentrum	2392
Informationstechnik	2104
Kernbankensystem	2020
medial	1224
Mobile	961
Online-Banking	682
Internetfiliale	633
Informationssicherheit	548
Anwendungs*	482
App	374
Email	279
Smartphone	236
Server	198
Smart	190
Video	190
Virtuell	172
Chat	164
Fintech	134
Tablet	103
Social Media	95
Kwitt	77
App S-Invest	74
Telearbeit	70
Betriebssystem	66
kontaktlos girogo	61
Messaging	61
Startup	60
Intelligence	59
Internet Companies	39
WLAN	36
Verschlüsselung	19
PayPal	16
Algorithmus	14
Echtzeitüberweisung	13
Kassenanwendung	13
Laptop	13
s-App	11
Mobilfunk	10
Industrie 4.0	8
Venmo	7
Mobiles Bezahlen	5
Visualisierung	5
M-Payment	4
Apple Pay	3
Near Field Communication	3
Bitcoin	2
Robo Advisory	2
Barcodes	1
Big Data	1
Dashboards	1
Digitalwährung	1
Finanzcheck	1
Gestensteuerung	1
Google Pay	1
Internet der Dinge	1
Machine	1
Mobile Payments	1

Table III.2-9: Correlations

Variable	Mean	*SD*	Profitability (RoA)	Net Income (m)	Inhabitants (k)	Branches	Employees	Business volume (m)	Credit volume (m)	Customer accounts (k)	Customer deposits (m)	DT count	VCM	VPM	CIM	Sales Growth (customer deposits)	Sales Growth (credit volume)	Branch Growth	Employee Growth	Interest rate margins
Profitability (RoA)	.17	.442	1																	
Net Income (m)	5.20	13,528	.885**	1																
Inhabitants (k)	204.58	229.492	.036	.418**	1															
Branches	38.54	30.954	.046	.391**	.888**	1														
Employees	608.92	562.269	.040	.420**	.889**	.884**	1													
Business volume (m)	2820.13	3128.405	.032	.424**	.902**	.858**	.977**	1												
Credit volume (m)	1818.89	2243.905	.037	.426**	.872**	.808**	.959**	.978**	1											
Customer accounts (k)	271.69	263.351	.038	.423**	.925**	.892**	.965**	.960**	.922**	1										
Customer deposits (m)	2095.90	2306.222	.033	.428**	.914**	.865**	.972**	.993**	.962**	.968**	1									
DT count	11.33	10.544	−.014	.075**	.235**	.210**	.193**	.227**	.208**	.214**	.238**	1								
VCM	2.23	2.630	−.015	.036	.133**	.170**	.144**	.154**	.154**	.132**	.151**	.738**	1							
VPM	1.89	3.328	−.003	.066**	.172**	.167**	.161**	.176**	.174**	.164**	.181**	.764**	.515**	1						
CIM	2.16	3.121	−.011	.061**	.167**	.178**	.148**	.173**	.148**	.157**	.186**	.725**	.447**	.596**	1					
Sales Growth (customer deposits)	3.03	7.235	−.015	−.001	.040	.059**	.053*	.046*	.038	.048*	.046*	.017	.008	−.007	.012	1				
Sales Growth (credit volume)	3.44	8.118	−.004	.009	.036	.066**	.032	.026	.004	.039	.032	.031	.003	.016	.037	.831**	1			
Branch Growth	−1.43	10.068	.019	.022	.028	.073**	.061**	.044	.038	.053*	.041	−.041	−.035	−.039	−.039	.627**	.630**	1		
Employee Growth	−1.19	7.053	−.007	.001	.020	.061**	.060**	.033	.027	.046*	.025	−.070**	−.044	−.063**	−.066**	.777**	.774**	.683**	1	
Interest rate margins	2.03	0.089	.017	.001	−.005	.041	.028	−.028	−.040	.024	−.043	−.371**	−.255**	−.293**	−.322**	−.033	−.061**	.137**	.198**	1

III.3 How does digital technology for sales and service co-creation impact job perceptions of salespeople in banks? − A study on job characteristics, IT support in customer interaction, and job satisfaction of customer advisors

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Working paper

Abstract: Despite the growing impact of digitalization on personalized human advisory, the literature lacks studies on the impact of digital technology for service co-creation on the job perceptions of salespeople. The banking industry is particularly affected by growing demands in digital customer interaction, so traditional banks are restructuring their organizational units, with far-reaching consequences for customer advisors. Against this background, we examine the job characteristics theory in the unique context of technology-facilitated customer advisory in banking. This paper is the first that studies the threefold impact of digital technology on job perceptions of salespeople in banks. We develop a moderated-mediation PLS structural equation model to study the direct, indirect, and moderating influence of IT support in customer interaction (CI) on customer advisors' job characteristics and job outcomes. The PLS model is tested with data from 160 advisors across 18 banks. The paper's outcome is an evaluated moderated mediation structural equation model, highlighting the facilitating role of digital technology for customer advisors in digitalization. Firstly, we reveal that IT support in CI exerts a positive direct positive influence on job satisfaction. Secondly, we elaborate on the indirect positive impact of IT support in CI on job satisfaction via workplace characteristics of feedback, customer proximity, and job meaningfulness. Thirdly, we find a moderated mediation relationship showing that digital technology can buffer the negative consequences of low task variety and strengthen feedback's positive effects on job satisfaction via job meaningfulness. The results underpin the importance of appropriate, tailored, and up-to-date customer data, connective user interfaces, and optimized workflows for facilitated knowledge-sharing to support salespeople and improve the perceptions of their job.

1 Introduction

The way customers interact with financial service firms has changed sharply in digitalization (Pousttchi and Dehnert 2018), in particular on the sales-service interface of banks (Rapp et al. 2017). The transformation in banking is linked to introducing digital technologies such as data analytics, chatbots, and video consulting. Customer relationship management (CRM) systems show a high potential to leverage the high data intensity of banking services, especially in the retail business segment (Winter 2002). Core banking solutions allow the classification of customer relationships with integrated CRM systems to meet specific customer needs, such as suitable products and services in the context of customer advisory. This study focuses on the collaborative components of CRM to support salespeoples' customer interaction (CI), such as addressing customers, generating individualized offerings, and managing hybrid CIs via personal and digital channels (Nüesch et al. 2015; Winter 2002). A Delphi study shows that digital technologies impact CI, making a change of the underlying bank processes necessary (Pousttchi et al. 2015). Hence, incumbent banks have implemented new forms of information technology (IT) support in personalized advisory. More recent releases of core banking software solutions have entailed different forms of digital assistant technologies. This entails unified advisor and customer interfaces with standardized process workflows (Nüesch et al. 2014). IT affects the daily work practices of customer advisors, for instance, relieving traditionally manual tasks by providing standardized processual guidelines or analytical capabilities by digital technology. New employee job roles and specifications accompany this development as digital technology reshapes work designs (Forman et al. 2014). Digital work designs often augment human capabilities to improve job outcomes in the pursuit of standardization and automation of work (Richter et al. 2018). The digital transformation (DT) of information, processes, and customer interaction (CI) changes the sales function (Guenzi and Habel 2020). Hence, there is a growing need for research on sales and service professionals in digitalization (Singh et al. 2019).

However, there has only been a little research on IT in sales and service encounters, such as co-creation with clients (Giesbrecht et al. 2017). Plus, there has only been meager recent research that analyzes the potential impact IT can have on job outcomes for salespeople (Guenzi and Nijssen 2021). To the best of our knowledge, there is no research on how IT influences the job perceptions of customer advisors in banking, despite its high relevance for practice. Such a salespeople-centric study would provide new insights into how IT support is relevant to the versatile job perceptions of customer advisors and tackle important research priorities.

Against this background, this study examines the relationship between IT support in CI and job characteristics on two critical outcomes: job meaningfulness and job satisfaction. We draw on the job characteristics theory in the context of technology-facilitated customer relationships. Our research design suggests a moderated mediation model. Besides the potential direct impact of IT support on job outcomes, the interactions between job characteristics and IT support may also influence job meaningfulness and satisfaction. We conducted a survey study with 160 customer advisors from 18 banks to determine the particular role of IT support in CI. The outcome of the paper is an evaluated PLS structural equation model that explains how IT support influences the work regarding the job outcomes of customer advisors in banks.

The paper is structured as follows: We provide the background for our study in section two. In section three, we develop the research model. In section four, we evaluate the model and present the results. In section five, we discuss the findings along with the implications for research and practice and conclude the paper.

2 Theoretical background

2.1 Research setting

2.1.1 IT support in customer interaction

Our study focuses on the value creation impact of DT within banks, which increasingly rely on digital customer interaction as another dimension of DT (Pousttchi 2020). As the customer becomes more involved in the value creation process in the digital banking world, additional offerings such as video consulting are integrated, and the value propositions change towards co-creating value with customers. In this regard, banks follow the concern that customers “commit sufficient resources to ensure the actor's goal achievement through a marketing interaction" (Taylor et al. 2020, p. 260). We will analyze how these value creation changes in digitalization affect the job perceptions of salespeople in banks.

Hence, our research setting is the sales and service interface of banks (Rapp et al. 2017). The study tackles digitally augmented human-centered work settings, which are typical for traditional banks. Here, customer advisors offer advice on bank products and services in face-to-face consultations. Regarding the research setting under study, we first conducted a literature search on the multifaceted role of IT in relevant scientific databases (i.e., AISel, IEEE Xplore, ACM DL, EBSCOhost, ScienceDirect, SpringerLink, Google Scholar). We identified the most relevant literature within relevant research strands (i.e., IS and marketing research, including sales and services). After screening the initial set of papers, we narrowed down the result, including journals to level "B" following the German VHB JOURQUAL3 list, and assigned the most relevant papers to underlying topical concepts (Webster and Watson 2002).

The research can be roughly divided into two research streams: (1) IS studies on the impact of IT on CI (e.g., Ryu and Lee 2018; Theotokis et al. 2008; Wells et al. 1999), (2) marketing research on the impact of IT for CI, such as sales and services (e.g., Froehle 2006; Froehle and Roth 2004; Guenzi and Habel 2020; Jayachandran et al. 2005; Singh et al. 2019).

In the first stream of research, studies examine the changing customer interaction based on digital technologies more generally (Alt, Ehmke et al. 2019; Alt and Puschmann 2012; Nüesch et al. 2015). We especially will look at the role of IT in customer interactions (Wells et al. 1999). In particular, the moderating role of a customer–technology contact was analyzed in another study (Theotokis et al. 2008). Further research underpins that the process, the product/service, and the IT perspective must be considered jointly for customer-centric information systems (Liang and Tanniru 2006). Ryu and Lee find that IT plays three different roles in service innovation, i.e., a direct, indirect, and moderating influence (Ryu and Lee 2018).

The marketing literature provides another solid foundation for the impact of IT support in CI in sales and services in the second research stream. Our research especially points to the role of IT in forging relationships in sales and service (Hunter and Perreault 2007). Singh et al. (2019) systematize the literature on the sales profession in the age of digital technologies. They address organizational issues and individual aspects, such as the effects of technologies on salespeople, customer interaction, performance, and context conditions, and set a research agenda. Froehle and Roth systematize different technology impact types on customer interaction (Froehle and Roth 2004). The mediating and facilitating types are most relevant for sales-oriented one-to-one-consultations in banking. In addition, Jayachandran et al. highlight that information processes are vital for building up customer relationships, as IT plays a supportive role for CRM (Jayachandran et al. 2005). Limbu et al. provide a comprehensive literature review on salesforce automation (Limbu et al. 2014), which refers to sales technology applications in customer relationships. We take upon the view of IT as a means of forging the customer relationship from this stream of studies. Guenzi and Nijssen (2021) analyzed the impact of resources and demands on salespeople's motivation to embrace DT initiatives. They found that transformation resources can increase employee stress levels. Our setting is banking services, whereas their study is situated in the electrical tools industry. In contrast to their study, we do not focus on the stress perspective but the concrete effects of digital technologies on salespeople's job characteristics and outcomes.

Accordingly, our conceptualization will focus on the facilitating impact of the relationship between the IT and the sales employee and the relationship between the employee and the customer as demanded in recent research (Froehle and Roth 2004; Singh et al. 2019).

Overall, prior research has vastly neglected the job perception perspective on the impact of digitalization on salespeople. Since IT is changing the way, the work is organized, especially in banking, this points to an important yet unexplored research problem.

2.1.2 An affordance lens on service co-creation in banking customer advisory

Our study examines the impact of digital technology on job perceptions of customer advisors in 18 German savings banks ("Sparkassen"), i.e., legally independent organizations from the same umbrella organization. We described the implications of a new core banking system and organizational transformation in another study (Dehnert 2020a) and will shortly summarize the setting in the following.

A new core banking solution ("OSPlus_neo") was introduced in Sparkassen that offers standardized and simplified decision-making functionalities based on data analytics and new digital channels for customer interaction. New interfaces for collecting further customer data were introduced on the customer side. These interfaces also extend the digital customer interaction from the salespeople's point of view (e.g., direct mails, video banking, WhatsApp chats, and in some cases, chatbots). Customer self-service was accelerated, and data integration along the channels was improved to standardize customer interaction and establish more data-based customer profiles (e.g., by releasing data silos). However, our analyses have shown that implementation has progressed differently in these 18 independent banks (Dehnert 2020a). For example, some salespeople complained about the lack of data and channel integration. Others highlighted the sluggish alignment of underlying business processes. Some salespeople feared the decline of social interaction due to work standardization and specialization, such as customer service centers, often associated with managing an increasing number of customers.

The core banking software provides several new affordances to customer advisors. In the literature, 'affordances' describe or specify the action potentials associated with IT to achieve immediate concrete outcomes (Majchrzak and Markus 2012). Affordances emerge from organizational structures and technological features afforded to specified groups or individual actors, such as customer advisors. Organizational affordances display action potentials for organizational action (Strong et al. 2014). Individual affordances display the action potentials of customer advisors to achieve immediate concrete outcomes in response to their customers' needs in their daily work (Volkoff and Strong 2013). The individual affordances studied in the banks entail predefined process workflows and a shared view of advisory topics with customers on the same screen. The software now follows a value co-creation approach (Giesbrecht et al. 2017; Haki et al. 2019) to promote interactive cooperation in the human-technology environment (vom Brocke et al. 2018). In particular, the new software was designed to facilitate information exchange and customer co-creation in the advisory setting (Burgoon et al. 2000; Grace et al. 2008; Mills and Morris 1986). Assuming the customer's relationship commitment (e.g., by sharing important information and participating in the digitalized sales process), the customer consultant can share his knowledge and experience augmented by IT (e.g., data analytics). The customer can run through the standardized workflow and provide data to the advisor in advance. In the consulting setting itself, the customer can, for example, look at the shared screen; this is realized, for example, through the integration of consulting via iPads or shared desktop screens. The customer is thus actively involved in the consultation and can participate much more actively in the problem-solving process, i.e., finding the optimal product offering in the sense of value co-creation. Customer advisors who receive more actionable data on the customer may provide better individual advice through more data-driven personal contact. Figure III.3-1 summarizes the setting graphically.

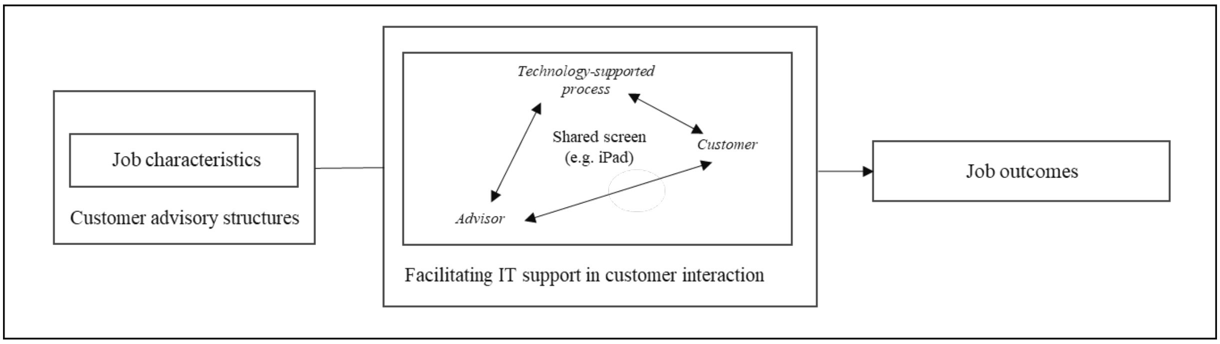

Figure III.3-1: Digitalization of customer advisory as the research setting

2.2 Job characteristics

Job characteristics play a crucial role in understanding the influence of IT on working practices. Thereby, we draw upon prior research from the management discipline (Glisson and Durick 1988; Hackman and Oldham 1980; Morgeson and Humphrey 2006; Pierce and Dunham 1976). From among the multiple aspects discussed on job design in the literature so far (for a synthesis, see Parker et al. 2017), we will focus on the motivational and the interactional aspects (Lysova et al. 2019).

Regarding job characteristics, the organizational transformation of the banks under study initially impacts three critical motivational dimensions. These are three job characteristics that may have a powerful influence on customer advisors. While a job design might influence the task variety and autonomy perceived, new job settings, such as in customer service centers, might also impact how the advisors perceive feedback from the job (Hackman and Oldham 1976; Humphrey et al. 2007). Therefore, we incorporate three motivational dimensions:

- *Task variety* as the extent to which a customer advisor pursues a variety of tasks to complete his or her job (Hackman and Oldman 1980, p. 78);
- *autonomy* as the extent to which a customer advisor perceives freedom in performing his or her work (Hackman and Oldman 1980, p. 79); and
- *feedback* as the extent to which a customer advisor receives precise information about the effectiveness of his or her job performance (Hackman and Oldman 1980, p. 80).

Additional interaction-related job characteristics were developed based on the literature and our manager and employee questionnaire. Many advisors stated that the appropriate time to invest in the actual customer conversation is critical to complete their advisory tasks, which refers to the task identity of their job. The advisors further argued that banks' digital measures influence the perceived proximity to their customers, which also relates to how they can significantly impact their customers in the personal advisory. This becomes a crucial aspect in times of increasingly indirect and technology-mediated forms of CI, which banks proactively initiate to save costs. Hence, both characteristics are also influenced by redesigning the work in the course of the IT system renewal. Thus, we include two additional banking advisory-specific characteristics:

– *Task identity (time invest)* as the extent to which a customer advisor can complete the actual advisory consultation with a customer from the beginning to the end in his or her job (Hackman and Oldham 1980, p. 78), and
– *customer proximity* as the extent to which a customer advisor perceives the advisory setting with customers as direct and undisguised.

2.3 Job outcomes: Job meaningfulness and job satisfaction

Changes in job designs may affect work outcomes considerably. Research has included job characteristics as antecedents, for instance, in several studies on user satisfaction (Karimi et al. 2004). A solid foundation for this study is the finding that specific users' requirements, corresponding to need fulfillment in the job, need to be considered to enhance user satisfaction (Au et al. 2008).

Job satisfaction describes the "extent of positive emotional response to the job resulting from an employee's appraisal of the job as fulfilling or congruent with the individual's values" (Morris and Venkatesh 2010, p. 145). The experience of job satisfaction as one key outcome evolves along with several informational steps. According to the job satisfaction model by Staw (Staw and Cohen-Charash 2005), there is the first phase of exposure to work conditions. The work impressions are then recognized and evaluated in preliminary states, such as job meaningfulness, stored into memory, and, finally, expressed as job satisfaction. There are mechanisms of influence in this process, such as social support, favoritism (Staw and Cohen-Charash 2005), and, as we argue, the impact of IT support in CI.

However, IT may also affect the perceived job meaningfulness state of an employee. In a broader sense, job meaningfulness describes whether employees regard their work as significant, i.e., intrinsically valuable and worth doing (Martela and Pessi 2018). There have been first studies on job meaningfulness (Rosso et al. 2010). Prior research has, for instance, confirmed a link between job characteristics and job meaningfulness (Grant 2007). In addition, meaningful work was highly motivational, improving performance, commitment, and satisfaction (Pratt et al. 2003). Other studies found that job meaningfulness plays a more important role for employees than pay and rewards, opportunities for promotion, or working conditions (Cascio 2003).

Job meaningfulness could be related to the task, organization, interaction, job, and goals (Bailey and Madden 2016). Work should be designed to promote a sense of purpose and positive impact on others, contributing to greater meaningfulness (Grant 2008). Scholars indicate that work redesigns need to consider the perceived meaningfulness of work to impact job outcomes positively (Johns 2010). For example, scholars developed and found support for a theoretical model that puts experienced meaningfulness as a mediator for job outcomes such as satisfaction (Barrick et al. 2013), a finding confirmed in later meta-analyses (Allan et al. 2019). Meaningful work may broadly correlate with work engagement, commitment, and job satisfaction, particularly in a people business such as customer advisory (Allan et al. 2019). More recent studies point to IT and data as potential aspects for perceiving meaningfulness at work (Stein et al. 2019). Surprisingly little research so far has explored where and how people find their work meaningful (Bailey and Madden 2016), and none in the context of IT support in CI for banking. Job meaningfulness in banking advisory may be reflected by the relationship-forging nature of the work practices and the inherent job characteristics that are typically related to the customer advisor role.

3 Development of the research model

3.1 Structural model: Hypothesis development

The study examines the role of IT support in CI in the relationship between job characteristics and job outcomes. We examine the potential direct, indirect, and interaction effects of IT support in CI on job outcomes. Accordingly, elements from different theories are combined (Figure III.3-2).

Firstly, we elaborate on the potential indirect effects of IT support on job outcomes by analyzing the direct impact of IT support in CI on the job characteristics, which is then mediated towards the job outcomes. Social exchange theory, for instance, states that perceived organizational support may affect job perceptions directly (Cropanzano and Mitchell 2005). Following this, we argue that IT support could change the perception of job characteristics in customer advisory.

Typically, more and more elements of work are being assigned to an IT system that is supportive. Nevertheless, this could imply that the variety of spontaneous creative or higher-order managerial tasks in the advisory work setting may be perceived stronger with increasing levels of IT support (Alvarez 2008; Morris and Venkatesh 2010). IT support might be perceived as directly improving the task variety of an employee at work overall. Therefore, we hypothesize:

H1a: IT support in CI impacts the task variety of the job positively.

In addition, IT support could imply that employees feel more autonomy in their job. Therefore, we hypothesize:

H1b: IT support in CI impacts the autonomy of the job positively.

Feedback may be perceived as more intense for increasing levels of IT support since core banking systems collect data about customer relationships. On the one hand, IT support might have a direct impact on the feedback received from supervisors. On the other hand, it is also conceivable that the new technology will enable individuals to receive better feedback from work itself (Oldham and Da Silva 2015). Feedback from customers may, for instance, provide rewards, insights, or new perspectives that help the employees to perform their jobs better. Therefore, we hypothesize:

H1c: IT support in CI impacts the feedback of the job positively.

IT support may also affect task identity as the time to invest available can be used better (Froehle and Roth 2004). Hence, customer advisors may perceive that they can advise the customer more comprehensively within the scope of a single consultation time frame. Therefore, we hypothesize:

H1d: IT support in CI positively impacts the job's task identity (time to invest) positively.

IT support may also affect the nature of the customer relationship directly. It could help reduce the distance between customer and advisor as outlined in the literature on customer-technology relationships (Theotokis et al. 2008). Therefore, we hypothesize:

H1e: IT support in CI impacts the customer proximity of the job positively.

Secondly, we run analyses on the moderated mediating relationships since IT support may also contribute to the job outcomes as a moderator in the advisory work context. IT support could amplify or mitigate the relationships between job characteristics and job outcomes. Previous research has shown that context satisfaction can enhance or mitigate the perception of positive and negative job characteristics (Kulik et al. 1987). Therefore, we argue that IT support is an essential context for customer advisors at the digital workplace in banks. Based on the service co-creation setting, both advisor and customer interact with the banking CRM system, which points to the facilitating role of technology. In this regard, the perceptions of the job characteristics on job outcomes may be moderated by the perceived IT support in customer-centric work (Abdel-Halim 1981; Schneider and Bowen 1985). Thus, IT support in CI may reduce role stress and change the impact of specific job characteristics on job outcomes. For instance, information exchange is crucial in building relationships with customers as a consultant (Day 1994). In line with customer contact theory (Theotokis et al. 2008), we argue that IT support in CI is vital to maintain the focus on the relationship forging job tasks. Another argument is that customer advisors must use attentional resources to handle undesirable (unsupportive) IT-related work, which may distract them from the richness inherent in their job. In contrast, IT support might relieve stress by providing the necessary affordances, such as accessing, analyzing, and communicating information in service co-creation (Hunter and Perreault 2007). Consequently, the impact of job characteristics may change regarding the perceived meaningfulness of work.

Accordingly, it might also be reasonable that a decreasing task variety due to organizational redesigns might reduce the perception of the job as being more meaningful. Hence, the advisor would not feel able to deliver value to customers. The theoretical conjecture is that IT support helps to provide similar job meaningfulness perceptions despite a reduced task variety, primarily by relieving corresponding job strains and role stress. Therefore, we hypothesize:

H2a: The effect of decreasing task variety on job meaningfulness will be moderated such that the relationship is less negative by increasing IT support in CI.

We further argue that IT support could interact with an employee's perceptions of increasing job autonomy on job meaningfulness. Theoretically, an increasing level of IT support may ensure that a customer advisor can enjoy the freedom in the actual advisory role more, i.e., working with greater freedom and supportive IT might improve the advisor's job perceptions more (Ohly et al. 2006). Therefore, we hypothesize:

H2b: The effect of increasing job autonomy on job meaningfulness will be moderated such that the relationship is more positive by increasing IT support in CI.

We further suppose that IT support helps to perceive feedback more positively by relieving customer advisors of unpleasant tasks (van Dijk and Kluger 2011). Therefore, we hypothesize:

H2c: The effect of increasing feedback on job meaningfulness will be moderated such that the relationship is more positive by increasing IT support in CI.

It would also be conceivable that IT support in CI moderates the impact of task identity (time to invest) on job meaningfulness. Hence, how well the consultant can perform the advisory work may not only be directly influenced by the use of IT. The IT support in CI could also mitigate the fact that time pressure harms job perceptions. Therefore, we hypothesize:

H2d: The effect of task identity (time to invest) on job meaningfulness will be moderated such that the relationship is more positive by increasing IT support in CI.

Furthermore, it is conceivable that the proximity of customer contact is impacted by the IT support in its impact on job meaningfulness as IT acts as a strengthening factor for this relationship. Therefore, we hypothesize:

H2e: The effect of customer proximity on job meaningfulness will be moderated such that the relationship is more positive by increasing IT support in CI.

Thirdly, the IT support perceived may directly increase positive perceptions of job meaningfulness and job satisfaction in customer advisory. IT ideally complements human capabilities, such as creative thinking and social behaviors for improved customer services. As we explained, this includes contextualizing the advisory job tasks with predefined advisory guidelines and data analytics functionalities.

The incorporation of new supportive workflows could contribute to the perception of meaningfulness. Thus, we hypothesize:

H3a: IT support in CI is related to job meaningfulness positively.

We further suppose that the satisfaction of needs regarding the work requirements is promoted by IT support directly (Limbu et al. 2014). Hence, we argue that IT support directly affects job satisfaction as the positive interactions will directly affect employee job satisfaction. Therefore, we hypothesize:

H3b: IT support in CI is related to job satisfaction positively.

A moderated mediation occurs when the strength of an indirect effect depends on the level of some variable, i.e., when mediation relationships are contingent on the level of a moderator, such as IT support in CI (Preacher et al. 2007). We conclude our moderated mediation analysis by investigating the relationship between job meaningfulness and job satisfaction (Hayes 2015). This notion is consistent with other studies in the literature demonstrating that job significance is one of the strongest positive predictors of job satisfaction (Thatcher et al. 2002). Prior research indicates a strong connection between the significance and meaningfulness of work (Martela and Pessi 2018). We hypothesize that job meaningfulness is an essential antecedent of job satisfaction (Allan et al. 2019):

H4: Job meaningfulness is related to job satisfaction positively.

Figure III.3-2 shows the three-part moderated mediation research model.

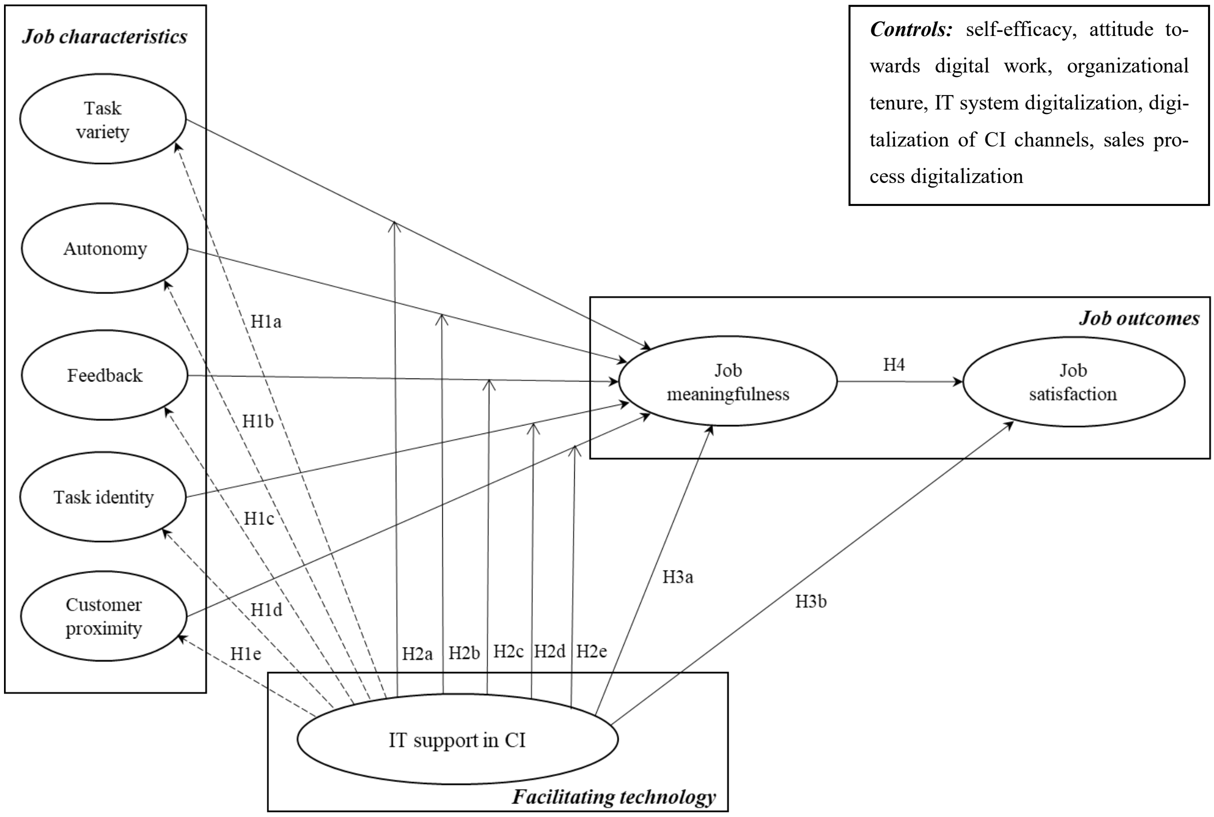

Figure III.3-2: Research model

3.2 Measurement model: Operationalization

The development of the measurement models follows. Firstly, we defined the conceptual topic of the constructs. Secondly, we determined the indicators to represent the constructs completely. Finally, we examined the validity of the indicators and their relationships with the constructs. We could either use a formative or reflective operationalization for each measurement model. A measurement model is defined reflectively if each indicator describes an outcome of the construct, whereas a measurement model is defined formatively if each construct indicator describes an additional characteristic leading to the construct (Fassott and Eggert 2005). While reflective measurement models measure the effects of a construct by the indicators, formative measurement models measure different individual composing (not necessarily causal) aspects of a construct as completely as possible (Hair et al. 2014, p. 119).

3.2.1 IT support in customer interaction

The operationalization of the construct IT support in CI demands a definition at first (MacKenzie et al. 2011). The construct measures how well a customer advisor is supported by IT in human-personalized consultancy work with customers. The IT support in CI relates strongly to the factors that increase the perceived usefulness of the system for the intended advisory job task (Davis 1989). We developed the construct based on the collection of affordances identified in the software documentation and from interviews with the bank employees (Dehnert 2020a). The new core banking software in the cooperative advisory setting of our study provided several IT-related affordances to support the work of customer advisors in the participating banks under study. We developed a list of formative measurement items for

IT support from these affordances (MacKenzie et al. 2011). The developed construct captures the composite aspects of IT support in CI (Hair et al. 2014, p. 119; Hair et al. 2018, p. 9). The index was developed using a MIMIC model to ensure the validity of the formative construct (Diamantopoulos and Winklhofer 2001), pointing to a reflective construct with items from the perceived usefulness scale (Davis 1989). The index showed a high and significant correlation (0.514, $p < 0.001$) with the scale by Davis and a good model fit, with a high chi-square (57.972) and an SRMR value below 0.08 (Henseler et al. 2014), indicating a high nomological validity of the formative measurement.

3.2.2 Job characteristics

As indicated above, we incorporated five job characteristics into our research model. We used reflective scales from a recent version of the job design survey, the “Work Design Questionnaire” (WDQ) by Morgeson and Humphrey (Morgeson and Humphrey 2006), for the constructs task variety and autonomy. The construct feedback was operationalized formatively, drawing on the WDQ (Morgeson and Humphrey 2006): feedback from supervisors and feedback from customers. This is an established approach described in the literature: “If the reflective items are measuring exactly the same facet of the construct, and the content validity of the construct would not be affected, all of the reflective items except one could be removed from the measure” (Petter et al. 2007, p. 636). This allows us to include two composite aspects of feedback on the job.

The task identity (time to invest) construct was developed based on Froehle and Roth's duration belief construct (Froehle and Roth 2004). Our formative items reflect the composite phases of a bank consultation. There are three phases to consider: Contact, information, and sales (cf. Schütz 2012, pp. 7 ff.). In the contact phase, the conversation is initiated. This phase aims to build up the relationship and establish the basis for the conversation with the customer. It includes the prior collection of information on the customer to make informed and appropriate recommendations. In the information phase, products and services are introduced to the customer. The consultant makes further personalized recommendations to conclude a contract in the sales phase. Once the customer has made the decision, the advisor might need to take care of the necessary formalities in the after-sales process, which we do not consider in this study. The advisor must consider the customer's personal and financial circumstances, investment objectives, and possibilities. The construct was measured by a semantic differential.

The customer proximity construct was developed based on Froehle and Roth's intimacy belief construct (Froehle and Roth 2004). The central question is how the actual advisory work is carried out (i.e., personal or impersonal). The dimensions are based on a prior bank-specific study (Pousttchi et al. 2015). The construct was measured by a semantic differential, too.

3.2.3 Job outcomes

The reflective scale for job meaningfulness is based on existing conceptualizations of meaningful work (Martela and Pessi 2018). The construct points to the overall evaluation of work as intrinsically valuable and worth doing. For job satisfaction, we rely on reflective items by Janssen (2001). The construct points to job satisfaction as “a pleasurable or positive emotional state resulting from the appraisal of one's job or job experiences” (Locke 1976, p. 1300).

3.2.4 Controls

Research has shown that user predispositions may be confounders in job outcomes (James and Jones 1980; Oldham and Fried 2016; Woodroof and Burg 2003). We included self-efficacy, the attitude of the employee towards digital work, digitalization of CI channels, and organizational tenure as control variables. Self-efficacy was measured using two items of a reflective measurement scale (Compeau and Higgins 1995). The attitude towards digital work was measured by a single item, where advisors indicated their preference between pen-and-paper and digital work. Organizational tenure was measured by using a single item as well (Simmering et al. 2015). Digitalization of CI channels asked the salespeople to assess the channel digitalization for their job. We included two additional two-item constructs from the manager survey on sales process digitalization and IT system digitalization, which we matched with the employee survey data. Individual characteristics, such as age and gender, could not be collected for reasons of data privacy protection.

4 Results: Evaluation of the research model

4.1 Data collection

The questionnaire was sent to 18 participating community banks belonging to the same umbrella organization. The customer advisors participating were asked to agree or disagree on a five-point Likert scale from *do not agree at all* to *totally agree* or a corresponding semantic differential. A total of 196 customer advisors took part in the study. After completeness and reliability checks, a final data set from 160 customer advisors was used. Organizational tenure was distributed among the participants as follows: A total of 2.2 percent of the participants had been working as a customer advisor for less than one year, 22.5 percent between one and five years, 26.1 percent between five and ten years, and the majority of 49.2 percent for more than ten years. In addition, a survey of the managers of these relationship managers was conducted to elaborate on the context of the value creation shifts.

The measurement and structural model are evaluated in the following. The evaluation and test of the models were performed with the software SmartPLS 3.3.2. Variance-based partial least squares structural equation modeling (PLS-SEM) is similar to multiple regression analysis. In contrast, covariance-based structural equation modeling does not focus on explained variance but reproduces the theoretical covariance matrix (Gefen et al. 2000). Since the measurement properties of constructs are less restrictive with PLS-SEM, constructs measured by fewer items and non-normally distributed data can be used (Hair et al. 2014, p. 19). Hence, PLS-SEM can be used for explorative prediction-oriented studies.

4.2 Measurement model

The reflective constructs and their corresponding indicators are shown in Table III.3-1. The evaluation of the reflective measurement models includes several steps, described in the following.

Table III.3-1: Evaluation of the reflective measurement models

Construct	Composite reliability	AVE	Indica-tor	Item	Loading						
					Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Task variety	0.817	0.601	VAR1	My daily work as an advisor involves plenty of different interactions.	0.838						
			VAR2	My work activities as an advisor are very versatile.	0.650						
			VAR3	My daily work as an advisor includes many different tasks.	0.824						
Autonomy	0.784	0.547	AUT1	In my daily work as an advisor, I perceive a high level of autonomy.		0.753					
			AUT2	I have high freedom of action in my daily work as an advisor.		0.772					
			AUT3	I act very independently in my work as an advisor.		0.692					
Customer proximity	0.762	0.521	PROX1	I interact with my customers primarily in a very immediate (direct) way.			0.739				
			PROX2	I interact with my customers mainly in a very personal way.			0.820				
Job meaningfulness	0.853	0.593	MEAN1	I regard my work as an advisor as responsible work.				0.748			
			MEAN2	I perceive the outcomes of my work as an advisor very strongly.				0.725			
			MEAN3	I find the work as an advisor meaningful.				0.830			
			MEAN4	I can develop myself personally in work as an advisor.				0.772			
Job satisfaction	0.896	0.811	SAT1	I am satisfied with my work as an advisor.					0.898		
			SAT2	I enjoy working as an advisor.					0.904		
IT system digitalization*	0.783	0.648	SYST1	How progressed is your institution in implementing the OSPlus_neo solution of your bank group?						0.891	
			SYST2	How do you assess the actuality of your IT systems architecture?						0.684	
			SYST3	How much progress has been made with the introduction of the OSPlus_neo solution at your bank?						0.815	
Sales process digitalization*	0.933	0.874	SPRO1	How digital are the processes in your institute? Business area with direct end-customer contact (sales)							0.907
			SPRO2	How do you rate the digitalization of your institute in the sales processes?							0.962

*Notes. *managerial survey data.* All construct item loadings fulfill the $p < 0.001$ significance level, except for SYST2 with $p < 0.01$.

Content validity, i.e., the degree to which the construct meaning is represented by the indicators, has been examined using exploratory factor analysis in SPSS statistics. Thereby, all factors have been loaded the highest on their respective constructs. Indicator reliability, i.e., the degree of explanation of the indicator variance by the construct, was also checked. As depicted in Table III.3-1, most of the items have ideal significant loadings above 0.7; loadings below 0.4 did not occur. This confirms the reliability of the indicators. Removing indicators would not have improved statistics. Construct reliability, i.e., the degree of explanation of how well a construct is measured by its indicators, was tested using composite reliability. The PLS-SEM literature recommends using composite reliability because Cronbach's alpha is sensitive to the number of items (Hair et al. 2014, p. 101). The PLS-SEM algorithm underestimates alpha as it prioritizes indicators according to their individual reliability. The composite reliability values are above 0.7 and below 0.9, as recommended in the literature. A minimum alpha value of 0.5 is recommended for constructs with two indicators, 0.6 for three and 0.7 for four or more indicators (Ohlwein 1999, p. 224). All constructs met this requirement as well. Therefore, we can presume that the construct operationalization is reliable. Moreover, convergent validity, i.e., the extent to which one indicator correlates positively with another indicator of the same construct, was checked by average variance extracted (AVE). If, on average, more than half of the variance is explained (AVE > 0.5), this is considered optimal (Hair et al. 2014, p. 103). This criterion is fulfilled for all constructs. Discriminant validity describes the degree of difference in the measurements of different constructs. It was tested using the Fornell Larcker criterion (Fornell and Bookstein 1982). The AVE of a construct was, in any case, higher than the squared correlation with another construct. The constructs were shown to be discriminant from each other. Further testing of the heterotrait-monotrait ratio (Henseler et al. 2015) did not reveal any noticeable discrepancies since all values were below the recommended value of 0.90. Table III.3-1 shows the evaluation of the reflective measurement models.

The constructs feedback, task identity (time to invest), and IT support in CI in the research model were measured formatively. The evaluation results of the formative measurement models are depicted in Table III.3-2. The evaluation of the formative measurement models includes several steps, described in the following.

Table III.3-2: Evaluation of the formative measurement models

Construct	Indicator	Item	Weight	Loading
Feedback	FEED1	I receive feedback on my work through my supervisors.	0.521***	0.851***
	FEED2	I receive feedback on the quality of my work through visible work results with customers.	0.616***	0.904***
Task identity	IDEN1	Time to invest in the contact phase	0.682***	0.733***
	IDEN2	Time to invest in the information phase	0.230	0.366
	IDEN3	Time to invest in the sales phase	0.681***	0.607*
IT support in CI	ITS1	The information provided is appropriate to the needs of the customer.	0.216***	0.762***
	ITS2	The information provided is tailored to my needs as an advisor.	0.324***	0.754***
	ITS3	The data about the customer in the system is always up to date.	0.277*	0.524***
	ITS4	The user interface helps me to stay in touch with the customer.	0.153*	0.680***
	ITS5	The user interface helps me to share my knowledge with the customer.	0.206*	0.698***
	ITS6	The user interface provides me with appropriate work processes.	0.269**	0.733***
Digitalization of CI channels*	CHAN1	Application of video consulting	0.493***	0.956***
	CHAN2	Application of robo advisory	0.236[†]	0.758***
	CHAN3	Application of chatbots	0.393***	0.888***

*Notes. *managerial survey data* Significance levels: *** $p < 0.001$, ** $p < 0.01$, *$p < 0.05$, † $p < 0.10$.

A confirmatory tetrad analysis was performed to specify the measurement model of the construct IT support in CI (Gudergan et al. 2008). The confirmatory tetrad analysis indicates that a measurement model is formative if it includes at least one significant tetrad. Numerous tetrads were significant, confirming that the construct IT support is formative. As indicated above, the MIMIC model confirmed the content validity in the appropriate conceptualization of the construct with formative items. We used the 'Mode A' indicator weighting for formative construct calculations, which is recommended for studies such as ours in the literature with small and medium sample sizes (below 500 respondents) and low to medium R^2 values, as well as for the estimation of weights with potential correlations between the indicators (Becker et al. 2013). Table III.3-2 shows the evaluation of the formative indicators.

Next, the indicator relevance was tested based on the variance inflation factor, which tests for multicollinearity of the items. A variance inflation factor smaller than “2” is considered optimal (Kock and Lynn 2012). All indicators fulfilled this criterion. Furthermore, nomological or external validity, i.e., the relevance of the formative indicators for the measurement model, was checked based on the significance levels of each indicator. An indicator that is not significant and has an outer loading smaller than 0.5 must be deleted, which was not the case in our study.

4.3 Structural model

We tested four structural models: A control variables model, the main effects model with job satisfaction as the dependent variable, a mediated model incorporating the job meaningfulness construct, and a moderated mediation model incorporating the different interactions between job characteristics and IT support on the job outcomes. We first calculated the coefficient of determination (R^2). After this, the significance of the path coefficients and the p-values were determined using bootstrapping. The procedure was performed with 5000 random samples. Table III.3-3 shows the results of the evaluation of the structural model.

Furthermore, predictive relevance, i.e., the model adaptation to the empirical data, was determined by blindfolding. A Q^2 value larger than zero for an endogenous latent variable indicates that the partial least squares path model is relevant for this construct (Stone–Geisser test). Our model passed this test for both job meaningfulness (0.276) and job satisfaction (0.375).

Table III.3-3: Evaluation of the structural model

	Path coefficients			
	Controls	**Direct effects model**	**Mediation model**	**Moderated mediation model**
R^2 Job meaningfulness			0.506	0.533
R^2 Job satisfaction	0.012	0.406	0.509	0.509
Attitude towards digital of employee → Job meaningfulness			−0.024	−0.021
Attitude towards digital of employee → Job satisfaction	−0.011	−0.029	−0.015	−0.014
Self-efficacy of employee → Job meaningfulness			−0.009	0.001
Self-efficacy of employee → Job satisfaction	0.053	−0.080	−0.074	−0.074
Tenure → Job meaningfulness			−0.015	−0.021
Tenure → Job satisfaction	0.103	−0.049	−0.046	−0.046
Task variety → Job meaningfulness			0.313***	0.276***
Task variety → Job satisfaction		0.246***	0.096	0.096
Autonomy → Job meaningfulness			0.173*	0.230**
Autonomy → Job satisfaction		0.256***	0.181*	0.181*
Feedback → Job meaningfulness			0.318***	0.328***
Feedback → Job satisfaction		0.223***	0.071	0.074
Task identity → Job meaningfulness			0.103	0.088
Task identity → Job satisfaction		0.068	0.02	0.021
Customer proximity → Job meaningfulness			0.178**	0.180**
Customer proximity → Job satisfaction		0.109	0.023	0.023
IT support in CI → Task variety		0.060	0.067	
IT support in CI → Autonomy		0.084	0.084	
IT support in CI → Feedback		0.215**	0.215***	
IT support in CI → Task identity		0.175†	0.176*	
IT support in CI → Customer proximity		0.276***	0.263***	
IT support in CI → Job meaningfulness			0.078	0.096
IT support in CI → Job satisfaction		0.180**	0.145*	0.145*
Task variety x IT support in CI → Job meaningfulness				−0.151*
Autonomy x IT support in CI → Job meaningfulness				0.061
Feedback x IT support in CI → Job meaningfulness				0.130*
Task identity x IT support in CI → Job meaningfulness				0.042
Customer proximity x IT support in CI → Job meaningfulness				0.031
Job meaningfulness → Job satisfaction				0.463***

Note. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

4.3.1 Direct effects (H1, H3)

The path coefficients depicted in Table III.3-3 indicate that IT support in CI exerts a significant positive direct influence on the job characteristics of feedback, task identity (time to invest), and customer proximity. IT support in CI directly influences these characteristics, which are all directly related to interaction with people. Thus, we accept H1c, H1d, and H1e but reject H1a and H1b.

Furthermore, we found that job satisfaction is directly positively influenced by IT support in CI. This verifies the notion of IT support in CI being a positive direct influencing factor on job satisfaction. The more supportive the IT is, the more satisfying customer advisors perceive their work. This is not the case for job meaningfulness. Thus, we accept H3b but reject H3a.

One of the advantages of formative operationalization is that we can interpret the impact of each indicator on the construct, which also highlights those indicators of IT support in CI that have a positive influence on the job outcomes. Firstly, we find the most substantial impact in the appropriateness of the information provided (i.e., the actionable knowledge derived from the customer data) to the needs of both customer and advisor. Secondly, the user interface is critical for passing on knowledge from the advisor to the customer. Finally, appropriate processes are necessary, such as standardized workflows.

4.3.2 Moderation (H2)

In cases with a single potential mediator (i.e., job meaningfulness), a single moderator (i.e., IT support in CI) could exert its influence on the direct path, the first stage of the indirect path, the second stage, or any combination of those three (Holland et al. 2017).

Following our research model, we checked the first stage of the indirect path, i.e., the moderating role of IT support between the job characteristics and job meaningfulness. IT support moderates the relationships of two job characteristics with job meaningfulness – namely, task variety and feedback – were moderated by IT support, as evidenced by significant interaction terms. Thus, we accept H2a and H2c. In particular, the negative interaction term task variety x IT support in CI shows a negative relationship with job meaningfulness. The positive interaction term feedback x IT support in CI confirms that IT support strengthens the impact of feedback on job meaningfulness. Contrary to our expectations that all motivational job characteristics would be moderated by IT support in CI, this was not the case for autonomy. The interaction term autonomy x IT support in CI also shows a positive relationship, though not significantly. Thus, we refute H2b. This was also the case for the interactional characteristics, which have been shown to have a positive direct relationship with IT support. Thus, we also reject H2d and H2e.

Figure III.3-3 and Figure III.3-4 show the graphs of the two significant interaction effects. The graphs indicate two different task variety and feedback interaction patterns (Holland et al. 2017). Firstly, the interaction between task variety and IT support is negative buffering (compensatory). More precisely, IT support has a pronounced negative effect on the task variety and job meaningfulness relationship. The higher the IT support, the weaker the relationship between task variety and job meaningfulness. Hence, the more IT support (dotted line), the less pronounced is the negative impact of shrinking task variety on job meaningfulness. The less IT support (dashed line), the more pronounced is the negative effect of a low task variety on job meaningfulness. The solid line shows the relationship between IT variety and job meaningfulness without the moderating influence of IT support. This indicates that unintended adverse effects of task variety on job meaningfulness, such as often following re-organizations such as customer contact centers, can be weakened by increasing levels of IT support.

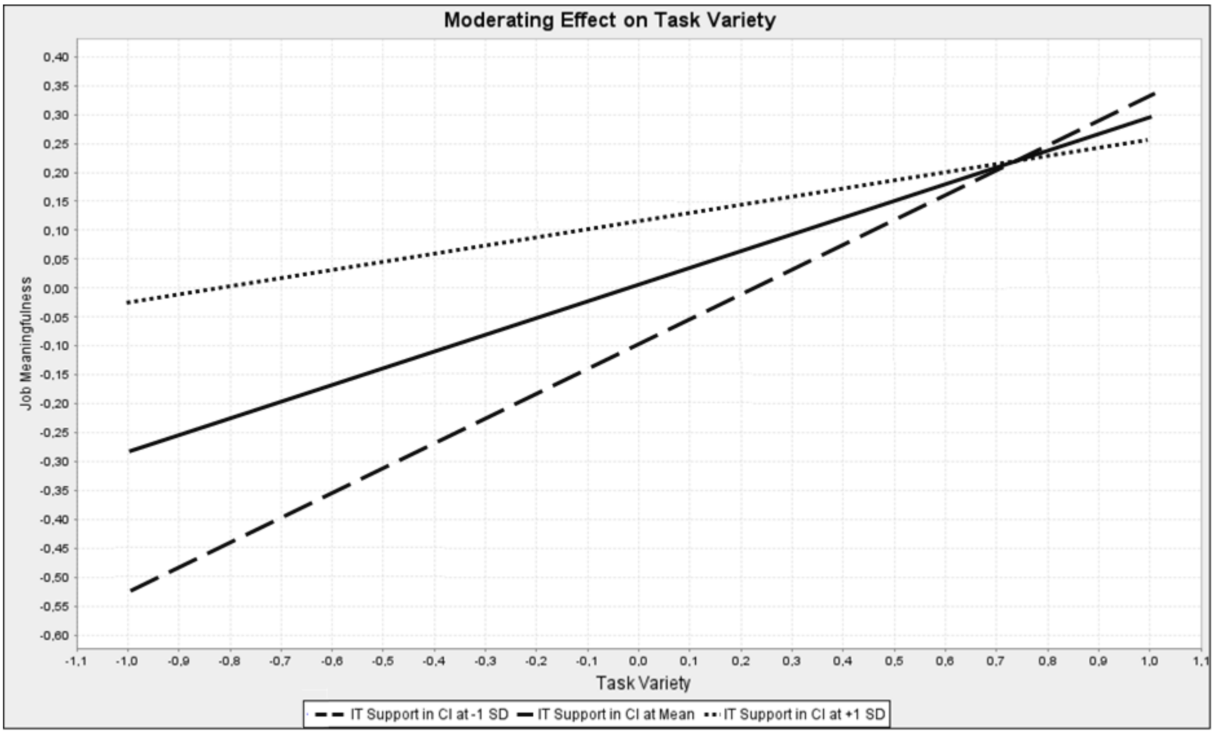

Figure III.3-3: Moderating effect of IT support in CI on the relationship between task variety and job meaningfulness

Secondly, the interaction between feedback and IT support is enhancing (synergistic). Given a perceived IT support that is one standard deviation above the mean, feedback was shown to have a much more positive impact on job meaningfulness compared with IT support one standard deviation below the mean value. Hence, the more IT support is perceived, the greater the impact of additional feedback on job meaningfulness. This indicates that the natural benefits of feedback on job meaningfulness are strengthened by IT support in CI. We also found a synergistic relationship for job autonomy; however, this effect was not significant.

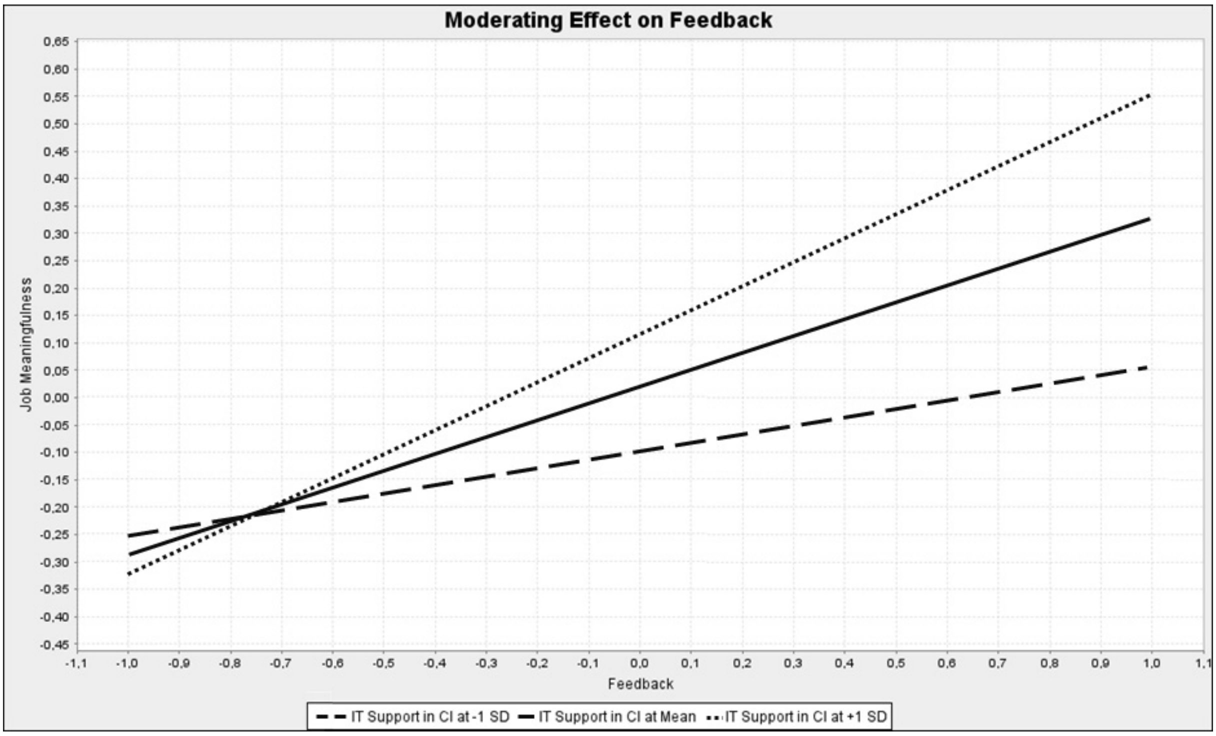

Figure III.3-4: Moderating effect of IT support in CI on the relationship between feedback and job meaningfulness

We also determined the substantive explanatory contribution of the moderators. Meta-studies in management found that small effect sizes are a reoccurring pattern for moderating variables (Aguinis et al. 2005). The effect sizes of the two significant interaction terms on job meaningfulness are small to medium (task variety x IT support in CI: 0.053, feedback x IT support in CI: 0.043). The moderated mediation model explains 53 percent of the variance in job meaningfulness, an increase of 5 percent over the mediated model.

4.3.3 Mediation (H4)

We hypothesized that job meaningfulness mediates the relationship between job characteristics and job satisfaction. Accordingly, the direct relationships between predecessors and target variables and the indirect relationships via the mediator must be examined. Bootstrapping the significance levels of indirect effects can be considered state of the art to examine mediation effects in structural equation modeling (Preacher et al. 2007; Zhao et al. 2010).

Firstly, we found that the direct path coefficient from IT support on job satisfaction decreases slightly from the main effects to the mediated model when job meaningfulness is included. This indicates that IT support in CI shares its effect on job meaningfulness and satisfaction. However, Table III.3-4 shows that this mediation is not significant Secondly, our results show that job meaningfulness transmits the indirect effects from IT support in CI on the job characteristics feedback and customer proximity towards job satisfaction ($p < 0.05$ and 0.10, respectively). Thirdly, the comparison of a moderated and moderated mediation model reveals that the size of the path coefficients between task variety, feedback, and job satisfaction diminishes, just as the significance vanishes. In contrast, the size of the path coefficient between autonomy and job satisfaction diminishes only slightly. The results in Table III.3-4 also confirm that the moderated relationships for task variety and feedback on job satisfaction are mediated by job meaningfulness ($p < 0.10$). This finding, finally, indicates a first stage moderated mediation of IT support on the relationship between the job characteristics of task variety and feedback, job meaningfulness, and job satisfaction. Thus, we partially accept H4, identifying a mediation of job meaningfulness on job satisfaction from IT support towards feedback and IT support towards customer proximity, and for the interaction between IT support and task variety as well as IT support and feedback.

Although it is difficult to detect significant effects with small sample sizes (Kraemer and Blasey 2016, pp. 105 f.), the results suggest that the significant relationships are present and reproducible for banking customer advisory. Therefore, together with its direct effect, IT support in CI can profoundly impact job satisfaction since the cumulated specific indirect effects have a similar order of magnitude as the direct effect.

Table III.3-4: Specific indirect effects of IT support in CI on job satisfaction

	Path coefficient	*p*-value
IT support in CI → Job meaningfulness → Job satisfaction	0.045	0.159
IT support in CI → Task variety → Job meaningfulness → Job satisfaction	0.010	0.530
IT support in CI → Autonomy → Job meaningfulness → Job satisfaction	0.007	0.453
IT support in CI → Feedback → Job meaningfulness → Job satisfaction	0.032*	0.045
IT support in CI → Task identity → Job meaningfulness → Job satisfaction	0.008	0.265
IT support in CI → Customer proximity → Job meaningfulness → Job satisfaction	0.022†	0.062
Task variety x IT support in CI→ Job meaningfulness → Job satisfaction	−0.070†	0.064
Autonomy x IT support in CI → Job meaningfulness → Job satisfaction	0.028	0.437
Feedback x IT support in CI → Job meaningfulness → Job satisfaction	0.060†	0.063
Task identity x IT support in CI → Job meaningfulness → Job satisfaction	0.019	0.533
Customer proximity x IT support in CI → Job meaningfulness → Job satisfaction	0.014	0.620

Note. Significance levels: * $p < 0.05$, † $p < 0.10$.

4.4 Additional contextual analyses

We performed additional contextual analyses to examine common method bias and endogeneity concerns. Common method bias is a potential threat to the validity of most survey studies (Podsakoff et al. 2003). The results of prior research concerned with the objectivity of employee job ratings suggest that employees generally provide accurate descriptions of their job characteristics, which might be shaped somewhat by employees' dispositions and external conditions (Oldham and Fried 2016). However, to avoid issues with common method bias, we took several measures regarding research and questionnaire design. Regarding procedural remedies, the participating customer advisors were, for instance, assured that their results would remain anonymous and not be sent to their employer. In addition, we counterbalanced the question order during the development of the questionnaire (i.e., not measuring related independent and then dependent variables in their particular order). We also used different scale anchors (e.g., using verbal labels). Moreover, the questionnaire was adapted to the terminology used in banking advisory, reducing difficulties in apprehension. The questionnaire was validated with bank managers and experts beforehand.

Regarding statistical remedies, we used the latent variable scores and applied two different approaches to test for common method bias. Firstly, we ran Harmon's single-factor test, where the principal component analysis showed the first factor extracted accounts for 20 percent of the variance, thereby initially reducing our concerns about common method bias. Recent findings, however, indicate that the single-factor test shows limited effectiveness in detecting the presence of common method bias (Aguirre-Urreta and Hu 2019). Therefore, we followed a marker variable approach (Rönkkö and Ylitalo 2011). We chose organizational tenure as a marker variable that is theoretically not related to the substantive variables of our study (Williams et al. 2010) and an indicator used commonly for the study of common method bias in organizational studies (Krishnan et al. 2006). The marker variable was run on each independent variable and, subsequently, the model including the marker variable was compared with the baseline model (Simmering et al. 2015). Overall, the regression paths and significances did not change remarkably across these tests, indicating that the data do not have a method variance problem. Thus, we conclude that common method bias is not a serious concern in this study.

We further tested the bank-level instrument variable IT system digitalization, measuring how advanced the introduction of service co-creation banking processes was considered from the managerial side. This variable was used as an anchor variable to compare the potential impact of multi-level organizational influences on job perceptions (Kock 2020). The IT system digitalization variable is positively correlated with the perceived job autonomy (0.199, $p < 0.05$) − another insight on the impact of the digital work redesign on the salespeople. However, the construct does not directly influence the dependent job satisfaction variable and does not impact the other identified relationships. In addition, the variable digitalization of CI channels shows a negative direct impact on customer proximity, underscoring the lower perceived customer proximity in digital video or chatbot consulting settings, leaving all other relationships unchanged. Furthermore, the bank-level sales process digitalization has a significant negative impact (−0.194, $p < 0.05$) on the perceived task variety by the salespeople − a relationship we expected for digital work redesign. However, the construct does not directly influence the dependent job satisfaction variable and does not impact the other identified relationships. We conclude from these additional contextual analyses that there is likely no endogeneity problem.

The control variable digitalization of CI channels was also tested as a moderator variable with a PLS multi-group analysis (PLS-MGA). To do this, we divided the sample into two groups (low, high) using the control variable construct scores. The results show a significant moderating impact of channel digitalization on the relationship between customer proximity and job meaningfulness. Concretely, customer proximity has no impact on job meaningfulness for digital advisory (0.040) but a strong impact in personal advisory settings (0.450, $p < 0.01$). Hence, customer proximity barely influences the perception of job meaningfulness in digital sales settings via video consulting or chatbots, where customer advisors have less face-to-face contact with customers. Hence, the positive influence of IT support in CI via customer proximity on job meaningfulness primarily applies to the personal advisory setting.

5 Discussion and conclusion

5.1 Key findings

We explored the role of digital innovation in customer-centric advisory settings (Ryu and Lee 2018). We drew on theoretical lenses at the interface of organizational, IS, and service research to examine the role of IT in the customer advisory setting of banking (Orlikowski and Barley 2001). A threefold impact of IT support in CI on advisors' job perceptions was pointed out.

The first important finding is that IT support in CI positively affects job satisfaction, given the action potentials emanating from the core banking IT solution under study. We further examined the significant direct impact of IT support on the job characteristics of feedback, task identity, and customer proximity, changing these job perceptions.

We identified that the potential negative impact of task variety on job meaningfulness could be buffered by IT support in CI that is perceived more strongly. What can be drawn from this finding is that although IT-driven transformations could be accompanied by a long-term reduction in the variety of tasks, the advisors under study seem to get along with this change well when they perceived higher IT support in CI. Higher levels of perceived IT support may patronize the routinization of work, for instance, by pre-defined workflows or reduced paper-based aspects of work, leading to a better focus on the core tasks of work. This also motivated the core banking system provider and bank managers to introduce the new advisory software solution. However, it ultimately hinges on the implementation of the customer sales and service processes.

By contrast, the moderator analysis revealed a strengthening effect of IT support on the relationship between feedback and job meaningfulness. IT support exerts a positive synergistic effect on the relationship between feedback and job meaningfulness. Thus, advisors perceive the advantages of direct customer feedback more positively. This finding aligns with the broader literature on antecedents and outcomes of task feedback (van Dijk and Kluger 2011).

Finally, we found support for a (moderated) mediation effect of job meaningfulness on job satisfaction among four significant relationships that involve IT support in CI. Our study thus confirms a multifaceted influence of IT support in CI on customer service employees' work perceptions beyond its direct impact.

5.2 Implications for research

Our study provides several contributions. For the first time, the threefold influence of IT support on job characteristics, the relationship between job characteristics and job outcomes, and the job outcomes were investigated in the banking sales environment. A structural equation model was developed, integrating the organizational, marketing, and IS literature around job perceptions in sales. Using this model, we expand the previously limited amount of quantitative research on job perceptions in the area of IT-supported sales work. We extend prior research on the multifaceted impact of IT support in CI, such as business processes, data analytics, and the user interface, on the job perceptions of customer advisors in their relationship-forging work. We further highlighted the digitalization impact on job characteristics, such as task variety, autonomy, and customer proximity for personal and digital advisory services. We thus addressed the growing need for research on sales and service professionals with a study on the digitalization of sales in banking (Singh et al. 2019).

Our study points out that augmenting human services with IT can help improve job perceptions in digitalizing work settings towards automation and standardization. IT can directly improve job satisfaction in the banking sales context if it fulfills salespeoples' needs (Au et al. 2008). The direct impact of IT support in CI on job characteristics further highlights that IT helps improve job perceptions, such as feedback from the job. We underpin the potentially positive role for improving relationships with customers and managers via IT (Wells et al. 1999). This finding highlights the role of IT as a form of perceived organizational support (Limbu et al. 2014). The identified positive influence of well-designed digital technology on customer proximity underpins that IT is beneficial for relationship-forging tasks in sales (Hunter and Perreault 2007) and service co-creation (Prahalad and Ramaswamy 2004). Plus, the results show that digitalized customer channel interactions, such as video consulting and chatbots, will reduce customer proximity (from the employee perspective).

Another set of findings highlights the critical role of IT as a contextual factor in sales (Kulik et al. 1987). Hence, we found that IT support moderates the job-related role perceptions of customer advisors, such as task variety and feedback (Stamper and Johlke 2003). Our results indicate that job standardization can show its benefits without necessarily bearing the associated adverse effects of a decreasing task variety but instead leveraging the positive effects of increasing feedback. Our findings regarding the buffering impact of technology extend research on the standardization of work (Karatepe et al. 2004; Ohly et al. 2006; Zeithaml et al. 1988). We see that technology can help improve contextual conditions, such as the perception of feedback and intensified customer contact for job meaningfulness (Theotokis et al. 2008). The study shows that well-designed IT is necessary to tackle the challenges of increasing job standardization and a declining number of salespeople.

Regarding the interactions of job characteristics and IT support in CI, we uncovered job meaningfulness as a mediator on job satisfaction. The moderated mediation influences point to an indirect (i.e., long-term) effect of IT support in CI on job satisfaction beyond its immediate direct effect. Hence, our contribution finally shows that job meaningfulness is a crucial preliminary recognition state on the path towards job satisfaction in IT-supported sales (Staw and Cohen-Charash 2005).

5.3 Implications for practice

We explored how IT fits into increasingly digital business interactions for banking. Since job satisfaction was confirmed to impact service quality and profitability in several studies substantially, the identified relationships are vital to consider by practitioners (Yee et al. 2008). Our findings suggest some warning implications for bank managers. Firstly, poorly designed IT systems, not supportive of daily advisory work requirements, could negatively influence several critical job perceptions. Banks need to consider the business processes, data strategy, and interface design to leverage the positive impact of IT for salespeople. Digital technology that performs the analytics and structures the sales workflows could support salespeople to better focus on their job's behavioral, relationship-forging nature (Grace 2019). Secondly, banks should also keep an eye on job meaningfulness perceptions and consider the interaction with IT support in CI. With troublesome IT, mediocre (i.e., monotonous) work designs could probably exert a substantial adverse effect on perceived job meaningfulness, leading to increased employee frustration and low job satisfaction. Thirdly, the analysis shows that cumbersome IT support in CI could nullify positive feedback and customer proximity effects on job outcomes. Overall, IT support in CI can be regarded as an essential factor in reconciling the conflicting goals of economic and organizational objectives in banking work design, on the one hand, and the remarkable aspects of work psychology, on the other. In this regard, IT can help resolve the area of potential conflict between the economic interests of banks and the working conditions of employees, given the increasing cost pressure in a branch-based personal advisory.

5.4 Limitations and future research

Despite its strengths, the study also has limitations. Firstly, we draw on the subjective perceptions of bank advisors on their jobs and not on objective measures of job performance, such as sales volume or customer satisfaction. However, prior research has frequently shown that psychological outcomes of work, such as job engagement and satisfaction, strongly influence job performance (Loveman 1998). Secondly, this work only focused on job characteristics and explored determinants of IT support and its relationship with associated job outcomes. We did not include organizational change measures during the IT deployment, such as organizational support (Tarafdar et al. 2010), but directly measured the effects of perceived IT support on the employee level. Further research may investigate such organizational aspects of sales job redesigns in more detail and the underlying psychological mechanisms of sales employees. Thirdly, we focused on the individual group of customer advisors in banks whose personal characteristics we were not permitted to collect further for privacy protection reasons. Another potential limitation is the good responder bias, and especially the social desirability bias. This effect is difficult to treat or diagnose. However, we have provided anonymous participation to all customer advisors. Regarding the credibility of the results, it can be noted that the data set comes from different banking institutions, meaning that it represents a wider range of individual working conditions and job perceptions. We did not find any hints suggesting that the banking job environment influenced our participants. Prior studies also indicate that common method bias is rarely an issue in moderation analysis studies (Siemsen et al. 2010). Validating the findings outside the considered banking group and potentially outside the banking sector could also be of particular interest for future research. The results present important insights for research on digitalized sales and service work. The findings are likely to be relevant for various collaborative, digitalized advisory settings since many service industries face similar challenges like banks, such as insurance companies or healthcare service providers. The effects of the potential interplay between digital automated and personal human advisory should also be studied intensively in future research.

Ⅳ Solutions

IV.1 What makes a data-driven business model? A consolidated taxonomy

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Abstract: The usage of data to improve or create business models has become vital for companies in the 21st century. However, to extract value from data it is important to understand the business model. Taxonomies for data-driven business models (DDBM) aim to provide guidance for the development and ideation of new business models relying on data. In IS research, however, different taxonomies have emerged in recent years, partly redundant, partly contradictory. Thus, there is a need to synthesize the common ground of these taxonomies within IS research. Based on 26 IS-related taxonomies and 30 cases, we derive and define 14 generic building blocks of DDBM to develop a consolidated taxonomy that represents the current state-of-the-art. Thus, we integrate existing research on DDBM and provide avenues for further exploration of data-induced potentials for business models as well as for the development and analysis of general or industry-specific DDBM.

1 Introduction

The 21st century can be considered as the data era. Phrases like "Data is the new oil" (Parkins 2017) are widely used, and highlight the importance of data as a resource for businesses. Four of the six most valuable companies in 2020 are data-driven tech companies: Microsoft, Amazon, Alphabet, and Facebook (Javornik et al. 2019; Murphy et al. 2020). Globally and industry-wide, other companies try to follow and benefit from the developments in data-driven technologies like Big Data or Artificial Intelligence to extract the value of data (Chen et al. 2012; Günther et al. 2017). This provides new challenges and opportunities for both research and practice. Consequently, a new research strand has emerged around the topic of *data-driven business models* (DDBM) in recent years. Using data as a key resource, a DDBM enables value creation through activities of data processing and analytics (Hartmann et al. 2016; Schüritz and Wixom 2017) to offer data, knowledge, actions, or non-data products/services as a value proposition (Hartmann et al. 2016; Schüritz et al. 2017), and captures its value through exploitation and monetization (Schüritz et al. 2017).

Available research provides empirical and qualitative evidence and approaches for tackling the challenges of creating and conceptualizing DDBM (e.g., Engelbrecht et al. 2016; Kühne and Böhmann 2018). Particularly, a great part of the DDBM research focuses on the development of tools and methods for the design and ideation of DDBM (Fruhwirth et al. 2020; Lange and Drews 2020), including taxonomies and frameworks. For instance, Hartmann et al. (2016) have provided a first framework for DDBM by adapting the logic of generic business model frameworks to the context of data as a key resource. Further research has explored such business models from a service-dominant logic and particularly explicates data-driven services (DDS) and the role of value co-creation therein (Azkan et al. 2020). Accordingly, a service-oriented business model describes the integration of services into the business model or the usage of services to design new ones. Examples of such taxonomies with a focus on data-driven services are Rizk et al. (2018) or Azkan et al. (2020).

Given the increasing relevance of data in contemporary business models and its economic importance, IS research should sharpen the understanding of the core elements of DDBM and DDS. However, there is yet little analytical consolidation of existing DDBM and DDS taxonomies and frameworks. Instead, IS-related research provides several partly contradictory or redundant conceptualizations. Against this background, we aim to synthesize existing literature for the development of a consolidated taxonomy. Taxonomies are important tools as they provide both researchers and practitioners with fundamental categories to analyze and understand complex domains (Nickerson et al. 2013). This particularly accounts to promising and under-researched phenomena like DDBM. Thus, our interest lies in the question: *What makes a data-driven business model and what are its core elements?* In response to this question, we build upon current research on DDBM and DDS and develop a consolidated taxonomy on the basis of 26 IS-related taxonomies and 30 empirical cases, following the guidelines from Nickerson et al. 2013. The remainder of this paper is structured as follows: In Section 2, we explain the applied methods, before we present and analyze our results in a systematic manner in Section 3 and 4. We close the paper with a conclusion and discussion on limitations and avenues for future research in Section 5.

2 Methodology

In view of our research question, we pursued a two-phase approach. First, we conducted a systematic literature review (SLR) on DDBM and DDS taxonomies. At this, we followed the guidelines from Webster and Watson (2002), and vom Brocke et al. (2009), which provide a rigorous and traceable approach to systematically identify and structure relevant literature on DDBM and DDS. Second, we compared and synthesized the identified taxonomies through defining the common building blocks, and developing a consolidated taxonomy of DDBM and DDS according to Nickerson et al. (2013). Here, we rely on 30 empirical cases with DDBM to validate and refine our taxonomy. The detailed research process is depicted in Figure IV.1-1 and described in the following sub-sections.

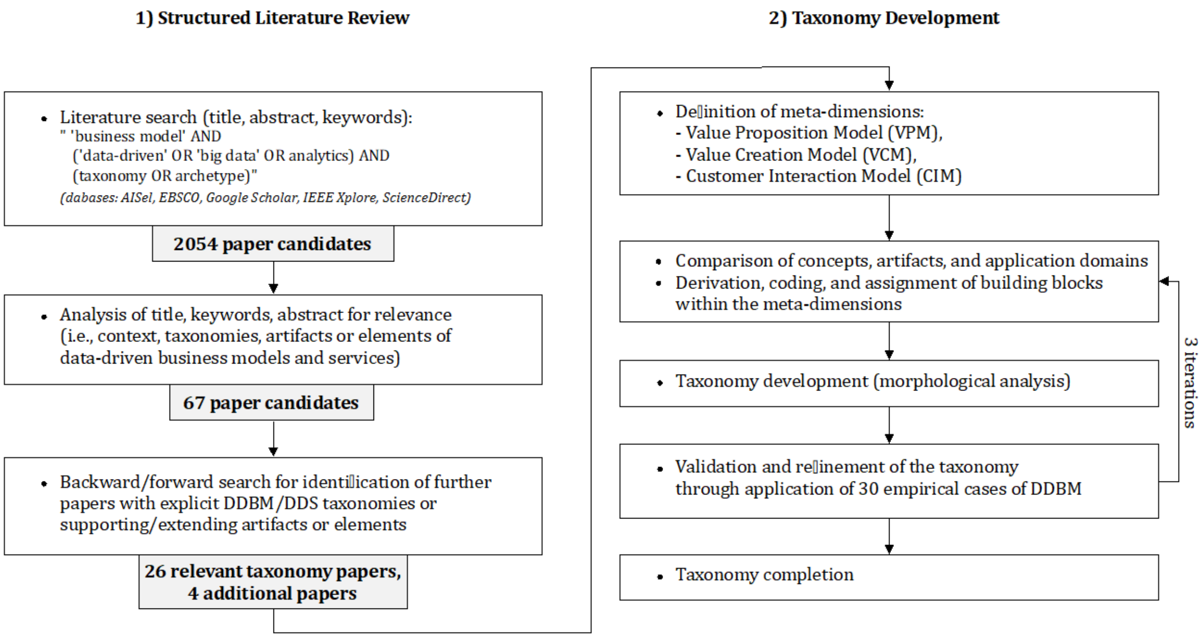

Figure IV.1-1: Two-step research design

2.1 Phase 1: structured literature review

In phase 1, we conducted a SLR. In a first step, we searched for IS-related publications within relevant scientific databases (AISeL, Ebsco, Google Scholar, IEEE, ScienceDirect) with DDBM- and DDS-related terms to receive information about the core elements and taxonomies: “'business model' AND ('data-driven' OR 'big data' OR analytics) AND (taxonomy OR archetype)”. This search left 2054 potential paper candidates for further analysis.

In a second step, we excluded all publications that were not peer-reviewed and three researchers independently analyzed the remaining publications' titles, keywords and abstracts for relevance. We analyzed the full texts of the remainders and proceeded with a forward and backward search to identify additional relevant papers. This analysis left a total of 67 potential paper candidates.

In a third step, we conducted an internal workshop with our working group to select and compare all papers that specifically either provide taxonomies, inherent elements, and characteristics, or design artifacts for DDBM or DDS. Design artifacts also include business model canvases, which provide a structured overview of DDBM elements. We excluded taxonomies that omit the data dimension, even if a business model's or service's foundation relies on data (e.g., carsharing or platform business models). Finally, we identified a total of 26 papers that contain taxonomies and/or characteristic elements of DDBM or DDS, and four additional papers that provide supplementary information on specific parts (e.g., the customer segment).

2.2 Phase 2: taxonomy development

The second phase focused on the development of a consolidated DDBM taxonomy on the basis of the 26 remaining papers from the SLR. At this, we basically rely on the guidelines from Nickerson et al. (2013) for a systematic taxonomy development that combines inductive and deductive reasoning. Accordingly, we first defined meta-characteristics for a first-level classification of any elements of our taxonomy. Given the nature of digital business models, we applied the three dimensions of digital transformation (DT) as meta-dimensions from Pousttchi et al. (2019).

In a second step, we collated the 26 papers with regard to their concepts, methods, artifacts, and application domains in order to derive and define the core elements of DDBM and DDS. These elements were first assigned to the meta-characteristics, and then inductively coded to first-level and second-level items. Here, we followed Mayring's proposed procedure for inductive categorizing as part of a qualitative content analysis (2000). The coding was conducted by three researchers separately, and disagreements were discussed until consensus was reached. Furthermore, we evaluated the identified items from the taxonomies and papers for their general applicability. We sorted them out, if they are too limited or use-case-specific, and do not allow for generalizability. For instance, Möller et al. (2020) provide the items "optimization service" and "visibility service," which imply very specific services. Likewise, Azkan et al. (2020) differentiate the platform type. However, a DDBM does not necessarily induce a platform. Based on the derived items from the identified taxonomies, we derived and defined building blocks and respective characteristics of DDBM.

In a third step, we condensed all building blocks and characteristics into a consolidated taxonomy. Here, we applied the morphological analysis, a highly systematic method to structure multi-dimensional problems (Ritchey 2013; Zwicky 1966), to synthesize all building blocks of a DDBM by means of a morphological box. Accordingly, the characteristics of each building block are mutually non-exclusive, meaning it is possible to select more than one characteristic for each building block (Nickerson et al. 2013). This was necessary because the identified building blocks were derived from existing taxonomies where the authors also used the approach of non-exclusive characteristics (Hunke et al. 2019).

In a fourth and final step, we validated the conceptually developed taxonomy through the application of 30 empirical DDBM cases. For the identification of suitable cases, we conducted online research to find economic reports and overviews of companies with DDBM. Among these reports, we selected as many cases as necessary to achieve saturation in terms of complexity, depth, variation, and context (Gentles et al. 2015). This step caused further refinements of our building blocks and their characteristics. In the following, we repeated step 2 to 4 three times in order to bring the conceptual findings in accordance with the empirical cases until our taxonomy was stable (Nickerson et al. 2013). As a result, we developed an integrated DDBM taxonomy with 14 building blocks and their characteristics of a DDBM.

3 Comparison and analysis of existing taxonomies

As a result of our SLR, we identified 26 papers that contain taxonomies or structuring elements for data-driven business models or services. For the purpose of further comparison and analysis, we sort these taxonomies along with two distinguishing categories: value-proposition focus and application scope. Some publications do not structure DDBM but DDS, which is why we distinguish the two. However, a service can be a business model per se (Azkan et al. 2020). With respect to the application scope of existing taxonomies, we distinguish between industry-specific and general taxonomies to explore the unifying and distinctive elements of these taxonomies. Both differentiations will help us to elaborate on differences and similarities for the development of a consolidated taxonomy of sufficient generalization. Figure IV.1-2 provides an overview of the categorized taxonomies.

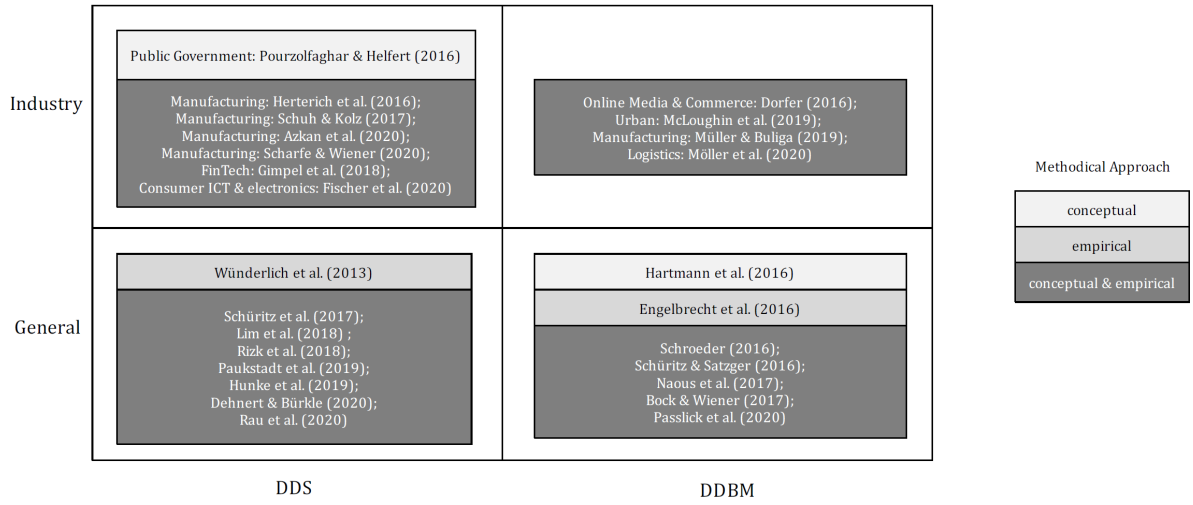

Figure IV.1-2: Categorization of existing taxonomies

Among the 26 taxonomy papers, eight provide *generally applicable* taxonomies for *DDS* (e.g., Dehnert and Bürkle 2020; Hunke et al. 2019), while another seven papers provide *industry-specific DDS* taxonomies, of which four focus on manufacturing data (Azkan et al. 2020; Herterich et al. 2016; Scharfe and Wiener 2020; Schuh and Kolz 2017), one on public government and administration (Pourzolfaghar and Helfert 2017), one on fintech and banking (Gimpel et al. 2016) and another one on smart home and consumer electronics (Fischer, Heim et al. 2020). In terms of *DDBM*, we identified seven *generally applicable* taxonomies (e.g., Bock and Wiener 2017; Engelbrecht et al. 2016; Hartmann et al. 2016) and four with an industry-specific focus, i.e., online media and commerce data (Dorfer 2016), urban data (McLoughlin et al. 2019), manufacturing data (Müller and Buliga 2019), and logistics data (Möller et al. 2020).

Additionally, we classified the taxonomies by their methodological background, i.e., conceptual and/or empirical. Most publications combined conceptual and empirical approaches, as proposed by the guidelines for taxonomy development from Nickerson et al. (2013). Nevertheless, some researchers used purely conceptual (e.g., Hartmann et al. 2016) or purely empirical approaches (e.g., Engelbrecht et al. 2016). The following sub-sections provide a detailed comparison and analysis of the quadrants.

3.1 DDBM taxonomies

General. Seven identified papers provide industry-agnostic taxonomies for DDBM. For example, the paper from Hartmann et al. (2016) is one of the first (and most-cited) contributions that scrutinizes the elements of DDBM. Particularly, the researchers focus on such companies that rely on "data as a resource of major importance" to develop a taxonomy "that allows systematic analysis and comparison of DDBM." At this, they pursue a conceptual approach with deductively generated dimensions (value proposition, key resource, key activity, market and customer segment, revenue stream, and cost structure). Through the review and synthesis of the literature on business models, data mining, and analytics, they inductively derive characteristics for each dimension. Key resource, for example, becomes *data source* (internal or external). While internal data is generated inside or through the company, external data is acquired, customer-provided, or freely available. According to the authors, the *key activity* of a

DDBM is likewise important. This dimension describes how data is used to generate value. At this, the authors rely on Rayport and Sviokla's (1995) concept of virtual value chains. Hartmann et al. (2016) identify the steps of data generator, acquisition, processing, aggregation, analytics, visualization, and distribution. With respect to DDBM, the authors also emphasize the importance of the *value offering*, which is based on Fayyad et al. (1996) and can be divided into two categories of raw and interpreted data in form of information or knowledge. Hartmann et al. (2016) extend these by non-data-based products and services as a possible offering.

Contrarily, the paper from Engelbrecht et al. (2016) provides an empirically developed, industry-agnostic taxonomy for DDBM based on expert assessments of 33 DDBM from startups. The researchers coded these qualitative data to derive the three most relevant characteristics of DDBM: *data source* (user or non-user), *target audience* (consumers or organizations), and *technological effort* in terms of the complexity of data collection, processing, and analytics (low or high). Therefore, this contribution does not focus on a complete DDBM taxonomy but rather on the relevance of its components. The other publications pursue a combined conceptual-empirical approach to scrutinize the elements of DDBM.

Industry-specific. Four identified papers provide taxonomies with a focus on certain industries. For instance, McLoughlin et al. (2019) apply the taxonomy structure of Hartmann et al. (2016) to 40 cases in order to explore the value generating elements and value propositions of urban data business models. In this context, the researchers argue against the data source dimension. Instead, they highlight the importance of key resources, which not only imply data but also software and hardware components to capture and deliver value. Consequently, they propose a self-contained data framework to sub-classify data by the categories *velocity*, *variability*, *variety,* and *type*.

For another thing, Möller et al. (2020) provide a taxonomy of optimization and visibility services for DDBM in the logistics industry. At this, they pursue a combined conceptual-empirical approach with 49 cases. The key resource data is assigned to the meta-dimension *service platform*, which is further divided into five dimensions: *resource*, *source*, *flow*, *activity*, and *feed*. These dimensions describe what the data is about (resource), who creates it (source), how it is provided (flow), what has to be done before it can be further used (activity), and the delivery frequency (feed). In view of our research question, especially these four taxonomies provide a solid foundation for our integrated taxonomy. While the taxonomy from Hartmann et al. (2016) offers some common ground, those publications help to identify eligible components in the intersection of different industries.

3.2 DDS taxonomies

General. Eight of the identified papers provide industry-agnostic taxonomies for DDS. For example, Rizk et al. (2018) provide a taxonomy for data-driven digital services, which is based on a conceptual-empirical approach. At this, they propose four main characteristics through the value chain of big data and extracted knowledge. *Data acquisition mechanism* describes how data is generated or acquired, while *data exploitation* explains how value is extracted from data, especially through information processing and advanced analytics. *Data utilization* describes how the generated insights are provided to the customer (e.g., through visualization or recommendations). Finally, *service interaction* describes how the customer interacts with the service (e.g., application, product, or embedded service).

Lim et al. (2018) provide a nine-factor framework for data-based value creation in information-intensive services based on a literature review and case study research. They provide more information on how to close the gap between having data from various sources and creating real value with it in services. The steps can be clustered into three meta-steps: *data collection, information creation, and value creation.* For data collection, the *data source*, the *data collection* itself*,* and the *data* are the three factors that need to be considered. For information creation, the factor data is the input to the factor *data analysis* that finally leads to the factor *information on the data source.* In the subsequent value creation step, the *information* needs to be *delivered*, e.g., through visualization to the *customer (or information user).* The outcome is the final factor *value in information use* like, for example, a driving person who is assisted by a car infotainment service that guides easily through the traffic.

Table IV.1-1: Identified first- and second-order items from literature

Authors	Focus	First-order Items	Second-order Items
Bock and Wiener (2016)	DDBM	n/a	Digital offering; Digital experience; Digital platform; Data analytics; Digital pricing
Engelbrecht et al. (2016)	DDBM	n/a	Data Source; Target Audience; Technological Effort
Hartmann et al. (2016)	DDBM	n/a	Data Source; Key Activity; Offering; Target Customer; Revenue Model; Specific Cost Advantage
Naous et al. (2017)	DDBM	Value creation (VC), Resource-based and value configuration (RBVC)	VC: Value Proposition; Customer Segments; Customer relationships; Channels; Revenue streams RBVC: Key resources and activities; Key partners
Passlick et al. (2020)	DDBM	n/a	Key activities; Value promise; Payment model; Deployment channel; Customer segment; Clients; Information layer
Schroeder (2016)	DDBM	n/a	Data users; Data suppliers; Data faciliators
Schüritz and Satzger (2016)	DDBM	Data infusion patterns	Data-infused Value Creation; Data-infused Value capturing; Data-infused value proposition via creation; Data-infused value proposition via capturing; New data-infused business model
Möller et al. (2020)	DDBM (Logistics)	Value Proposition (V), Service Platform (S), Interface (I), Organizing Model (O), Revenue Model (R)	(V): Optimization Service; Visibility Service; Modality; (S): Data Resource; Data Source; Data Flow; Data Activity; (I): Data Feed; Delivery Mechanism; Data Interface; (O): Access to API; API Documentation; (R): Revenue Model; Price Basis; API-Based Revenue
McLoughlin et al. (2019)	DDBM (Urban Data)	n/a	Key Resource; Key Activity; Target Customer; Revenue Models; Cost Structure; Data
Müller and Buliga (2019)	DDBM (Manufacturing)	n/a	Value Creation; Value Offer; Value Capture
Dorfer (2016)	DDBM (Online media & commerce)	BMs for cognitive benefits, (CB); BMs for social-interactive ND cognitive benefits, (SICB); BMs for social-interactive benefits (SIB)	CB: General Information gathering; Transaction specific information gathering SICB: General information gathering over social interaction; Social-driven initation of transactions SIB: Networking and contact-management in the context of relationship management; Sharing of content in the context of identity-management
Dehnert and Bürkle (2020)	DDS	n/a	Autonomous acting capability; Sensing capability; Interoperability; Coupling control; Ecosystem; Interaction; User mapping; Data capability; Analytical capability; Output medium
Hunke et al. (2019)	DDS	n/a	Data Generator; Data Origin; Data Target; Analytics Type; Portfolio Integration; Service User Role
Lim et al. (2018)	DDS	n/a	Data source; Data collection; Data; Data analysis; Information on the data source; Information delivery; Customer (information user); Value in information use; Provider network of the service provider and partners

Authors	Focus	First-order Items	Second-order Items
Paukstadt, Strobel and Eicker (2019)	DDS	Service Concept (SC), Service Delivery (SD), Service Monetization (SM)	(SC): Value Proposition; Bundle; Main Outcome; (SD): Visibility; Mode of Operation; Actor Interaction; Main Interface; (SM): Payment Mode; Pricing Model
Rau et al. (2020)	DDS	Consumer (C), Data (D), Interaction (I)	C: Consumer Relief; Consumer Benefit; Consumer Risk D: Data Source; Data Analysis; Smartness I: Trigger (T); Representation (R); Integration (I)
Rizk et al. (2018)	DDS	n/a	Data Acquisition Mechanism; Data Exploitation; Insights Utilization; Service Interaction
Schüritz et al. (2017)	DDS	n/a	Subscription; Usage Fee; Gain Sharing; Endure-ads; data-tailored offering; buy-and-sell-data; pay-with-data
Wünderlich et al. (2013)	DDS	Interaction patterns	Interactive service; Self-service; Machine-to-machine service; Provider active service
Azkan et al. (2020)	DDS (Manufacturing)	Value Creation (VCr), Value Delivery (VDe), Value Capture (VCa)	(VCr): Value; Outcome; Analytics Type; Data Sources, Data Types; Aggr. Level; (VDe): Service Delivery; Service Flow; Platform Type; (VCa): Pricing Model; Payment Mode
Fischer, Heim et al. (2020)	DDS (consumer electronics)	Digital Service (DS), Smart Product (SP)	DS: Configuration; Data Analytics; Service Object; Benefit; Duration of Service SP: Capability Level; Communication; Data Source
Gimpel et al. (2018)	DDS (Fintech)	Interaction (I), Data (D), Monetization (M)	I: Personalization; Information exchange; Interaction type; User network; Role of IT; Hybridization; Channel strategy D: Data source; Time horizon; Data usage; Data type M: Payment schedule; User’s currency; Partner’s currency; Business cooperation
Herterich et al. (2016)	DDS (Manufacturing)	Material properties (MP), Organizational characteristics (OC)	MP: Data origin; Initiation of data transmission; Relevant data; Data analysis; Digital platform access; OC: Service automation; Lifecycle context; Service innovation
Pourzolfaghar and Helfert (2016)	DDS (Public Government)	n/a	Types; Purpose; Design
Scharfe and Wiener (2020)	DDS (Manufacturing)	Application (A), Integration middleware (IM), Connectivity (C), Machine (M)	A: Application domains; Service type IM: Data analytics; Data sources; Deployment scenarios; Middleware solution C: Interoperability; Communication direction; Interaction partners M: Control autonomy; Actutator purposes; Sensor measure. Objects; Production types
Schuh and Kolz (2017)	DDS (Manufacturing)	n/a	Focus of service provision; Key activities; Revenue model; Connection/implementation; Key resources; Effort for Individualization; Customer access/system integration; Duration of business relationship; Data sources; Data base

Hunke et al. (2019) provide another dominant taxonomy to conceptualize the use of data and analytics in services, based on a conceptual-empirical approach. At this, they identify meta-characteristics through a literature review and conduct four iterations with 85 cases from IBM, Microsoft, and Oracle. The taxonomy has six dimensions: *data generator*, *data target*, *data origin*, *data analytics type*, *portfolio integration*, and *service user role*. The authors offer an interesting perspective by the separation of data generator and data target. Here, data generator describes a person, process, or object that generates the data. This might be an object with sensors. In contrast, the data target is what the generated data is about. Therefore, they are extending data target with the characteristic environment. The data generator (the object with sensors) could measure weather data and therefore needs a distinct data target. Another interesting dimension is the *data analytics type.* Here, the authors provide four types based on four respective questions: *Descriptive* answers the question to “what happened?”, *diagnostic* to “why did it happen?”, *predictive* to “what will happen?” and *prescriptive* to “what should be done?”.

Industry-specific. Azkan et al. (2020) provide a DDS taxonomy for manufacturing industries, also based on the conceptual-empirical approach from Nickerson et al. (2013). As meta-dimensions, they define *value creation* and *value delivery* (from service science), as well as *value capture* (from business model literature). Value creation includes the main value and outcome, the data analytics type, the data sources and types, and the aggregation level, while value delivery describes how the service is delivered, how the service flow is managed, and what type of platform is offered. Finally, value capture contains the pricing model (i.e., subscription-based, transaction-based, or indirect), and how the customer pays (i.e., through the product or service, or data).

Altogether, the service perspective provides useful elements for the development of our consolidated taxonomy. For one thing, data turns out to be pivotal for DDS (and thus, DDBM), be it in terms of generation or exploitation. For another thing, value creation, proposition, and capture appear to be key dimensions to categorize DDBM and DDS. For value creation, especially the factor data analysis plays a key role in the identified taxonomies as these are the steps that finally extract the value out of data. Finally, customer communication, integration, and interaction seem to be considerable components in the design of DDBM or DDS. Table IV.1-1 summarizes all components of DDBM and DDS derived from the 26 taxonomies and builds the basis for further elaboration.

4 Development of a consolidated taxonomy

Based on the identified items of DDBM and DDS from available literature, we followed the further guidelines from Nickerson et al. (2013). Thus, we defined building blocks of our consolidated taxonomy from literature and cases through 4 iterations (in total), and assigned these building blocks to meta-dimensions. Regarding these meta-dimensions, we rely on the three dimensions of DT (Pousttchi et al. 2019), i.e., value proposition model (VPM), value creation model (VCM), and customer interaction model (CIM). Given the digital nature of DDBM, this classification seems particularly suitable. First, the VPM determines the products and services proposed to the market and their revenue models. This view is appropriate because the extraction of data offers both new types of products or services and ways of generating revenues. Second, the VCM determines how digital technologies affect business processes, organization types, and staff. With regard to DDBM, this view is eligible because such business models force new ways of data usage and skills for value generation. Third, the CIM includes all types and mechanisms of interaction with customers. This dimension can be interesting for DDBM, as data can transform the interaction between the customers and enterprises. Table IV.1-2 presents the final 14 building blocks (and their guiding questions) with the three meta-dimensions.

Table IV.1-2: Guiding questions for each building block of the consolidated taxonomy

Meta-Dimension	#	Building Block	Description
Value Proposition Model (VPM)	[1]	Value Proposition	What does the company offer to the customer?
	[2]	Value Capture	How does the company earn money through the business model?
Value Creation Model (VCM)	[3]	Data Generator	Who or what is generating the data?
	[4]	Data Origin	Where does the data come from?
	[5]	Data Target	About whom or what is the generated data?
	[6]	Data Activity	How is the data handled?
	[7]	Data Analytics	How is the data analyzed?
	[8]	Insights Utilization	In which form are the insights provided to the customer?
	[9]	Cost Structure	How are the costs determined?
Customer Interaction Model (CIM)	[10]	Customer Segment	What kind of customer is it?
	[11]	Target Customer	Who is the customer group?
	[12]	Interaction Type	How does the customer interact with the offering?
	[13]	Service Flow	When is the service provided?
	[14]	Customer Relationship	How is the company supporting the customer?

4.1 Building blocks in the value proposition model

The value proposition model includes two building blocks. *Value Proposition (1)* describes what the company offers to the customer. This building block determines the overall outcome of the business model and is strongly influenced by the aspect of data. This building block consists of the following characteristics: *Data*, *Information/Knowledge*, *Actions*, and *Non-Data Product* (Fayyad et al. 1996; Hartmann et al. 2016; Rizk et al. 2018; Schüritz et al. 2017). Except for Non-Data Product, these characteristics represent the structure of the Data-Information-Knowledge-Wisdom Pyramid (Jifa and Lingling 2014). *Data* describes offering the raw data without the attached meaning, while *Information/Knowledge* describes the provision of interpreted or analyzed data. This could be, for example, provided in form of recommendations or visualizations and the customer can use these to make decisions. *Actions* come one step further and describe how the company itself takes action for the customer, based on the analyzed data. These actions can be, for example, the decision-making, the execution of specific process steps, or the matchmaking of the customer. A more concrete example is predictive maintenance, where the company proactively replaces the part of a machine based on predictive analytics. The last characteristic of the Value Proposition is the Non-Data Product or Service. An example is an object that receives added value through data (Hartmann et al. 2016) like a watch that is equipped with a sensor.

Value Capture (2) highlights how to gain revenues from the DDBM. It is an important building block because a business model can only sustain in the long run if it creates revenue to cover the costs. The characteristics are based on Hartmann et al. (2016) and Schüritz et al. (2017). *Subscription* describes a periodical payment from the customer. Contrastingly, through a *usage fee,* the customer has to pay as much as he uses the service or product. One factor to measure the usage could be data volume. *Gain sharing* describes how the service or product provider receives a percentage of the revenue that the customer makes through the usage of the offering. *Advertising* describes revenues that are received through advertisers. *Buy-and-sell-data* describes a multi-sided approach, where the provider gains revenues by creating data profiles of the customer and selling them to third parties. *Pay-with-data* describes how the customer provides personal data that can be used in new services or to create new services. Finally, an *asset sale* describes a modus where the offering is provided for a fixed one-time payment.

4.2 Building blocks in the value creation model

The value creation model consists of seven building blocks that are closely related to the key resource data. *Data Generator (3)* describes who or what generates data for the BM. Hence, this important building block describes one core aspect of the key resource data. For this building block, we rely on the approach of Hunke et al. (2019) for analytics-based services. First, *customer* refers to data that is generated by the direct consumer types of the business model through the usage of an analytical service. This also includes customers of the customer (B2B2C). *Non-customer* refers to humans who generate data for an analytical service but do not consume the service themselves directly, such as social media portals (Hunke et al. 2019). *Process* describes data that is generated through structured activities or tasks performed by people or devices (Hunke et al. 2019). Examples here might be business processes, like manufacturing or consumption processes. *Object* describes data that is generated through physical objects that are equipped with sensors (Hunke et al. 2019). To include other possible Data Generators, we added the characteristic *other*.

Data Origin (4) depicts if the data is generated inside the company (*internal*) or outside of the company (*external*) (Hartmann et al. 2016; Hunke et al. 2019; Lim et al. 2018). This building block determines if the company needs to acquire or obtain the data from external sources or if it is provided through internal sources. External and internal sources are both containing specific restrictions and challenges, like privacy, cost, or effort that needs to be considered to get the data. A DDBM may use internal and external data sources to create its offering.

Data Target (5) represents the flip side of the building block data generator and describes the focus of the collected data. Thus, we can not only identify what or who generates the data but also what or whom the data is about. At this, we extend the structure from Hartmann et al. (2016) by the approach from Hunke et al. (2019) for the generalization because it provides a broader perspective through explicating the data generator more specifically. Consequently, the characteristics resemble those from the building block data generator. One example to clarify this distinction is the following: A smartwatch can generate health data about the customer. Therefore, the smartwatch is the Data Generator, and the Data Target is the customer. Regarding the data target, we add *environment* (e.g., weather), which is oftentimes the objective of data collection and analytics. Plus, we propose *other* to include potential future data targets that are not covered by the existing characteristics.

Data Activity (6) summarizes all activities that have to be done after the data is generated and before it is analyzed (Fayyad et al. 1996; Hartmann et al. 2016; Hunke et al. 2019; Lim et al. 2018; Rizk et al. 2018). This building block sharpens the understanding of what to do with the data after its generation. The generated data oftentimes is not directly utilizable where it is generated. Therefore, it is important to understand and determine what needs to be done with data. Here, *data collection* describes the activity of collecting and accessing the generated data, while *data organization* describes the activity of storing the collected data. *Data preparation* describes how the collected data needs to be manipulated for the purpose of further analysis or usage (Hunke et al. 2020).

Data Analytics Type (7) describes what advanced analytics methods can be applied to the data in order to extract information or knowledge from it (Fischer, Heim et al. 2020; Hartmann et al. 2016; Hunke et al. 2019, 2020; Lim et al. 2018; Rizk et al. 2018; Scharfe and Wiener 2020). This is an important building block within most taxonomies. It determines what has to be done to actually generate the value from data (and gaining a competitive advantage). The explicit characteristics are *descriptive, diagnostic, predictive,* and *prescriptive* (Hartmann et al. 2016; Hunke et al. 2019). Additionally, we added *none* as a characteristic in case the business model relies on the raw data only as the offering.

Insights Utilization (8) describes how the generated insights are provided to the customer (Hartmann et al. 2016; Hunke et al. 2020; McLoughlin et al. 2019; Rizk et al. 2018). This building block might seem redundant on its face with the building block value proposition. However, we decided to create a separate building block as it completes the concept of the virtual value chain or the knowledge-discovery-in-databases chain (Fayyad et al. 1996; Rayport and Sviokla 1995), and thus sharpens the focus on how the company will finally provide the value proposition to its customers. The characteristics of insights utilization are distribution, visualization, and execution (Hunke et al. 2020; Rizk et al. 2018). First, *distribution* describes the simple supply of the data or information to the customer. This could be, for example, through a data file or an application. Second, *visualization* describes if the company uses advanced techniques to provide the information more comprehensively or graspably to the customer. For instance, infographics present data and information by means of visual and graphical charts and figures to provide the message more catchily and intuitively. Third, *execution* describes if the company uses the information to guide the customers' actions (e.g., digital nudges, or recommendations) or if the company itself processes information for the customer (e.g., schedule query from a database).

Cost Structure (9) adds the perspective of how costs are determined (Hartmann et al. 2016; McLoughlin et al. 2019; Osterwalder and Pigneur 2010). This building block represents the flipside of the revenue model, and thus decides on the success of the entire business model. Here, we rely on Osterwalder and Pigneur (2010) and McLoughlin et al. (2019) to determine the main distinction between value-driven and cost-driven. While *value-driven* determines the price of a product or service through the value that the product or service might give to the customer, *cost-driven* determines the price through the concrete costs that are caused by the creation and offering of the product or service. Additionally, we added the characteristic *other* if the DDBM relies on mixed or other cost structures.

4.3 Building blocks in the customer interaction model

The customer interaction model consists of five dimensions. *Customer Segment (10)* describes if the DDBM is *business-to-business (B2B)*, *business-to-customer (B2C)*, or *business-to-administrative (B2A)* (Engelbrecht et al. 2016; Hartmann et al. 2016; Lim et al. 2018; Passlick et al. 2021; Wirtz 2019). This building block is a foundation for any business model as it determines to whom the offering is provided and therefore, why the business model may even exist.

Target Customer (11) describes if the business model addresses a *new customer group*, an *existing customer group,* or a *multi-sided customer group* that consists of different actors (Osterwalder and Pigneur 2010, pp. 16 ff.; Weking et al. 2020). Thus, this building block complements the customer segment because it offers a different strategic alignment and influence of data-driven products and services in a business model. Especially for incumbent companies, it might be interesting to define if they should focus on their existing customers, try to reach for new segments, or intermediate between two or more groups together.

Interaction Type (12) highlights how the customer is interacting with the company. This is an important building block because it displays how the customer actually receives the offered value. Characteristics within the interaction type are *application*, *product*, or as an *embedded service* in another service or product (Rizk et al. 2018). Consequently, the interaction can be orchestrated through hardware, software, or combined components. However, especially in terms of B2B, a fourth possible interaction type might be an *API* that provides the data for further processing or usage (Möller et al. 2020).

Service Flow (13) describes if the customer receives the offering manually, in pre-defined time-steps, through specific events, or in a stream (Azkan et al. 2020; Lim et al. 2018; Rau et al. 2020). At *manually*-driven service flows, the customer is proactive in requesting the service. For instance, if it is required to download a document. *Predefined time-steps* describe processes if the service flow comes in intervals. This might be a configured push news service that delivers the latest information on a daily basis. Contrastingly, *event-driven* means that specific (possibly pre-determined) conditions have to occur to trigger or activate the service flow. For example, the detected (or predicted) failure of a production machine might cause an alarm warning in the monitoring system of the production site. *Stream* describes a service that is continuously offered. This might be a smartwatch that always provides the heartbeat or a dashboard over the actual processes in real-time. Altogether, this building block is important because it gives a glance at the time- and activity-related requirements that the corresponding data resources need to fulfill (e.g., availability, currentness) as well as the upstream and downstream events and processes that need to be considered for the further offering of the value proposition.

Customer Relationship (14) is the last building block in the taxonomy and basically relies on Osterwalder and Pigneurs (2010) Business Model Canvas. This building block determines how the company interacts with its customers for marketing and communication reasons. We added this building block even though it was not mentioned in one of the eight DDBM or DDS taxonomy papers. However, we argue that it is important to understand how the company supports the customer in the long term and how the relationship can be built and sustained. Therefore, we included this building block to complete the Dimension of Customer Interaction. The characteristics contain: *personal* (i.e., face-to-face or virtual communication with humans), *self-service* (i.e., customers can troubleshoot by themselves through, e.g., FAQs), *automated* (i.e., IT-based service control points like chatbots), *community* (i.e., special interest groups of customers like social media channels), or *other* types of interaction (i.e., mixed or indefinite). Figure IV.1-3 provides an overview of all building blocks and their characteristics. The figures in parentheses within the cells represent the counts of the applied empirical cases.

	Building Block	Characteristics						
VPM	Value Proposition	Data (3)	Information / Knowledge (29)	Actions (9)	Non-Data Product/Service (6)			
VPM	Value Capture	Subscription (22)	Usage Fee (7)	Gain Sharing (0)	Advertising (1)	Buy & Sell Data (1)	Pay-with-data (1)	Asset Sale (9)
VCM	Data Generation	Customer (13)	Non-Customer (12)	Process (10)	Object (19)	Other (0)		
VCM	Data Origin	Internal (15)	External (25)					
VCM	Data Target	Customer (18)	Non-Customer (15)	Process (7)	Object (8)	Environment (6)	Other (0)	
VCM	Data Activity	Data Collection (26)	Data Organization (26)	Data Preparation (30)				
VCM	Data Analytics Type	Descriptive (8)	Diagnostic (7)	Predictive (26)	Prescriptive (16)	None (0)		
VCM	Insights Utilization	Distribution (28)	Visualization (25)	Execution (17)				
VCM	Cost Structure	Value-Driven (27)	Cost-Driven (3)	Other (0)				
CIM	Customer Segment	B2B (27)	B2C (7)	B2A (1)				
CIM	Target Customer	New Customer (24)	Existing Customer (8)	Multi-Sided (3)				
CIM	Interaction Type	Application-based (24)	Product-based (4)	Embedded Service (7)	API (7)			
CIM	Service Flow	Manual (25)	Pre-defined Time (4)	Event-Driven (15)	Stream (16)			
CIM	Customer Relationship	Personal (25)	Self-Service (9)	Automated (8)	Community (5)	Other (0)		

Figure IV.1-3: Consolidated taxonomy of DDBM

4.4 Application of the taxonomy

We applied the final taxonomy to thirty cases of DDBM to validate the identified building blocks. Figure IV.1-3 shows in parentheses the actual number of cases for each characteristic in the building blocks. The strongest impact in terms of value propositions has the characteristic information/knowledge (29 cases), while DDBM also offer actions (9), additional non-data products and services (6), and data (3). The value is captured mostly via subscription-based (22), asset sale (9) as well as usage fee (7) revenue models. The data stems largely from (smart) objects (19), customers (13), or potential customers (12) as well as processes (10). Hence, a greater share of the data comes from external (25) rather than internal (15) sources. The data target is in most cases the customer (18), while non-customers could also receive data (e.g., for advertising purposes) in many cases (15), with objects (8), processes (7), and environment (6) following. Most of the activities are related to all three aspects of data collection, organization, and preparation. While most DDBM draw on descriptive (28) and predictive (26) data analytics, less do so for prescriptive (16) and diagnostic purposes (7). The insights are utilized for visualization (25) to a greater extent, while less for execution (17) and distribution (8). Most DDBM take a value-driven perspective (27) instead of a cost-driven one (3). The sampled DDBM especially have B2B customers (27), while B2C (7) and B2A (1) customers are far less in the focus. These DDBM especially provide an opportunity to gain access to new target customers (24) instead of existing ones (8) or to become part of a platform interaction model (3). The interaction itself largely corresponds to different types, such as embedded services (7) and APIs (7) as well as proprietary applications (24) and products (4). The corresponding services often require data manually (25), automatically in continuous data streams (16), or event-driven (15) in most cases, while less often they draw on pre-defined time modes (4). Finally, most of the DDBM are used for personal customer relationships (25), while many of them also rely on self-service (9) as well as automated (8) or community services (5).

In the following, we provide an exemplary instantiation of the taxonomy application. Synfioo is providing a data-driven service for supply chain and logistics. The concrete offering (building block [1]) is *information/knowledge* through making the supply chain transparent, providing track and trace functions, and offering fault reports. Synfioo captures [2] value through a *subscription-based* model. The data generator [3] is done by *processes* like transport, loading, and sending. Another data generator can be *objects* that are for example equipped with RFID-technology. The data origin [4] is *external*, through logistic companies and the customers of Synfioo. The data targets [5] are *processes* and *objects* that are part of the supply chain, e.g., traffic, vehicles, stocks, and transportation processes. The data activity [6] that Synfioo needs to do is *collecting* the different data from over fifty global data sources, then *organizing* this data and *preparing* it to make [7] *predictions* of the estimated arrivals or provide a *description* of the current dispatching process. The insights are utilized [8] through *visualization* and the *distribution* of the insights. For this DDBM it is not possible to make a clear statement of the cost structure [9] because of a lack of information but we estimate that it is *value-driven*. The customer segment [10] are the supply chain managers and therefore *B2B*. Synfioo is trying to reach a *new target group* [11] because they are currently a start-up and do not own an existing customer base. The interaction type [12] is determined through their *application* or the *API* that they are providing for the integration into third-party software like ERP-Systems. The service flow [13] is *manual*, *event-driven*, and also in form of a *stream* regarding the tracking of the current supply chain. Regarding their website, the customer relationship [14] seems to be *personal* through direct interaction through demo versions or consultancy. The appendix provides an overview of all cases applied to the consolidated taxonomy.

5 Conclusion, limitations & outlook

Our starting point was to understand the building blocks of a DDBM from the current standpoint of IS research and to give an overview of the existing taxonomies in this area, particularly in view of the economic potentials of DDBM and DDS. To integrate the different aspects from prior research, we conducted a structured literature review and followed the taxonomy development approach from Nickerson et al. (2013). The outcome of the paper is a consolidated taxonomy for DDBM with 14 building blocks within the dimensions of DT, based on a systematic taxonomy development approach with 26 existing taxonomies from literature and 30 DDBM cases for validation.

For researchers, the consolidated taxonomy provides a systematic synthesis of available academic DDBM taxonomies and thus adds a puzzle piece towards a coherent understand of DDBM from an IS perspective. Plus, it offers the possibility to further investigate the different building blocks that can be used as a blueprint for the development of further industry-specific taxonomies. For practitioners, the consolidated taxonomy primarily serves as a guidance tool. The developed taxonomy provides a simple and precise overview of the building blocks that practitioners need to consider when developing or transforming a DDBM. Although the developed overview and taxonomy provide both scientific and practical value, it still underlies limitations. As we followed a qualitative research approach, biases in terms of search terms, selected papers, and building blocks cannot be excluded.

Follow-up activities could include further cases to derive potential archetypes of DDBM and DDS. Further research could also analyze specific taxonomies and archetypes of DDBM and DDS, such as in retail, legal, or digital health. Another possible step would be a combination of the conceptual approach for DDBM with a design science implementation approach to explore potentials and barriers from developing and introducing DDBM.

Appendix

A Taxonomy Application with Cases

		Value Proposition Model (VPM)											Value Creation Model (VCM)																											Customer Interaction Model (CIM)																			
		Value Proposition				Value Capture							Data Generation					Data Origin		Data Target						Data Activity			Analytical Goal					Insight Utilization			Cost Structure			Target Customer			Customer Segment			Interaction Type				Service Flow				Customer Relationship					
Case	Description (DDBM feature)	Data	Information/Knowledge	Actions	Non-Data Product/Service	Subscription	Usage Fee	Gain Sharing	Advertising	Buy-and-sell-data	Pay-with-data	Asset Sale	Customer	Non-Customer	Process	Object	Other	Internal	External	Customer	Non-Customer	Process	Object	Environment	Other	Data Collection	Data Organization	Data Preparation	Descriptive	Diagnostic	Predictive	Prescriptive	None	Distribution	Visualization	Execution	Value-Driven	Cost-Driven	Other	B2B	B2C	B2A	New Customer	Existing Customer	Multi-Sided	Application-based	Product-based	Embedded Service	API	Manual	Pre-defined time	Event-Driven	Stream	Personal	Self-Service	Automated	Community	Other	Link
Aiservce	Smartglass that describes blind people's environment through audio output		x		x							x				x		x		x				x		x	x	x	x		x					x	x				x		x				x						x	x	x	x			https://www.aiserve.co/
Alerts for Engagement (IBM)	Provision of alerts for dangered workers by analyzing the geo-location and open data		x			x										x		x	x					x		x	x	x	x		x	x		x	x			x		x			x	x		x				x	x	x	x	x		x			https://www.ibm.com/products/weather-company-alerts-for-engagement
devAIce	AI-Based emotion recognition in different contexts			x		x										x			x	x	x			x				x	x	x						x	x			x			x					x				x	x	x					https://www.audeering.com/
Augmented Analytics (adverity)	Analysis of marketing data with ML for recommendations for action		x			x						x		x	x				x		x					x	x	x	x		x	x			x		x			x			x			x				x		x		x					https://www.adverity.com/analytics-platform/ai-powered-analytics/#augmentedanalytics
Campaign Analytics (LOTAME)	Platform to define target audiences and behavior tarcking of ads interactions		x			x							x	x	x				x		x					x	x	x	x		x				x	x	x			x			x			x				x			x	x					https://www.lotame.com/products/lotame-analytics/campaign-analytics/
Chat & Messegaing (Bold360)	Chatbot for customer support		x	x		x							x	x	x				x	x	x					x	x	x	x		x	x			x	x	x			x			x					x				x		x		x			https://www.bold360.com/features/conversational-ai
Cobrainer (Cobrainer)	ML-based matching platform for employee recruitment		x	x		x							x	x	x				x	x	x	x				x	x	x	x		x				x	x	x			x			x			x				x			x	x					https://www.cobrainer.com/recruiters
Fitbit (Fitbit)	Tracking band for gathering and analyzing health and movement data		x		x							x				x		x		x								x	x			x			x	x	x				x		x				x	x	x	x		x	x		x		x		https://www.fitbit.com/de/home
FoodTracks (Antegon)	AI-based predictions for the assortment to be produced by bakeries		x			x							x		x	x			x		x	x				x	x	x	x	x	x	x			x	x	x			x			x			x				x		x		x					https://www.foodtracks.de/en/
Google (Google)	A search engine for the web that creates revenues through advertising		x	x					x		x		x	x				x	x	x	x					x	x	x	x	x	x	x			x	x	x	x		x	x				x	x		x		x		x			x	x			https://www.google.com/
Helium10 (Helium 10)	Analysis of Amazon purchase trends for retailers		x			x							x	x					x	x	x					x	x	x	x	x	x	x		x	x		x			x	x		x			x				x	x	x			x		x		https://www.helium10.com/
I2x.ai (i2x.ai)	Analytics of customer support phone calls through AI		x			x							x						x	x								x	x	x	x	x			x		x			x			x			x		x		x			x	x					https://i2x.ai/de/
iCorr Production Analyzer (BHS C.)	App Plattform for information about the machine processes through sensors		x			x									x	x			x			x	x			x	x	x	x		x				x		x			x				x		x				x			x	x					https://store.icorr.io/apps/production-data-analyzer
iGurt (BPW)	Security belt that monitors the tension and gives an alarm if it is too low		x									x				x		x					x					x			x					x	x			x				x		x	x					x		x					https://www.bpw.de/produkte/digitale-loesungen/bpw-igurt
Insights (Factual)	Provision of customer analysis through location and behavior data		x			x							x	x					x	x	x					x	x	x	x		x	x			x		x			x			x			x				x			x	x					https://www.factual.com/products/insights/
In-Store Analytics (Bosch)	Security cameras that generate customer data, and analysis of customer behavior		x		x	x						x				x		x		x	x					x	x	x	x		x	x			x		x			x				x		x				x			x	x					https://www.boschsecurity.com/de/de/loesungen/dienstleistungen/in-store-analytics/
LANA Process Mining (Lana Labs)	Process mining for better performance in business processes		x			x									x	x			x			x	x			x	x	x	x		x																												https://lanalabs.com/en/lana-process-mining/
MVPindex (MVPindex)	Analysis of partnership investments for companies		x			x							x	x		x			x	x	x					x	x	x	x	x	x	x			x	x	x			x			x			x				x			x	x					https://www.mvpindex.com/solutions/brands
Plantix (PEAT)	App to identify diseases of plants by analyzing a photo through an AI system		x				x									x			x				x	x		x	x	x			x	x		x	x	x	x			x	x		x			x			x	x				x	x	x			https://plantix.net/en/
Real-Time Traffic (HERE)	Live traffic data to help drivers find the best routes	x	x			x	x							x		x		x	x	x	x					x	x	x	x	x	x	x		x	x		x			x			x	x		x		x	x	x			x	x	x		x		https://www.here.com/platform/traffic-solutions/real-time-traffic-information
Recommendation Engine (Inspora)	Chatbot that helps a customer's consumers during the shopping process		x	x		x	x						x	x				x	x	x	x					x	x	x	x			x			x	x	x			x			x			x		x		x		x		x	x	x			https://www.inspora.com/
Smart Thermostat V3 (Tado)	Thermostat with app that recognizes customer behaviour and adapts to it		x	x	x	x						x				x		x	x	x				x		x	x	x	x		x				x	x	x			x	x		x			x	x			x		x		x	x	x	x		https://www.tado.com/all-en/smart-radiator-thermostat
Synfioo (Synfioo)	Monitoring of supply chain and prediction of arrival times and logistic problems		x			x									x	x			x			x	x			x	x	x	x		x			x	x		x			x			x			x			x	x		x	x	x					https://synfioo.com/technology/
Target group data (Microm)	Creation of target groups for marketing by analyzing different data sources	x	x			x	x			x		x	x	x				x	x	x	x					x	x	x	x		x			x	x		x			x		x	x	x		x			x	x				x					https://www.microm.de/
ThinkSono (ThinkSono)	Use of ultrasonics and ML to detect deep vein thrombosis		x			x						x				x		x		x						x	x	x	x						x		x			x			x			x				x				x					https://thinksono.com/#detailed
TotalCare (Rolls Royce)	Full-service airplane turbines enabled through predictive maintenance		x	x	x		x								x	x		x	x			x	x			x	x	x	x		x	x			x	x		x		x				x		x				x	x	x	x	x					https://www.rolls-royce.com/media/our-stories/discover/2017/totalcare.aspx
Trends (Pulsar)	Tracks and visualizes social media trends		x			x							x	x					x	x	x					x	x	x	x		x				x	x	x			x			x			x				x			x	x					https://www.pulsarplatform.com/solutions/pulsar-trends/
Turbomonitor (Industrial Analytics)	Monitoring and analysis of vibrations and acoustic signals of turbomachines		x	x	x	x									x	x		x	x			x	x			x	x	x	x		x	x		x	x	x	x			x			x		x	x			x	x	x	x	x	x					https://industrial-analytics.io/en/turbomonitor/
Uber (Uber)	Matchmaking of drivers and ride takers through location-based data		x	x			x						x			x		x	x	x			x			x	x	x	x		x				x	x	x			x	x				x	x				x		x			x	x	x		https://www.uber.com/
Weather data packages (IBM)	Provision of weather-based insights per API	x	x				x					x				x		x	x					x		x	x	x	x					x			x			x			x	x					x	x				x					https://www.ibm.com/products/weather-company-data-packages
	Count	3	29	9	6	22	7	0	1	1	1	9	13	12	10	19	0	15	25	18	15	7	8	6	0	26	26	30	28	7	25	16	0	8	25	17	27	3	0	27	7	1	23	8	3	24	4	7	7	25	4	15	16	25	9	8	5	0	

Figure IV.1-4: Case validation for the developed taxonomy

IV.2 The impact of digital transformation on value creation in banking − Reference models for the platform economy

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Working paper

Abstract: Despite considerable research on the impact of digital transformation on traditional industries, there is little evidence of its impact on value creation in banking for the platform economy. Against this background, this paper systematically examines how digital platforms and ecosystems reshape the banking industry. The paper provides enterprise modeling artifacts to disentangle the impact of digital platform ecosystems on the banking industry. A design science research approach is applied with three steps: (1) Development of role-based reference models with an extended e3-value modeling method, (2) demonstration of the artifacts for value co-creation in banking platform ecosystems, and (3) evaluation of the artifacts with banking practitioners. The outcome of the paper provides a method for modeling and analyzing the impact of the platform economy on traditional banks from a value perspective. Our findings indicate how B2C industries, such as banking, evolve from a focus on core business towards access to innovation and resource control and, finally, strive for network-centric access to customers. The paper highlights the critical interaction between digital strategy-making in ecosystems and competitiveness in the platform economy, such as new roles, functions, and value co-creation mechanisms, considering the competitive threat at the customer interface.

1 Introduction

Access to emerging digital infrastructures in many traditional industries breaks up traditional value chains, leading to more decentralized value creation. Traditional companies who previously had a near-monopoly position must ensure universal access to their services (Clemons et al. 1996). Traditional banks, for instance, have not been affected by attacks on their value chain for a long time. However, significant changes could be attributed to lower costs and broader accessibility of digital technologies in digital transformation (DT) in recent years. Prior findings from a Delphi study indicate that the future customer interaction in banking could change from direct to more indirect forms (Pousttchi et al. 2015). New Fintech market players are developing innovative digital banking services, such as payments, investments, financing, and advisory services (e.g., Gomber et al. 2017, 2018; Puschmann 2017). Identity services also become a pivotal hub of customer interactions in banking (Garber et al. 2021). This development is fueled by new regulatory guidelines, such as the Payment Service Directive 2015/2366 (PSD2) in Europe, which promotes opening the previously closed banking market. The PSD2 gives third-party providers access to the customer's bank via dedicated interfaces on top of the core banking providers' regulated infrastructure (Vives 2019). If a customer gives consent, third-party providers may offer their services directly (Dratva 2020; Gozman et al. 2018; Zachariadis and Ozcan 2016). Digital platforms, such as Google, Apple, Facebook, and Amazon (GAFA), have already started offering financial services to banking customers, representing another competitive threat for incumbent banks (Alt and Zimmermann 2019). In the future, GAFA might be skimming off the banks' best shares and margins, for instance, by serving customers in the most attractive market segments. Banks do not want to surrender defenselessly to this development and are developing application stores, open interfaces, and allowing external service providers to offer innovative services on their platforms. Digital platforms provide the technological basis for enabling such cross-company interactions, and digital platform ecosystems realize the product, service, and business model innovations (Reuver et al. 2018). Digital platform ecosystems are based on the value-enhancing interactions of the participating actors in value co-creation and the successful management of partnerships (Wang 2021). Hence, one major challenge for banks is to make such ecosystems and their business models work in practice.

However, there is still little understanding from either research and practice on how digital platforms and ecosystems will lastingly impact value creation in the banking industry. Enterprise modeling (EM) helps to systematically model and analyze business models, value networks, and stakeholder concerns as it leverages knowledge for strategic decision-making (Sandkuhl et al. 2018). EM could support DT projects, such as identifying, evaluating, and selecting DT strategies, if the repertoire of methods is systematically applied (Sandkuhl 2021). The EM process must capture all relevant perspectives of the enterprise for the specific modeling purpose (Fill 2020). One of EM's main concerns is the continuous design of digital business ecosystems encompassing networked organizations (van der Aalst et al. 2018). However, comparatively few scholars have conducted research in this area, especially for the banking industry (Puschmann et al. 2012; Riasanow et al. 2018; Wigand et al. 2005). Prior contributions examined the decomposition of the universal bank model and corresponding sourcing models (e.g., Alt and Puschmann 2016, pp. 119 ff.). We have used e3-value reference modeling to explore the impact of digitalization on other traditional industries, such as telecommunication, retail, or the insurance industry (e.g., Pousttchi 2005, 2008; Pousttchi and Hufenbach 2011, 2014, Pousttchi and Gleiss 2019). We deduce a strong demand from research and practice to develop EM artifacts to analyze the impact of the platform economy on traditional banks, such as their future market positioning within boundary-spanning platform ecosystems.

Against this background, we use a design science research approach to develop EM artifacts analyzing the evolution towards future platform ecosystems in banking. We develop role-based reference models for banking in DT. We further demonstrate the artifacts for an identity and payment context as a typical use case for orchestrating multiple actors in a banking ecosystem. The outcome of the paper extends business informatics research with EM artifacts for studying the impact of the platform economy in the traditional economy. Our findings serve banking practitioners as a tool to analyze the impact of the platform economy on their business.

The paper is organized as follows: In the next section, we provide the study background on the platform ecosystem literature and its specifics in the banking industry. We introduce our methodology in the third section. In section four, we present our results, i.e., the development of the reference modeling artifacts and the demonstration for an application in the embedded finance context. In the fifth section, we evaluate our findings with practitioners. In the last section, we summarize the theoretical and practical implications, limitations, and future research options.

2 Theoretical background

2.1 Characteristics of the platform economy

In the digital world, the competition gets more closely linked to the development of digital infrastructures (Henfridsson and Bygstad 2013), with digital platforms as their constituent type (Abdelkafi et al. 2019). Firms create digital value propositions for customers and their partners (Payne et al. 2017; Taylor et al. 2020). However, individual strategy, business, and revenue model considerations continue to have relevance. *Corporate strategy*, for instance, entails the perspective on the competitive positioning in evolving industries (Montgomery 1994). Firms also compete in the digital age by offering the best value proposition or resource configuration to achieve a specific market position (e.g., Bharadwaj et al. 2013).

The *industry architecture* concept refined the traditional view of industries as static and monolithic to being permeable and evolving by considering firms as interrelated economic agents (Jacobides 2016). Traditional industries evolve as the groups of actors in an industry evolve, which occupy the roles and maintain the corresponding value flows (Jacobides and Winter 2005). As industries shape the roles in value creation, they also influence remarkably which business models are possible in an industry, with considerable consequences for industry actors' behavior (Jacobides 2016). However, as industry architectures evolve towards business ecosystems, researchers must consider the inherent cross-industry boundary-spanning relationships.

Digital platforms refer to a technology-enabled network of entities built around a platform sponsor offering a value proposition to customers (Cusumano et al. 2019, p. 13). From a socio-technical view, a digital platform is an extensible codebase based on technical elements with complementary third-party modules and the associated organizational processes and standards (Reuver et al. 2018). While a transaction platform is a "matchmaker" (i.e., a multi-sided platform, MSP), innovation platforms orchestrate applications and services by third-party developers around a platform core (Gawer 2014). Platform providers draw on third-party developers as boundary resources (Ghazawneh and Henfridsson 2013). Participating organizations rely on shared standards and open interfaces (Teece 2016).

Therefore, many digital platforms have become *platform ecosystems* by including external partners as platform complements, from which many are platforms themselves (Adner 2017; Ceccagnoli et al. 2012; Gawer and Cusumano 2014; Reuver et al. 2018). Hence, digital platform ecosystems provide a new link between several cross-industrial roles and functions as they mediate physical and digital business aspects across industries (Recker et al. 2021). Thus, ecosystem architectures in the digital age often entail a digital platform as the technical foundation, plus a set of roles and actors to realize business models primarily based on informal and standardized partnerships (Jacobides et al. 2018).

The management literature has acknowledged the intertwined relationships between inter-organizational networks and platform ecosystems. In the digital world, *value networks* are still a means for developing and contracting solid interfirm relationships. Firms may use several network strategies or 'moves,' such as acquisitions or divestitures, alliance formation, or dissolution, depending on their position in an industry, to reach specific strategic goals (Hernandez and Menon 2021). Hence, formal contracting is still the basis for developing the technology-enabled network of partners in a digital platform ecosystem. While formal relationships are used to create binding business relationships on the value network layer, i.e., the underlying regulated formal contracts or the informal collaboration between the participating, legally independent companies, relationships on the platform ecosystem layer are based on informal standards and non-generic complementarities, such as standardized application programming interfaces (APIs) or developer frameworks (Shipilov and Gawer 2020). A formal alliance, for instance, can enable non-generic complementarities that further build on informal relationships, such as app developer guidelines (Shipilov and Gawer 2020).

Firms may use several ecosystem moves to develop their platform ecosystem further. Two typical strategies to extend a platform ecosystem are inversion, i.e., developing new products or services around the platform core, and envelopment, i.e., adding new application areas to the platform core (Tiwana 2014, pp. 191 ff.). Consequently, digital platform ecosystems have become an additional lever for firms to reshape their business to their advantage. Such boundary-spanning practices have already been under study, for instance, in the media industry (Jeong et al. 2020; Pagani 2013; Tan et al. 2020), but none concerning the banking industry.

2.2 Value co-creation in platform ecosystems

A value proposition is the central offering that requires an alignment structure among the involved value contributors that develop their capabilities together in an ecosystem (Adner 2017; Kapoor 2018; Moore 1993). The service-dominant logic (SDL) stands representative for this paradigm shift towards coordination and cooperation in value co-creation (Lusch and Nambisan 2015; Skålén et al. 2015; Vargo and Lusch 2016). Value co-creation describes "processes and activities that underlie resource integration and incorporate different actor roles in the service ecosystem" (Lusch and Nambisan 2015, p. 162). The actors must coordinate their investments producing the value proposition as resource integrators for focal customers (Lusch and Nambisan 2015). A service ecosystem is "a relatively self-contained, self-adjusting system of mostly loosely coupled social and economic (resource integrating) actors connected by shared institutional logics and mutual value creation through service exchange" (Lusch and Nambisan 2015, p. 162). Blaschke et al. (2019) and Haki et al. (2019) develop design principles for value co-creation based on the SDL, which considers the co-creation between a service platform and resource integrators in a service ecosystem. While research on value co-creation takes different emphasis, such as on the provider-customer interaction or the whole service process, involvement, engagement, and participation are prerequisites of all value co-creating ecosystems (Oertzen et al. 2018).

Updated SDL publications point to value co-creation as always including a beneficiary, value as the anticipated subjective experience of the beneficiary, and necessary coordination through institutional arrangements (cf. Vargo and Lusch 2016; Vargo 2019). While SDL provides an abstract theoretical concept of service value exchange, the service logic literature is more specific on managing the value co-creation (Grönroos and Voima 2013; Grönroos and Gummerus 2014; Grönroos 2020). Service logic scholars point to the provider as the facilitator producing potential value in the provider sphere. The customer as the beneficiary is the co-producer of the service in the joint sphere where the actual value co-creation with one or more service providers occurs. Finally, value-in-use is created by the customer and facilitated by the providers in the customer sphere. The customer's service evaluation goes beyond functional characteristics as it considers the "individual motivation, specific competencies, actions, processes, and performances" of ecosystem participants (Ranjan and Read 2016, p. 293).

2.3 Orchestration in centralized platform ecosystems

Different forms of centralization and concentration of decision-making can be realized in platform ecosystems (Shipilov and Gawer 2020). Vergne (2020) differentiates two dimensions: decentralization of organizational communication and distribution of organizational decision-making. Vergne further argues that Bitcoin is one example of a decentralized and distributed blockchain infrastructure, whereas machine learning platforms foster centralized communications and concentrated decision-making power.

In this paper, we focus on platform ecosystems that follow the centralized and concentrated machine learning paradigm and thus entail an ecosystem orchestrator at the customer interface. Orchestration describes practices "as the activities through which actors purposefully build and manage the multi-stakeholder innovation network" (Reypens et al. 2021, p. 62). Orchestrators "mobilize multiple, diverse stakeholders to collaborate across organizational boundaries to achieve common objectives" (Reypens et al. 2021, p. 63). Actors that pursue the orchestrator role can be called "platform leaders" or "hubs," acting as relays for the information flows across the value network (Shipilov and Gawer 2020).

Accordingly, the network and ecosystem view come together in orchestration. Orchestrating hub firms have been described in their role as managers of network knowledge mobility, innovation appropriability, and stability (Dhanaraj and Parkhe 2006). The orchestrating hubs pursue diverse functions for co-creating the ecosystems' technical and organizational realization, such as sharing, combining, or standardizing (Wang 2021). The prior performance also impacts the ecosystem structures, which are constantly in flux, such as roles, capabilities, and value propositions. Thus, orchestrators act as environmental scanners (Reypens et al. 2021). Furthermore, orchestrators must create the ecosystem network value, i.e., induce innovation, legitimize the platform, and incorporate adjustments (Perks et al. 2017).

Ecosystem participants obtain specific roles and functions based on their capability "to perform a particular type of work" (Stirna et al. 2016, p. 259). Ordinary and dynamic capabilities have been stressed in the literature on platform ecosystems and DT (Tan et al. 2015; Teece 2018; Wang 2021; Yeow et al. 2018).

2.4 Platform ecosystems in banking as the modeling context

The rapidly evolving banking industry provides a relevant example to study the impact of the platform economy on incumbent organizations.

Traditional value creation focused on cost-effectiveness, such as sourcing partnerships with information technology (IT) infrastructure service providers. Prior research in this area has focused on the transition from value chains (Krotsch 2006; Lacity et al. 2004; Riese 2006) to networking models (Hoffmann and Reitbauer 2009; Ordanini and Pasini 2008; Puschmann et al. 2012; Teracino et al. 2014). Different banking models emerged as a result (Alt et al. 2009; Alt and Puschmann 2016, p. 127; Wigand et al.

2005). However, these contributions did not consider the developments in the platform economy, as discussed in practice (e.g., McKinsey 2020; Oliver Wyman 2020).

Digital platforms have become prevalent in banking since open banking regulations have forced incumbents to open up the formerly closed industry (Jacobides et al. 2016; Zachariadis and Ozcan 2016; Zetsche et al. 2017). Several contributions especially shed light on Fintech and open banking (Alt et al. 2018; Lee and Shin 2018). Fintech offer digital value propositions as alternatives to their established traditional counterparts (Alt and Puschmann 2012; Blohm et al. 2016; Drummer et al. 2017; Eickhoff et al. 2017; Lee and Shin 2018). Strategic alliances and acquisitions are greatly on the rise (Beyer and Saat 2017; Freitag 2016; Hornuf et al. 2018). Research on *banking platform ecosystem*s comprises only a few contributions so far (Drasch et al. 2018; Riasanow et al. 2018, 2021; Schmidt et al. 2018). None of these papers comprehensively addresses business model implications and market power threats for traditional banks in the platform economy.

The market entry of bank challengers is especially relevant for the context of *identity and payment services*. Digitalizing the private and public sectors largely depends on digital identity and payment services as driving factors for the orchestration of various economic actors in platform ecosystems. Therefore, these products are well suited for orchestration as they are central points of digital customer interaction via digital wallets, relevant at numerous interfaces in the digital economy, such as buying a car online. They can be enriched by additional services and thus allow a service provider to become the hub of a platform ecosystem. An important example is mobile payments (e.g., Kazan et al. 2018; Ondrus et al. 2015; Pousttchi 2008). The literature has also described success factors of electronic identity management, such as trust, transaction convenience, and process integration (Seltsikas and O'Keefe 2010). Additional intermediaries could weaken dominant market actors (Bazarhanova et al. 2020). Case studies on digital identity services point to the underlying value co-creation problem and its necessary "convergence of interests. resources, and governance" (Eaton et al. 2018, p. 70).

Our problematization offers an opportunity to study the impact of platforms ecosystems on traditional businesses through EM. The connection between identity and payment banking services provides an appropriate context to explore the coordinated investments of producers, their non-generic complementarities towards a focal value proposition, i.e., "embedded finance."

3 Methodology

We grounded our research in the observation that research and practice lack EM artifacts to grasp the effects of strategic decisions in platform ecosystems for banking. Particularly, banking practice should assess the strategic implications of the platform economy on all three dimensions of DT, which encompasses changes in value creation, new business and revenue models, and the transformation of customer interaction (Pousttchi 2020). A business model operationalizes corporate strategy by connecting the strategic and operational layer via value creation and value capture activities, which is our focus in the following (Al-Debei and Avison 2010).

3.1 Requirements

The problematized research treats platform ecosystems for banking under value co-creation aspects. An appropriate EM method would capture the evolving value creation for banking in the platform economy. Hence, we searched for relevant literature in the full texts in the literature databases AISel, Business Source Premier, and Google Scholar using the keyword string: *"enterprise modeling AND (business OR platform OR service) ecosystem."* We initially got over 1600 hits, which we screened manually for relevant articles. We introduce them in the next sections.

Several research papers focus on ecosystem modeling and analysis, such as in the context of e-commerce (Aldea et al. 2018). We find papers that explicitly focus on modeling platform ecosystems and develop their methodologies considering the unique role of boundary resources (Pauli et al. 2020). Other researchers have developed a modeling framework for business ecosystem architectures (Wieringa et al. 2019). Additional contributions have modeled smart mobility ecosystems (Faber et al. 2018; Ma et al. 2021). Service science entails several steps to design value constellations (Patrício et al. 2011).

Further relevant articles contribute either to requirements for EM methods or languages in the area of digital platform ecosystems. The scientific discussion is published mainly at conferences and rarely in journals. We discuss EM requirements and methods/languages from the literature in the following.

3.1.1 Modeling value co-creation in platform ecosystems

Scholars distinguish three components of value co-creation in an ecosystem. The *relational component* describes how participants interact to fulfill a common purpose (Betz and Jung 2021). Regarding this, scholars point to defining the scope, boundaries, and access requirements to the ecosystem for a concrete use case (Tsai et al. 2021). Tsai et al. also consider the alignment of visions and goals, i.e., actors' interests, and demand an evaluation of their performance. The *biotic component* describes participants or actors pursuing different roles, characterized by needs and capabilities (Betz and Jung 2021). There is a requirement to assign roles and responsibilities to actors and model their relationships in value flows, streams, or processes (Tsai et al. 2021). The value offering can be assembled by creating, exchanging, and using services or service components (Betz and Jung 2021). The *abiotic component* points to the environment as the functional structure of the interaction, which includes a typical architecture such as a digital platform that must be operated (Betz and Jung 2021). Regarding this, a reoccurring requirement is modeling the infrastructure and its innovation, such as digital platforms, as well as considering regulations (Tsai et al. 2021).

Accordingly, we deduce that value modeling would provide a suitable reservoir of roles, activities, and value exchanges to model the impact of platform ecosystems. However, we also need to incorporate the business model and coordination aspects for value co-creation by considering typical values, activities, and capabilities for mutual exchange between the ecosystem actors.

3.1.2 Enterprise modeling languages for value co-creation modeling

Furthermore, scholars systematized EM methods applicable for platform ecosystem analysis (Arreola González et al. 2019). A combination of strategy, business model, and process views is possible for the value model of reengineering and Eriksson Penker business extensions, which have not become widespread. A large number of papers already used e3-value modeling for industry and, to a smaller extent, ecosystem modeling (e.g., Riasanow et al. 2021). E3-value can represent multi-party transactions, which are typical for platform ecosystems (Roelens and Poels 2013). Both e3-value and the value delivery modeling language (VDML) are value-oriented EM languages. Drawing on the VDML, Poels et al. (2018) introduce a method for business model analysis, the Continuous Business Model Planning (CBMP). However, research on VDML is scarce, so we identified only one further publication (Muthuri et al. 2021).

The capability-driven development (CDD) methodology and the 4EM method are situated at the strategy level to analyze goals, processes, capabilities, or business functions (Bērziša et al. 2015; Sandkuhl et al. 2014; Stirna et al. 2016). CDD and 4EM are not suitable for our modeling purpose as they lack a value orientation. Furthermore, Poels assigns typical EM representatives to three model categories (Poels 2019): The first category is strategy models, including strategic plans, strategic dependency diagrams, VDML/CBMP strategy maps, and CDD goal models. The second category is business models, including several business model canvases, VDML/CBMP, and the business model cube. The last category is value models, including the e3-value modeling and VDML/CBMP business ecosystem models.

In sum, e3-value is suitable for modeling roles or actors and their value exchanges, while VDML allows mapping the strategic, business model, and value level of platform ecosystems.

3.2 Research approach

We follow a design science research approach to achieve our research goals (Peffers et al. 2007). Design science research is an established tool to develop models, methods, constructs, or instances useful in theory and practice (Hevner et al. 2004; March and Storey 2008). Modeling is generally seen as a way of “gaining control over the world” and “making decisions or answering questions about the world” (Rothenberg 1989, p. 76). Following March und Smith, a model "can be viewed simply as a description," that is, "a representation of how things are, situations as problem and solution statements" (March and Smith 1995, p. 256). We combine existing methods and multiple data sources (Henderson-Sellers et al. 2014, p. 32). We follow five steps.

In the first step, we identified and motivated our research problem. In the second step, we defined the objectives of a solution based on the literature, case studies, and interviews. In the third step, we develop role-based e3-value reference models across three phases of banking industry evolution. Reference modeling facilitates the inductive or deductive development of simplified or idealized system representations for deriving and deepening analytical knowledge and design principles (Becker and Delfmann 2004; Frank 2014). Reference models are used as a technique to generate theoretical and practical relevance in terms of description, explanation, and prediction (Fettke and Loos 2004; Wilde and Hess 2007). The generic roles have to be pre-conceived as far as possible based on current market developments to provide a suitable level of analytical abstraction. Theoretical abduction is used to develop future ("to-be") platform ecosystem models. We also map value creation activities that are realized within and between the roles. The e3-value models are implemented as thoroughly, accurately, and objectively as possible, avoiding false assumptions and biases (van der Linden et al. 2020). The resulting reference model serves as a repository including value creation roles, value flows, and activities for further modeling and analysis steps from a traditional bank's perspective (Frank 2014). Thus, we continue to make a case for strategic EM through a-priori desk research analysis and participatory EM.

In the fourth step, we demonstrate the artifact in the concrete context of a future payment and identity service ecosystem. We develop strategic archetypes for value co-creation in the banking ecosystem and instantiate the reference model for a future market scenario. The scenario development follows a negation and construction process, supported by the morphological method (Zwicky 1966, pp. 88 ff.). A set of identified uncertainties from the literature constitutes the decision criteria in the rows of the morphological box (Schoemaker 1995). Subsequently, we draw on the CBMP method to analyze the future market scenario. We analyze the interplay of value propositions, roles, values, and value activities in value co-creation between the ecosystem participants. Collaborative EM is used to derive business requirements and boundary conditions for the ecosystem orchestration (Fellmann et al. 2020).

In the final step, the reference models are evaluated with banking practitioners. We discuss how the EM artifacts could support traditional market actors to find their positioning in the value architecture and resolve the scalability problem of ecosystems in the platform economy.

Figure IV.2-1 illustrates the research approach. Each method is explained in detail in the following.

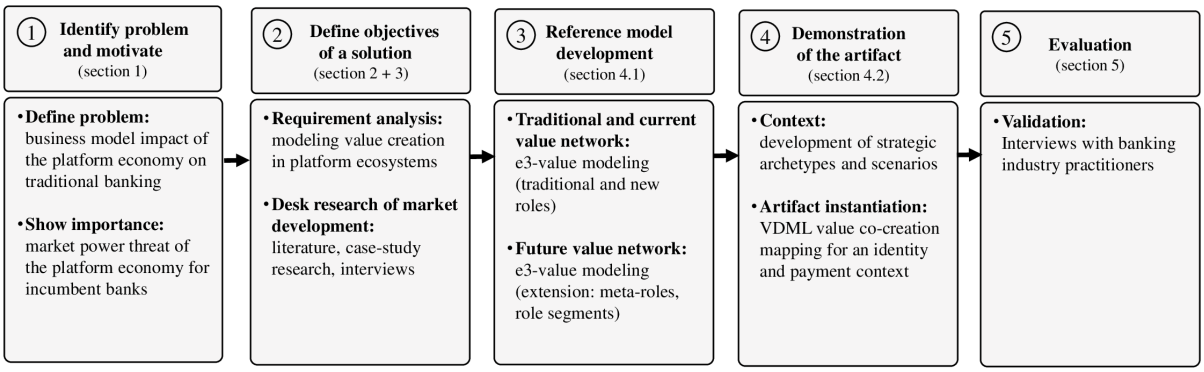

Figure IV.2-1: Research design following Peffers et al. (2007)

3.2.1 Role-based e3-value modeling

We use e3-value modeling as an appropriate EM language for business model analysis, value network design, and evaluation. It has been widely used for value-based requirements engineering that addresses the upper management as the central viewpoint holders (Akkermans and Gordijn 2003). The models represent actors or roles in economic exchange relationships to deliver customer value propositions. The relationships between actors or roles are represented as value flows (Arreola González et al. 2019).

While the original method draws on actors as the central modeling construct (Gordijn 2005; Gordijn and Akkermans 2001), we follow an extended role-based e3-value modeling approach (Pousttchi 2008; Pousttchi and Gleiss 2019; Pousttchi and Hufenbach 2011, 2014). In role-based e3-value modeling, an actor can occupy one or more roles by performing the activities inherent in a role, given it has the necessary capabilities associated with the role activities. In principle, companies are free to choose which activities they pursue in the market. However, some activities cannot be logically separated from one another, either due to regulatory requirements or industry-specific considerations. Thus, they constitute generic roles for value creation, reflecting the core value creation activities in the ecosystem from the perspective of the industry incumbent, i.e., the traditional bank (Wessel et al. 2021).

We have chosen the role-based modeling approach for several reasons. Firstly, specific role definitions are vital as they provide functional demarcations of the evolving value creation in platform ecosystems (Jacobides et al. 2018). Secondly, role-based modeling is already established in the banking sector. A role-based organizational model forms the starting point for further structured application development in banking, such as data models, object models, and the application system architecture (Schienmann and Bochenek 2001). A role concept has been followed in prior research on service orientation in banking (Alt and Puschmann 2016; Alt and Zerndt 2009). We draw upon this tradition in this paper and extend it with the developments in the platform economy. Thirdly, the role-based reference models enable the analysis of market constellations in platform ecosystems since one role can be occupied by several industry actors, such as traditional banks, near- and non-bank Fintech. Finally, this approach aligns well with the role concept in VDML for modeling value co-creation in ecosystems.

3.2.2 Value delivery modeling

We have chosen the VDML to account for the biotic component of a business ecosystem based on its broad linkages to the strategic and operational levels. The Object Management Group (OMG) defines value as "a measurable benefit delivered to a recipient in association with a business item or deliverable" (OMG 2018, p. 2). We model two value outcomes in VDML: the value delivered and the value captured. Thus, values associated with value propositions must be defined from the perspective of each recipient, so a specific value proposition is always dedicated to only one participant in the ecosystem. The VDML meta-model constructs combine the relationships between business model components (Roelens and Poels 2015).

Our choice of VDML finally results from its inherent ontological connection to the e3-value modeling perspective. In VDML, a participant is assigned to one or more roles that exchange value in cooperation (OMG 2018, p. 14). Each role exchanges deliverables with other roles, as it performs the activities that produce or consume deliverables (OMG 2018, p. 15). A role can only be filled by a participant "that has the capability required to perform the associated activity" (OMG 2018, p. 14). A value proposition provides the values associated with the deliverables by the recipient (OMG 2018, p. 12). Firms that want to provide a specific value proposition must perform the necessary activities by themselves or orchestrate (integrate) partners that perform them. Activities specify the internal operations and can be delegated to collaborations. A collaboration typically entails a business network between independent parties in the ecosystem (OMG 2018, p. 14).

3.2.3 Continuous business model planning

The CBMP method applies the VDML meta-model to specify how businesses create and deliver value (Poels et al. 2018). It provides a multi-perspective modeling approach through mapping different modeling views to a structured data model. The value management platform (VMP) provides a tool that enables participatory EM through alternating phases of drawing and mapping the identified values of an ecosystem. Hence, business model values are integrated into a prototype by mapping the inherent values in a structured data model.

The VMP allows the modeling of value co-creation in a platform ecosystem. This includes business models, participants, networks, as well as their value propositions and exchanges. Value streams, for instance, show the activities and their relationships for value co-creation. Competencies can be modeled for resources or capabilities needed to perform value co-creation activities. The VMP allows time-phased modeling, like this paper's future “to-be” modeling. Alternatives could also be explored for each phase, for instance, to account for different regulations and governance.

The VMP is suitable for conducting workshops with ecosystem stakeholders. We conducted modeling workshops and interviews with Verimi, a platform ecosystem orchestrator in Germany. We discussed the requirements to become a successful platform orchestrator in banking. The final outcome is a mapping of value propositions to roles, values, and activities for the specific context of identity and payment services.

3.3 Data collection

Our study is based on multiple sources of evidence. All current and conceivable future roles and functions from a bank's perspective in the banking ecosystem were systematized based on the data collected. For this purpose, desk research was conducted to assess current and future market developments in Europe, China, and the US and incorporate functional banking ecosystem requirements in the reference models. We combined the findings from the literature and case studies to derive the roles. We derived the traditional roles in banking from the Banking Industry Architecture Network (BIAN) and prior publications (cf. Alt and Puschmann 2016, pp. 129 ff.). The BIAN represents the industry standard to specify value creation activities of the universal bank model, the foundation of our observations in the traditional value network. The BIAN is a member-led group industry reference framework developed by important member institutions such as JPMorgan Chase, Citibank, and Commonwealth Bank (BIAN 2020). Additional case study data was collected on various Fintech firms in the current banking market. The literature on Fintech innovations (e.g., Gomber et al. 2018) inspired our case collection, which we complemented by current market research. We collected case studies from several industry publications and public databases to derive current and future roles in the banking industry (e.g., Crunchbase). We also interviewed industry practitioners on their strategies and actions in the platform economy.

Subsequently, detailed studies were conducted in the German banking market, focusing on the payment and identity service context to demonstrate the mutability of the developed reference model. Table IV.2-1 summarizes our data sources.

Table IV.2-1: Data sources for EM of platform ecosystems in banking

ID	Company	Main data source	Total analyzed sources	Headquarter region
Primary interview data				
1	PwC	Director Fintech & AI (22 min interview)	-	DE
2	ING	Consultant Fintech Strategy (41 min interview)	-	NL
3	Fincite	Director New Business & Accounts (35 min interview)	7	DE
4	Finleap Connect	Head of Sales & Business Development (38 min interview)	6	DE
5	Subsembly	Managing Director (45 min interview)	6	DE
6	Tink	Regional Director DACH (44 min interview)	6	SE
7	Verimi	Corporate Development Manager (360 min total interviews)	4	DE
Secondary case study data				
8	Amazon (Pay)	Murchison and Yamaoka 2019	5	US
9	Ant Financial	Heap and Pollari 2019	13	CN
10	Aptible	https://www.ventureradar.com/organisation/Aptible	5	US
11	Apple (Pay)	Hendrikse et al. 2018	5	US
12	Authada	https://www.crunchbase.com/organization/authada-gmbh	5	DE
13	Avaloq	https://www.it-finanzmagazin.de/avaloq-app-store	5	DE
14	Bankable	https://www.crunchbase.com/organization/bankable	5	UK
15	Bunq	https://www.crunchbase.com/organization/bunq	6	NL
16	Check24	https://www.it-finanzmagazin.de	5	DE
17	Compeon	https://www.crunchbase.com/organization/compeon	5	DE
18	Elinvar	https://www.crunchbase.com/organization/elinvar	3	DE
19	Finanzcheck	https://www.crunchbase.com/organization/finanzcheck	5	DE
20	FinApi	https://www.finapi.io	5	DE
21	FinReach	https://www.ventureradar.com/organisation/FinReach	5	DE
22	Fino Digital	https://www.ventureradar.com/organisation/fino-digital	5	DE
23	Finnova	https://www.crunchbase.com/organization/finnova	5	CH
24	Google (Pay)	Murchison and Yamaoka 2019	5	US
25	IdNow	Wittkamp and Schmitz 2020	5	DE
26	Iwoca	Liebenau et al. 2014	5	UK
27	Joonko	Wittkamp and Schmitz 2020	5	DE
28	Klarna	Heap and Pollari 2019	9	SE
29	Lending Club	Balyuk and Davydenko 2019	5	US
30	Mambu	Wittkamp and Schmitz 2020	5	DE
31	Monzo	Heap and Pollari 2019	5	UK
32	NDGIT	Berlin Group 2021	5	DE
33	Numbrs	https://www.financefwd.com/de/numbrs-unicorn	5	CH
34	N26	Heap and Pollari 2019	6	DE
35	Ownly	https://www.ownly.de	4	DE
36	PayPal	Murchison and Yamaoka 2019	5	US
37	Plaid	https://www.crunchbase.com/organization/plaid	5	US
38	Prosper	Balyuk and Davydenko 2019	5	US
39	Revolut	Heap and Pollari 2019	6	UK
40	Scalable Capital	Wittkamp and Schmitz 2020	5	DE
41	Smava	https://www.crunchbase.com/organization/smava	6	DE
42	Square	McKinsey 2019a	4	US
43	Solarisbank	https://www.crunchbase.com/organization/solarisbank-ag	6	DE
42	The Open Bank Project	Liebenau et al. 2014	5	DE
45	TransferWise	Heap and Pollari 2019	6	UK
46	Transpay	www.crunchbase.com/organization/transpayglobal	5	US
47	TraxPay	Wittkamp and Schmitz 2020	5	DE
48	Trustly	https://www.crunchbase.com/organization/trustly-group	5	SE
49	Verivox Outbank	https://www.crunchbase.com/organization/outbank	6	DE
50	WeAdvise	https://www.finconomy.de/en/weadvise-robo	5	DE
51	WeBank	Murchison and Yamaoka 2019	17	CN
52	Yolt	https://www.yolt.com	5	NL
53	Zopa	Balyuk and Davydenko 2019	6	UK

4 Results

We begin this section by examining the banking industry evolution across three phases. Our key point is to analyze how strategic actions impact the renewal of resources and network position in the industry and how these actions, in turn, impact the banking industry towards a platform-based ecosystem structure. We derive a reference model for future banking as a result. Subsequently, we demonstrate the application of the reference model for the value co-creation use case in identity and payment banking services. We use the developed roles from the reference models, enhancing them with value propositions, values, and activities for the ecosystem participants.

4.1 Development of a role-based reference model for the future banking ecosystem

Strategic goals lead to ecosystem and value network actions that change the market positioning of a firm in the value network (Hernandez and Menon 2021; Tiwana 2014). These strategic actions also shape the value network over time (Jacobides 2016). We analyzed the strategic actions of the market actors in banking and derived three development phases in the platform economy. Table IV.2-2 gives an initial overview of the identified phases for the banking industry evolution, which we disentangle in the following.

In the *first phase*, universal banks covered more or less the entire value creation (cf. Riese 2006, pp. 33 ff.). Thus, a focus on the core business was observable that entailed the refactoring or removal of a product or service not being completed yet (Tiwana 2014, p. 192). The determining network moves of the market players included divestitures of subsidiaries, the dissolution of strategic alliances, and the formation of new alliances (Hernandez and Menon 2021). Outsourcing allowed a bundling of transactions between two or more banks regarding external relationships with partners. These processing factories entail the provision of core banking services to partner banks. With an increase in such external partnerships, especially with external IT service providers, a disintegration process started slightly, and the industry evolved towards a value network structure. Digital platforms did not play any role in the banking industry at that time.

In the *second phase*, we observe the emergence of near-bank Fintech, typically in the form of digital platforms, such as the creation of entirely new roles in infrastructuring and the occupation of both new and existing roles in platformization (Constantinides et al. 2018). The main driver was access to innovation, including new Fintech products and services. These strategies are linked to developing platform-based products (Tiwana 2014, pp. 84 f.) or acquiring a bank or Fintech, i.e., the occupation of the corresponding role by an actor, and forming alliances that transact on the value flow connections between the roles (Hernandez and Menon 2021).

In the *third phase*, we find evidence of the widespread emergence of non-bank Fintech, claiming central roles and aggregating other MSPs in meta-platformization. The central goal of the market actors is to increase network centrality and gain access to customers (Hernandez and Menon 2021). To achieve this goal, firms draw on ecosystem strategies, such as envelopment, based on informal forms of cooperation through open standards, i.e., leading to new meta-roles (Tiwana 2014, pp. 172 f.). In addition, banks and

Fintech use traditional means of strategic network change, such as acquisitions and subsequent consolidation, to shape the ecosystem to their advantage (Hernandez and Menon 2021).

In the following, we derive three role-based e3-value models that reflect these developments accordingly.

Table IV.2-2: Overview on the banking industry evolution

Phase / Dimension	Traditional production (2000-2010)	Infrastructuring and platformization (2010-2020)	Meta-platformization (2020-)
Description	The transition from a traditional linear value chain towards a value network structure	Ecosystem emergence: The creation of entirely new MSP roles (infrastructuring) and the occupation of both new and existing roles (platformization)	Redistribution of the ecosystem: Market power shifts to (open) platforms that claim central roles and aggregate other MSPs
Strategic goal	Focus on the core business: Product orientation	Access to innovation and resource control: Integration of near-bank Fintech	Access to customers and network centrality: Integration of non-bank Fintech
Ecosystem move	Refactoring: Renewal or removal and reengineering of existing infrastructures	Inversion: Development of digital infrastructures, i.e., multi-sided platforms	Envelopment: Informal collaboration with open standards (APIs) on platforms to develop platform ecosystems
Network move	Divestitures, alliance formation, or termination	Acquisitions, alliances, and firm entries	Acquisitions (consolidation), alliances, and firm exits

4.1.1 Phase 1: Traditional production (2000–2010)

The starting point of our considerations is the universal bank model that represents the integrated banking industry architecture. The traditional banking value chain relates to banking products in the area of payments, investments, credit lending, and account management, as well as upstream and downstream services, such as payment processing (Tolkmitt 2007, p. 97). Our value modeling is concerned with the economic exchange relationships towards the customer in the value network. Hence, our modeling will include the central areas of finance and risk management, operations, products, and sales and customer service, but no cross-sectional functions such as finance.

We extracted the bank-specific business functions from the BIAN service landscape and arranged them into logically related functional groups. We categorized single activities of the BIAN into superordinate roles and examined their interrelationships. The conceptualized roles were synthesized with the corresponding value flows. We followed the previous literature in structuring the traditional banking business into five distinct areas and defining typical banking roles (Alt and Puschmann 2016, p. 130): transactions, interbanking, products, sales/services/marketing, and data management.

4.1.1.1 Transactions

The core of our reference model is the banking transaction area. We use this example to briefly explain the principles of role-based e3-value modeling (see Figure IV.2-2).

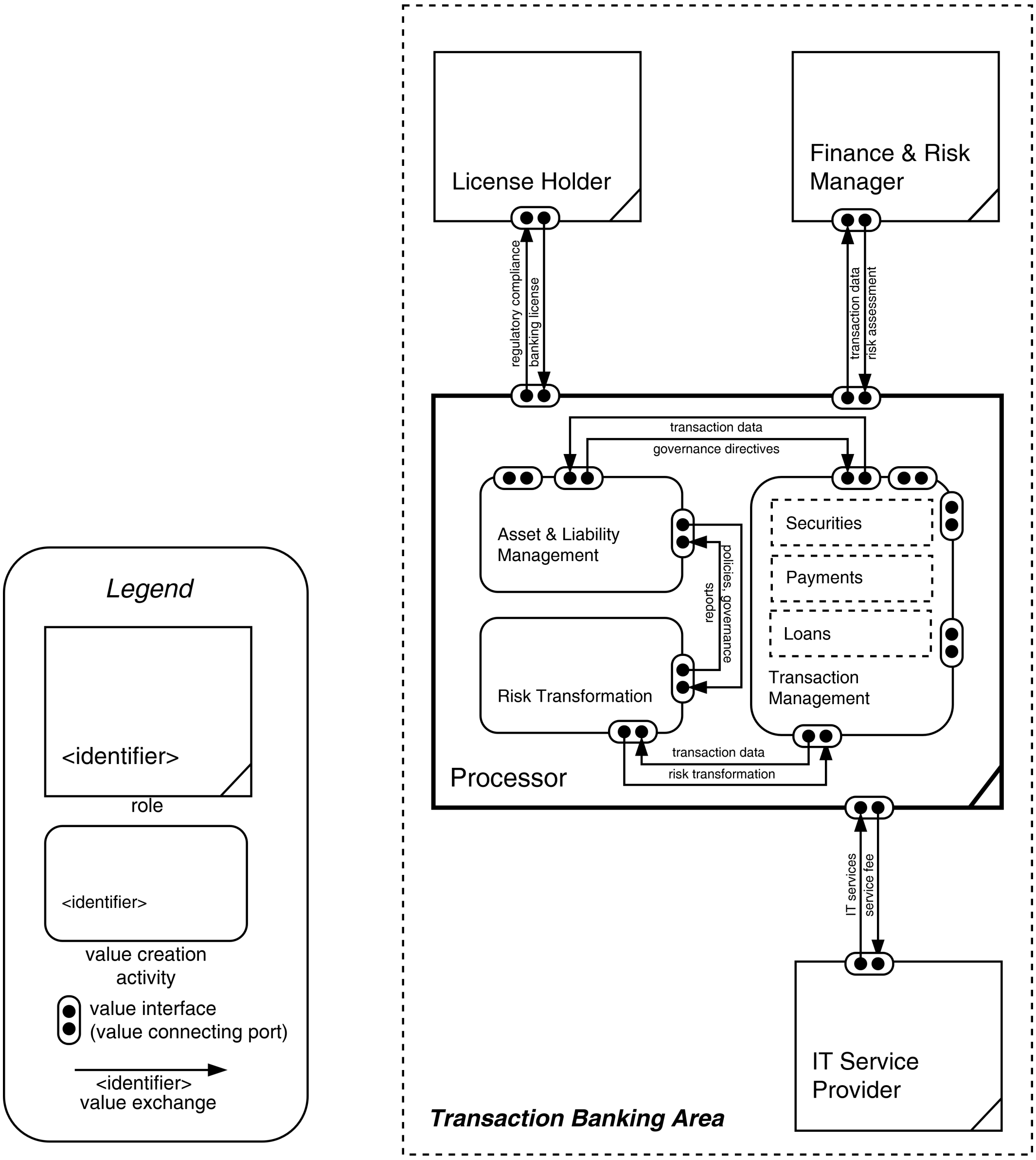

Figure IV.2-2: Transaction banking area

The transaction banking area entails the role of the *processor*, which concentrates on the transaction processing downstream of product and sales activities. The role represents the necessary business functions involved that can be modeled explicitly in an introspective analysis. The introspective analysis considers interdependencies within the core value creation activities of the processor. *Transaction management*, which relates to back-office activities in securities, payments, and loans, is central to the processor. This task is steered by the *asset and liability management* function, which oversees the bank's overall asset and liability make-up and direct activity, allocates capital, and defines policies to ensure the bank remains within its desired profile. *Risk transformation* includes taking and balancing individual risks by pooling them into collective ones. Typically, universal banks, such as Deutsche Bank, assume all of these responsibilities.

We further identify the processor's surrounding roles that operate between the customer-facing product and services delivery aspects of the banking value network and other operational and support entities. The modeled value flows represent value exchange streams between the role of the processor and its surrounding roles. Value exchange occurs via connected value ports and typically refers to the exchange of data, information, or physical representations.

Central to all banking-related activities is the role of the license holder. *License holders* are entitled to own and operate a bank while being supervised for compliance. The role includes providing supervisory activities, such as on-site inspections of the bank's records, operations, and processes and evaluating the annual reports. This role also enables many unlicensed banking services, leading to an increasing number of core banking services. All universal banks have a full banking license to perform processing and settlement tasks.

The role of the *finance and risk manager* covers all risk-related operational activities. The role pursues lending approvals, risk management of financial positions, detecting customer and inside fraud, compliance management, and reducing model risks.

From a resource perspective, the *IT service provider* supplies the processor (and all other roles similarly) with vital IT resources (e.g., standardized or customized hardware and software) to operate the IT systems and cross-functional support all activities. With the banks' focus on optimizing their core businesses, parts of the value creation process are no longer covered exclusively by the institutions but sourced from third parties (e.g., Sparkassen Finanz Informatik).

4.1.1.2 Interbanking

The reference model contains further necessary roles in the interbanking area. The processor passes authorized payment data, trade orders, and securities over to the respective roles in the interbanking area and, in turn, receives the services provided. The trade placement is executed by the *market operator* that captures the wholesale market's principal position, receives verified security orders from the sales or transaction bank, and is responsible for placing and receiving the trades executed. Securities are stored by the *custodian services provider* that holds an account with the central securities depositories and administers the custodial holding of securities held by a customer. The *clearing and settlement service provider* applies appropriate rules to allocate completed orders across counterparties and fulfills a correspondent bank agreement between banks (e.g., SWIFT). The payment infrastructure is provided by the *card network operator* that operates the payment network, a network of banks that process a particular brand of payment cards (e.g., Visa or Mastercard), and orchestrates the new acquirers' activities issuers, terms and conditions, and their status. The *central securities depository holder* is an actor administering the debt instrument's original certificate (e.g., German Bundesbank).

4.1.1.3 Products

In addition, the reference model entails product-related banking roles. The *customer account operator* orchestrates consumer accounts and captures a portfolio view with key customer (contract) data and consolidated activity. The customer account operator can conduct profitability and performance analysis across many possible customer dimensions by receiving and maintaining data from the customer data provider. The *payment service provider* takes care of the technical processing of payment methods for the merchant, including credit card, bank-based payments, such as direct debit and real-time bank transfer, and manages the relationship with the customer account operator (often of multiple acquiring banks) and the card and payment networks to authorize transactions. This role also manages the technical network connections and payment methods. The *merchant* is an actor at the point-of-sales that uses a merchant account by the acquirer. The customer account operator and payment service provider provide their data to the finance and risk manager to receive fraud detection services and regulatory compliance assistance.

The credit lending business is administered by the *credit manager,* which provides financing services and takes over other banks' credit businesses (e.g., sales banks). This role acts as the credit debt securitization initiator, processes non-performing loans, and passes them over to the recovery service provider to recover and realize these loans. Initiated by the credit manager, a *securitization services provider* pools and transform various types of contractual debt to open up refinancing opportunities and manage the associated credit risks. The *rating-/scoring-/ market data provider* indicates a consumer's creditworthiness and further assembles all forms of relevant market-related data. It passes the credit scores and all relevant information to the credit manager in exchange for a commission. A *credit agency* determines the initial and ongoing values of customer loan collateral. It maintains a credit history, but it does not assign a rating or scoring as an information provider.

The *investment service provider* handles the consumer front-end trading requests typically blocked/netted for market execution and places them via the processor and the market operator. The role establishes the trading policies for the client’s investment portfolio, such as complying with internal and regulatory procedures or governing the necessary disclosures and ‘know your customer’ (KYC) requirements.

The role of the *product developer* finally involves originating and testing new products, services, and processes. It maintains and assesses coverage and relative performance/profitability of the full range of products and product combinations/bundles offered, creates, imports, and maintains a wide range of product specifications.

4.1.1.4 Sales, services, marketing

Furthermore, the model incorporates sales, services, and marketing roles. The *sales manager* captures sales leads, offering products directly to customers and collecting contract-relevant customer data. The *customer service provider* then takes and forwards customer inquiries and gives customers interactive guidance. The *marketing service provider* manages marketing campaigns, such as sending advertising messages and collecting response data. Data analytics can be implemented to automate non-value-adding activities and provide individualized customer recommendations. These three roles commonly work closely together, draw on similar databases, or are even combined by one actor in the market, for example, the financial advisor (or customer relationship manager) as the customer's single contact person.

4.1.1.5 Data management

Finally, this relates to additional roles for data management. Customers' raw data is accumulated by the *customer data aggregator*, which, in turn, provides the data-collecting device or application to the customer. The aggregated data is transmitted to the *customer data provider*, which provides processed and pseudonymized data to the sales manager, product developer, and additional downstream roles. This role maintains a comprehensive set of digital customer data, including demographics, administrative, KYC-related properties, status and activity summaries, and location details to support more dynamic sales and servicing activities enabled by mobile devices.

Table IV.2-6 in the appendix provides a summary of the identified traditional banking roles. Figure IV.2-3 shows the complete role-based reference model of traditional banking. In sum, value creation in the banking industry in this phase involves a handful of critical roles and activities that are interdependent and, hence, require coordination to operate successfully. In the first phase, a single actor, the universal bank, mainly fulfilled the roles that typically cover the roles except for the interbanking area (i.e., card network operator, market operator, central security depository holder). However, the occupation of roles by third-party providers in the back-office of banks already indicates disintegration and higher specialization of the actors. The concrete scope depends on the degree of outsourcing involved. In addition, there are specialist banks, such as investment banks and sales banks, with a focus on individual areas of the value network.

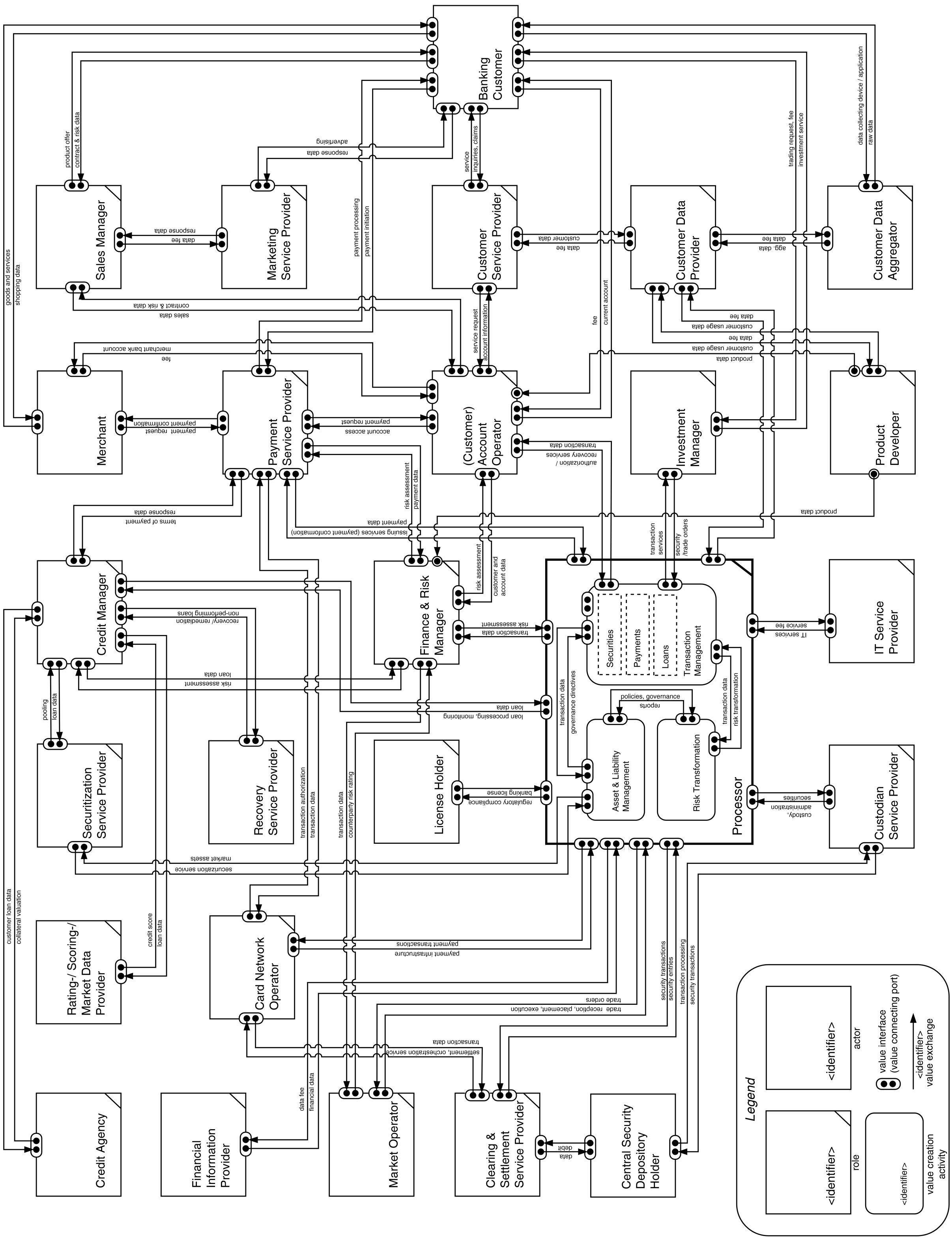

Figure IV.2-3: Traditional banking value network

4.1.2 Phase 2: Infrastructuring and platformization (2010–2020)

The second phase has led to new roles in banking, emerging from new actors entering the banking industry. This development phase includes the Fintech evolution (Alt and Puschmann 2016). In this phase, banks and Fintech strive for access to innovation and the control of the belonging resources, especially regarding evolving digital platforms. The evolution of the banking industry in this phase gives various examples of expanding ecosystem moves and underlying value network changes, such as firm node entries. A prerequisite for incumbents to fully participate in this phase is successfully refactoring the monolithic IT systems in the first phase.

We collected the providers' activities in the case protocol and assigned them to traditional or new roles. New roles emerge if the functions entail new platform-based business functions, whereas new entrants also provide alternative digital services for existing roles. The market trends were again categorized along with the five functional areas in banking. We used the literature on Fintech (Gomber et al. 2018) to systematize the identified services from the case studies across the five distinct banking areas.

4.1.2.1 Transactions

In the transaction area, the increasing share of cloud-based API services has led to the emergence of an *IT service MSP*, which brokers between banks and IT service suppliers. The IT service MSP realizes cloud service integration and customization. This role entails the vendor-side provision of FinTS or PSD2 interfaces from the processor, including data retrieval and provisioning. Case examples include Crealogix, Ndigit, IDNow, and WebID. It is conceivable that traditional banks provide the necessary functionality themselves, while neobanks could rely on Fintech partnerships. Moreover, Fintech, such as IDnow or Authada, provides digital identity services like multichannel authentication services to downstream roles and activities.

Neobanks, such as N26 or Revolut, occupy traditional transaction bank roles such as the *processor* and *license holder*. White-label service providers, such as Solarisbank, resell banking services to banks and Fintech to generate wholesale revenue based on *IT service providers*, such as Amazon Web Services. Another example is Deutsche Bank, which formed a strategic alliance with Google as the IT service provider, whereas China Merchants Bank relies on Tencent to develop cloud-based AI services. Regtech, such as Nordic Capital, have occupied the *finance and risk manager* role, providing data analytics for regulatory processes.

4.1.2.2 Interbanking

The interbanking area entails new entrants for faster payment settlements for the role of the *clearing and settlement provider*. The money transfer and foreign exchange entail the occupation of the *payment network operator*, *central securities depository holder,* and *market operator roles*. New credit scoring and approval providers such as Lenddo occupy the role of the *custodian service provider* and the *rating-/scoring-/ market data provider*. Distributed ledger technologies, such as blockchain, may change existing financial services' business models as well. The introduction of various forms of digital currencies is being discussed intensively. Here, a more flexible bundling of offerings based on decentralized infrastructures and smart contracts could be achieved, incorporating the traditional and new roles, such as IT services, products, and interbanking. Incumbents such as JPMorgan Chase, several Fintech innovators, and regulators established early partnerships. These developments towards decentralized finance could also be retrieved within several generic roles in our value network, e.g., the *payment service provider* or *investment manager*. Ripple, as a blockchain case, shows that intermediation is also possible in this area.

4.1.2.3 Products

In the area of products, the *infrastructure service provider* includes the provision of client-side API interfaces. This role uses the APIs of the IT service MSP and provides its interfaces to other product- and sales-oriented roles. In this regard, providers such as Tink, fintecsystems, finleap, and Subsembly act as a gateway that provides infrastructure services. Interface specialists, such as FinTecSystems and Subsembly, make it technically possible for third-party providers to access bank account interfaces. Another example is API aggregators, such as Bud or Tink, that proactively integrate digital services from other banks and Fintech. They consolidate the different IT-related processes in a single central, standardized, and coordinated manner.

Further innovative banking services have been developed, subsumed by the account information and payment initiation service provider. The *account information service provider* (AISP) collects account information electronically directly from the customer account operator via open APIs to provide consolidated and user-friendly information and overviews. The AISP is located between the customer and customer account operator and enables customers to share financial information quickly and securely with a lender or broker, for example, Credit Kudos (Allan 2020).

While AISPs have ‘read-only’ access to customer accounts, the *payment (initiation) service provider* (PISP) has ‘read-write’ access. Exemplarily, PISPs, such as Klarna, Apple, or Google Pay, have built several tie-adding relationships with other banks and Fintech. The customer authorizes them to initiate payments directly from their account with the account-holding financial institution. The PISP mainly captures new tools that automatically transfer a customer’s money between accounts to avoid overdraft fees, such as Trustly. The PISP applications include money management and savings apps. For instance, these tools automatically transfer a customer’s money between accounts on their behalf to avoid overdraft fees. For instance, these tools operate money transfers between customer accounts in real-time. New tools integrated with businesses’ back-office systems allow companies to manage payments and collections securely. Another example is Square that began as a pure payments processor but has turned into a platform-as-a-service provider for small- and medium-sized enterprises. This role requires connecting to existing acquirers or bringing along its own acquiring services, which is conceivable for Apple and Amazon, for example.

The role of the *lending MSP* represents an alternative to traditional lending offered by banks, as in online lending platforms. This role captures all activities related to digital platform offerings, which enable hybrid lending strategies and match borrowers' and investors’ risk preferences. Data-driven managed credit decisions are conceivable for this role. Fintech players with digital lending offerings include Funding Circle, Ferratum, and Zopa.

Furthermore, traditional roles have been occupied by new industry actors. The traditional *customer account operator* role is occupied by white-label service providers such as Solarisbank or neobanks such as Revolut for providing deposit services. Digital wallets are offered in the area of payment (e.g., Apple, Google, or crypto wallets).

Furthermore, traditional roles are occupied in credit lending, such as the *credit manager*, *securitization service provider*, and *recovery service provider* for non-performing loans. Fintech such as SoFi, Sindeo, or rocketmortgage provide digitally advanced credit loan solutions. The *investment service provider* also entails new entrants that provide digital services for digital brokerage and investing in the investment area. Robo advisors, such as Vanguard and Scalable Capital and the broker Trade Republic provide services for stock investments. Another example is the alliance between Deutsche Bank and QPLIX, an investment and personal finance management platform. In addition, third parties engage as *product developers* in open banking.

4.1.2.4 Sales, service, marketing

The *sales MSP* acts as a matchmaker for the customer and disintermediates the traditional sales function. This role operates directly at the customer interface, offering comparison and brokerage services for a wide range of traditional banking products (e.g., Check24, Verivox, Treefin, Numbrs, and Finanzblick) or with a focus on one specific product category (e.g., Zinspilot, Weltsparen, Smava, and Finanzcheck). It can become the customers' first contact point when comparing and brokering banking products online.

The *personal finance MSP* displays another new role in the value network that is likely to acquire data from various sources, such as the investment manager or customer data provider. It realizes personalized financial recommendations based on the evaluation and analysis of account transactions and provides support in managing, structuring, and planning the finances of banking customers. This role encompasses the analysis of customer account data turnover to improve liquidity management for customers. Mint became one of the first Fintech in real-time financial monitoring. Digital services are offered by Fintech, such as Moneymeets, and incumbent banks, such as ING (after the acquisition of the Fintech Yolt).

4.1.2.5 Data management

Following the latest technological advancements in cloud computing and data management, the role of the *external data MSP* integrates financial data of companies, public authorities, and science in a central data pool which have not yet been linked. Yodlee is a relevant example.

Neobanks, such as N26 or Revolut, represent relevant examples of third-party providers which occupy the traditional but evolving roles of the customer data aggregator and customer data provider. The *customer data aggregator* accumulates customers' raw data, which, in turn, provides the data-collecting device or application to the customer. An application might be a bank's mobile app for invoices/money transfer, credit checking, or assistance services. The *customer data provider* also evolves as it maintains a more comprehensive set of customer reference details, including demographics, administrative, KYC-related properties, status, and activity summaries.

In sum, our findings indicate that incumbent banks are surrounded by innovative, digitally empowered Fintech, especially at the product-related middle office and customer-related front office. Table IV.2-7 in the appendix provides a summary of the identified new banking roles. Figure IV.2-4 shows the role-based reference model for current banking. We find two major effects: Third-party providers creating entirely new roles by infrastructuring or occupying new and existing roles by platformization (Constantinides et al. 2018). For one thing, new roles are created in infrastructuring. Therefore, we include several multi-sided platforms and third-party provider roles in our conceptualization (see Figure IV.2-4, colored dark grey). For another thing, architectural control points are opened in *platformization*, with Fintech also occupying already existing traditional banking roles. Accordingly, innovative digital resources become both a disintermediation threat and an opportunity for traditional banks to expand resource access in the industry.

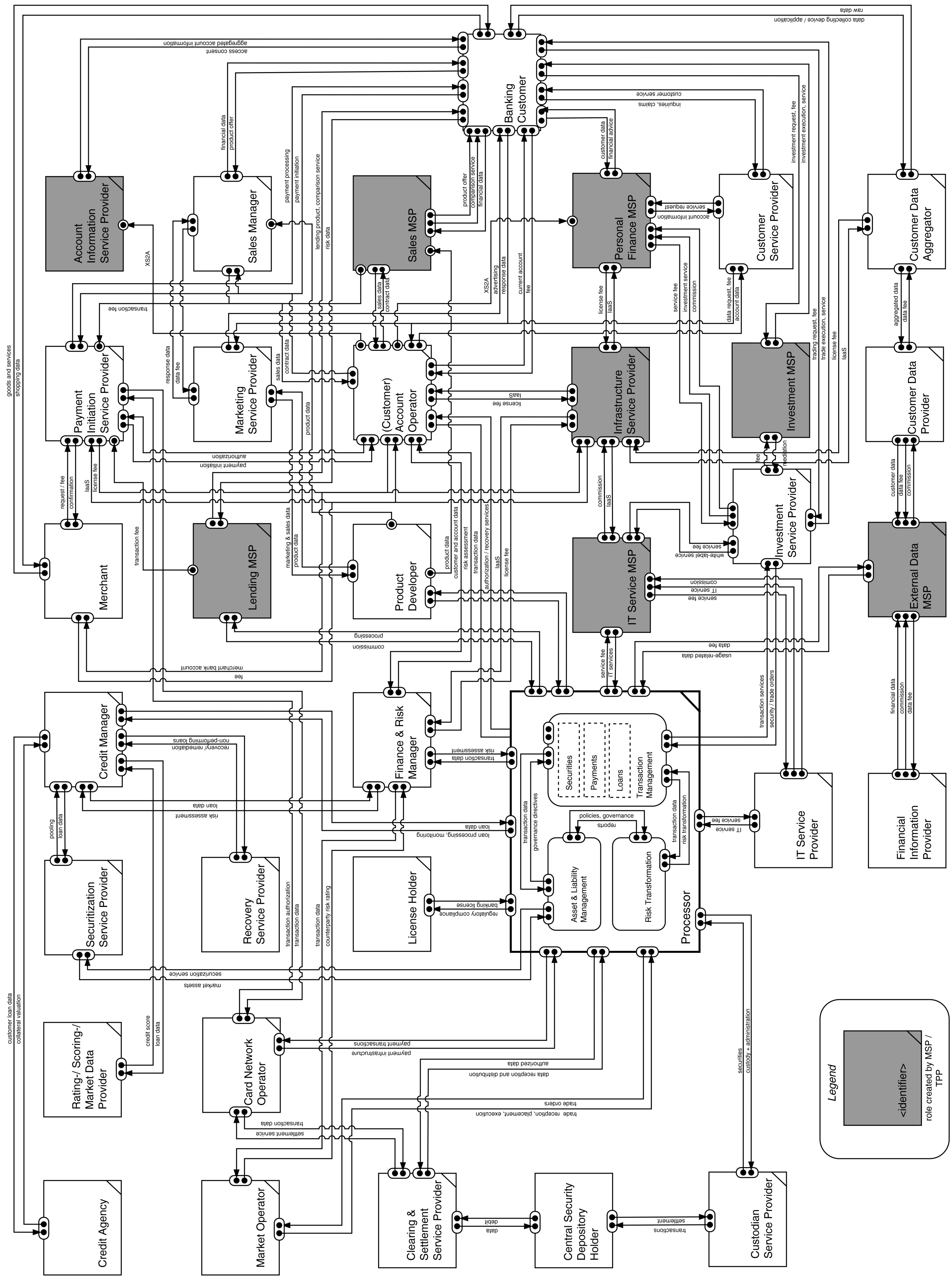

Figure IV.2-4: Current banking value network

4.1.3 Phase 3: Meta-platformization (2020–)

In the third phase, a customer-centric paradigm replaces the product- and service-oriented paradigms with non-bank Fintech gaining influence and aiming especially at network centrality and customer access. A hybrid interaction arises from the customer's point of view since customers can conduct bank-relevant transactions via several integrated digital channels across different providers (Nüesch et al. 2015). We describe the underlying mechanisms that enable embedded finance in the following.

In this phase, new entrants rely on prior industry developments, such as orchestrating services from other providers, typically banks and near-bank Fintech, into their platforms (Hagiu et al. 2020). To achieve this, firms, especially the non-bank Fintech, may not only rely on value network moves, such as acquisitions, but also on ecosystem moves, such as envelopment (Condorelli and Padilla 2020; Eisenmann et al. 2011; Tiwana 2014, p. 194). Envelopment strategies can take two forms: Non-bank Fintech that maintain critical resources, such as mobile operating systems, social media, or retail transaction platforms (e.g., GAFA), may either replicate a system to create a distinct derivative in a synergistic industry, such as banking, or incorporate resources from the adjacent industries into their platform ecosystem (Tiwana 2018). For instance, traditional service providers could be integrated as complementors. After a privacy policy linkage, where the enveloper asks consumers to consent to combine their data in both the source and target markets (Condorelli and Padilla 2020), the integration of bank-specific services, especially at the customer interface, is readily possible. The PSD2 provides a regulatory basis for this development. Similarly, traditional economy providers could join forces and develop such a platform ecosystem for value co-creation around banking use cases. The orchestration of two or more roles leads to a surrounding *meta-role* and a partial adjustment of the value flows to a hub and spoke structure (Hernandez and Menon 2021). For reasons of clarity, we do not model all emerging value flows from the meta-roles to the roles separately. The emergence of a meta-role follows mechanisms of a “platform of platforms” or what we call *meta-platformization* if the complementor is a platform itself (i.e., occupying an MSP role).

We thus define meta-platformization as the emergence of meta-roles linked to the development of platform ecosystems as meta-organizations (Kretschmer et al. 2020). Meta-roles could form to reduce the complexity of embedded finance, such as coordination and process integration problems. The evolving meta-roles provide integration or orchestration services that go beyond specific MSP roles. Accordingly, each meta-role entails orchestration tasks, such as formal and informal partnership management, to develop a focal value proposition and improve the overall customer service experience. As indicated in the background section, we denote these meta-roles as “hubs.” In addition, we define *role segments* within each meta-role, which bring cross-industrial actor capabilities into the ecosystem through value co-creation of services. Typical examples are product developers, intermediary sales MSP, as well as third-party providers joining the embedded services ecosystem. While the meta-roles provide the platform core, the role segments take on the generic activities of the respective complements. The development of hubs as bundles of complements depends mainly on the interaction of the actors via open interfaces, some of whom are platforms themselves. Thereby, we point to an overlapping superposition of aggregation layers to which the metaphor of the “Russian Matryoshka doll” fits well (Eisenmann et al. 2008). Accordingly, an absorbed complement may be a platform itself, nested inside the meta-platform.

Whereas we relied on case-based induction to develop the respective industry structures for the last phases, we now abductively analyze the further industry architecture evolution in the five distinct areas in banking based on international case studies. Table IV.2-8 in the appendix provides a concise summary of the identified meta-roles.

4.1.3.1 Transactions

A banking service provider could remain the operator of its infrastructure in the area of transactions, which is a costly issue (Kaya et al. 2020), especially if the refactoring has not been completed. A banking service provider could also rely on outsourcing (Haemmerling 2008; Lee et al. 2004; Qu et al. 2011; Zmuda 2006, pp. 81 ff.). Contrariwise, that would imply the long-term relocation of internal services to a third party, such as a transaction specialist or banking-as-a-service (BaaS) provider. This shift brings advantages such as access to innovative services but also structural dependencies. The IT services are typically provided by an external actor, such as Amazon Web Services or Google Cloud Services (e.g., the cooperation between Google and Deutsche Bank). Utilizing an outsourcing approach, a traditional bank would lose roles around the core processor but save costs to invest in other areas, such as product and service innovation (Asmussen et al. 2021). Outsourcing further entails creating a new actor that shares its transaction banking infrastructure among other banking service providers (Gulati and Singh 1998; Ramaswamy 1997; Rothaermel 2001). The *transaction hub* meta-role maintains the roles of the processor and finance and risk manager and is a formal license holder. The transaction hub follows a "white-label banking" service model and not a platform-based model, as no bilateral affiliation is required, i.e., no specific investment on the interbank side is necessary to participate. The transaction hub includes the role segment of the license holder to manage licenses from participating banks across different industry segments.

4.1.3.2 Interbanking

We also found evidence for industry consolidation in the interbanking area. The Interbank Information Network by JP Morgan is an evolving ecosystem in the global payments area. An example of a decentralized organization is JP Morgan's Onyx blockchain, which is an industry consortium. The roles could also likely merge into a meta-role here. Due to the developments around identity and payment services, it is likely that several types of market operators occur related to banking. Thus, we include a role segment of the market operator with structurally similar tasks. However, it is currently not apparent if there will be a centralized or a more decentralized distribution of information-specific interbanking services in the future. Our focus is also directed towards the customer interface, so we have not considered this area a future interbanking hub in the following.

4.1.3.3 Products

The *(open banking) product hub* meta-role is an example of an innovation platform in banking products and services. These services are typically built around the provider of a customer wallet, i.e., the customer account operator enhanced by internal and external product developers and extended by innovative lending, payment, or identity services. The IT service MSP provides a technical foundation to build an ecosystem around payment and identity services. The infrastructure SP provides additional resources for these roles.

The product hub meta-role includes the customer account operator as the basis of the product ecosystem and manages third-party partnerships and ecosystem governance for value co-creation. The customer account revolves around a wallet operated by the product hub. There would be no meta-role in more decentralized approaches, and the wallets would become role segments, as several evolving types of wallets would be managed by the users. However, it is plausible that most users will continue to place the security and management of wallets (and their keys) in central hands. The ecosystem further evolves from the payment to the identity use case. The corresponding role segment represents the structurally similar initiation of these services.

The primary relationship with the merchant evolves into a role segment of third-party providers, which is now occupied by participants from diverse industries such as mobility, healthcare, and insurance who participate in the expanded ecosystem. The role segment of the product developer includes developers from different segments that provide platform ecosystem developments such as service extensions from banking and non-banking areas (e.g., retail, administration, or insurance). Thus, the bank-specific modeling shows a role segment of a larger service ecosystem, which we model as one pool of roles.

The product hub further provides open interfaces for banking products and services, such as lending or investment. Such open banking initiatives have evolved at traditional banks, such as Crédit Agricole, BBVA, or Deutsche Bank, setting up open banking platforms. In this regard, strategic alliances between different industry actors are observable, particularly between the IT-centric near-bank Fintech and traditional banks.

Moreover, an engagement of GAFA companies in this area is also conceivable. GAFA formed strategic alliances with banks, such as Google with BBVA to provide checking accounts. Amazon already delivers its banking services (Amazon Cash) and could rely on strategic ecosystem moves to extend its roles to become a real product hub. Apple also introduced an equivalent product with Goldman Sachs, the Apple Credit Card, around which an ecosystem can be built. GAFA can also be expected to aspire strong access to identity services. German banks, for instance, have participated in a consortium to develop an independent ecosystem orchestrator around single sign-on identity solutions (i.e., Verimi).

4.1.3.4 Sales, service, marketing

The *sales hub* meta-role provides functionalities of transaction platform ecosystems. The sales hub meta-role is linked to a bundle of services regarding digital channels, the customer's account information, and personal finances and provides access to potential sales partners and the mediation of suitable product offerings, such as current accounts or lending services. This meta-role serves as a sales interface to other contextual service areas (e.g., social media, retail, healthcare). For instance, GAFA could provide many potential sales interfaces through smart products and services, mobile operating systems, or mobile apps. The integration of banking services into social media in Asia provides an example. Asian Fintech already mediate banking services via social media, such as WeChat Pay and AliPay in China or KakaoBank in South Korea. Comparable developments can also be expected in the western world. GAFA could apply ecosystem moves to occupy several sales-oriented roles in banking. Open banking regulations, such as the PSD2 in Europe, opened the door to provide such services due to the data-sharing consent. Furthermore, traditional banks have started initiatives in identity services to ensure frequent customer interaction as trusted service providers. One example is YES.com, the identity service of German savings banks. Unlike the Verimi identity consortium, which acts primarily as a product hub, Yes connects directly to a bank's sales interface.

4.1.3.5 Data management

The *data hub* meta-role is necessary to develop platform ecosystems with advanced data analytics functionalities. The data hub meta-role manages the data access from the transaction, product, and sales hubs and handles the commission and billing of data services across participating partners. The data hub fuels the sales- and product-related roles to provide individualized product and service offerings. The role segment of the data aggregator serves as an interface of data collectors across different value co-creation segments (e.g., retail, social media, or insurance). This meta-role cannot be typically obtained by a single actor since the necessary scaling effects of the data are achieved only through cooperation. Non-bank Fintech such as GAFA could likely obtain it. They have the advantage of large cross-sectional data from everyday user interactions on their mobile operating systems. They could obtain the essential but missing banking transaction data through recently formed bank-to-GAFA alliances. The traditional economy has struggled to establish such a data hub in a consortium.

Figure IV.2-5 shows a credible future value network for the banking ecosystem. As exemplified, new re-intermediating value flows are formed between the meta-roles and existing roles above the value flows between the roles. Commission-based services, for instance, are exchanged between the sales and the product hub. The transaction hub provides the back-office infrastructure for platform ecosystems. Hence, specific services on top of that, such as payments, can be efficiently settled through the hub. The data collected from transactions and customer interactions flows into the data hub and is available for product development and sales/marketing/services. As we are conceptually on the role level, an individual actor can occupy several meta-roles and roles. For instance, a platform ecosystem orchestrator could occupy the sales, product, and data hub meta-roles. A core-periphery structure will probably manifest utilizing the market power. The power structures of the platform orchestrator then correspond to the old universal bank model but are, in fact, based on a platform ecosystem logic.

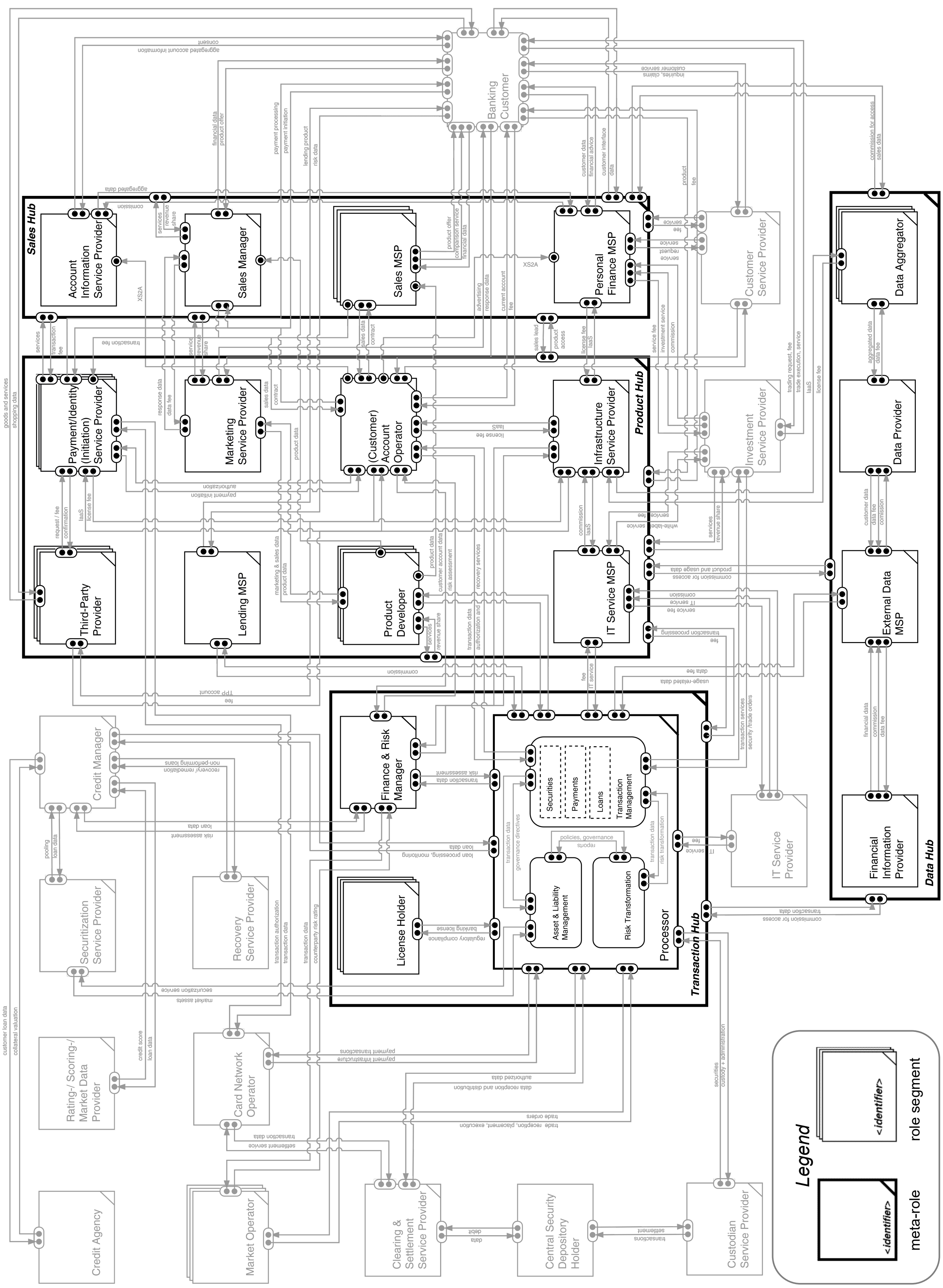

Figure IV.2-5: Future banking value network

4.1.4 Summary

We systematize the platform economy's impact of the platform economy on the banking industry evolution, linking our empirical findings with theory (Eisenhardt 1989; Hernandez and Menon 2021). The individual firm actions shape and are shaped by the circumstances specific to an industry (see Table IV.2-1). Table IV.2-9 in the appendix further lists case examples for the identified strategic moves in banking. We identified the characteristic pattern for each phase. A *pattern* characterizes the changing topology of the industry (Chircu and Kauffman 2000). Each pattern translates to a specific structure, openness, and modularity. *Structure* describes the inter-organizational relationships in the banking value network (Kumar and van Dissel 1996). *Openness* characterizes the degree of lateral access to the banking infrastructure (Baldwin and Hippel 2011; Boudreau 2010; Kazan et al. 2018). *Modularity* determines the composability of value-creating activities by different collaborating entities in ecosystems (Baldwin and Clark 2000, pp. 63 f.; Schilling 2000; Tiwana 2014, pp. 95 f.). Table IV.2-3 summarizes our considerations across the three phases.

In the first phase, the generic pattern was *intermediation*, leading to a vertically integrated industry structure. Most roles here were fulfilled by a single actor, the traditional universal bank. The bank was the middleman in the industry. The industry was closed in this phase, as coordination, trust, and avoiding too many new ties determined traditional bank strategies. With disintegration, however, roles no longer fell into the hands of the universal bank in an integrated manner but were divided among several actors in the back office. Hence, modularity likely already increased, providing more bridging tie opportunities between the actors (Hernandez and Menon 2021).

In the second phase, the generic pattern is *disintermediation*, leading to loosely-coupled partnerships between traditional and new roles. In disintermediation, revenue streams are cut off because the bank as the middleman could be replaced by new entrants. Infrastructuring relates to the further disintegration of the former integrated value network, while the intertwined platformization relates to the disintermediation of traditional banking roles by Fintech entrants (Constantinides et al. 2018). Consequently, the openness of the banking architecture likely increased in this phase (Hernandez and Menon 2021). New roles emerged due to the entry of new market actors, which created new value flows between traditional and new roles. Consequently, the industry became more modular as more bridging tie opportunities evolved (Hernandez and Menon 2021).

In the third phase, the generic pattern is *reintermediation*, leading to a core-periphery structure with a small group of firms that build platform ecosystems at the core and several smaller platforms as peripheral nodes (Hernandez and Menon 2021). The platform ecosystems break apart and reshuffle existing value relationships (Wigand 2020). The platform ecosystem paradigm could help late entrants to enter the market while also enabling traditional incumbents to defend their market position (Negroponte 1997). The modular components can be joined together or interact via appropriate interfaces, such as APIs. The dominant actors may control access to customers and partners by a high degree of network centrality, which could lead to either more open or more closed networks, depending on the strategies of the dominant actors (Hernandez and Menon 2021). Due to foreseeable market power concentration, the modularity could probably decrease in later phases when the meta-roles have been established by leading actors and service bundles accepted by customers, with fewer bridging tie opportunities in the hub and spoke structure after consolidation (Hernandez and Menon 2021). A more open network provides with many bottlenecks as complementary innovation drivers. Quite the contrary, a more closed ecosystem would focus more on fixed value propositions, thus creating stronger structures and greater dependencies (Shipilov and Gawer 2020).

Table IV.2-3: The impact of digital transformation on the banking industry

Phase / Dimension	Traditional production (2000–2010)	Infrastructuring and platformization (2010–2020)	Meta-platformization (2020–)
Pattern	Intermediation	Disintermediation	Reintermediation
Structure	Vertical integrated network	Loosely coupled partnerships between traditional roles and new roles	Core-periphery or hub and spoke structure, with hubs surrounding traditional and new roles
Openness	Closure (coordination, trust, avoiding too many new ties)	Openness (identify new structural holes)	Openness or closure (centrality and consolidation), depending on the orchestrator strategy
Modularity	Modularity increase, with more bridging tie opportunities	Modularity increase, with more bridging tie opportunities	Modularity decrease, with fewer bridging tie opportunities

4.2 Demonstration of the future reference model

4.2.1 Strategic archetypes of platform ecosystems in banking

We demonstrate the mutability of the reference model artifacts by explaining the value propositions for an embedded finance use case. Strategic archetypes can be developed to characterize market actors' strategies in the ecosystem (Greenwood and Hinings 1993; Miller and Friesen 1980; Wissema et al. 1980). Previous research has already made suggestions for systematizing archetypes in banking, however, the time of development and the terminology are not uniform (Alt and Puschmann 2016; Gozman et al. 2018; Kazan et al. 2018). We use the established terminology but update the archetypes for the platform economy.

Hernandez and Menon (2021) differentiate network-based strategies between access to resources (power), network centrality (status), exploring new product and service innovations (exploration), and generating revenues from existing structures (exploitation). When developing the reference model, value creation and customer interaction also turned out to be important yet discrete strategic directions for banking. We identified internal and external business model types for value creation (Turowski and Pousttchi 2004, p. 146). We further identified primary direct and indirect forms regarding customer interaction (Pousttchi et al. 2015). We derived four strategic archetypes from the combination of these two dimensions and typical strategic actions: orchestrator, integrator, distributor, and producer (Alt and Puschmann 2016; Gozman et al. 2018; Kazan et al. 2018). Figure IV.2-6 depicts the archetypes. The boundaries between orchestrator and distributor and as well as integrator and distributor are unilaterally open as they represent flexible evolving forms of digital platform strategies. In contrast, the producer remains firmly in its traditional role, leading to a typically more indirect interaction with customers in the platform economy.

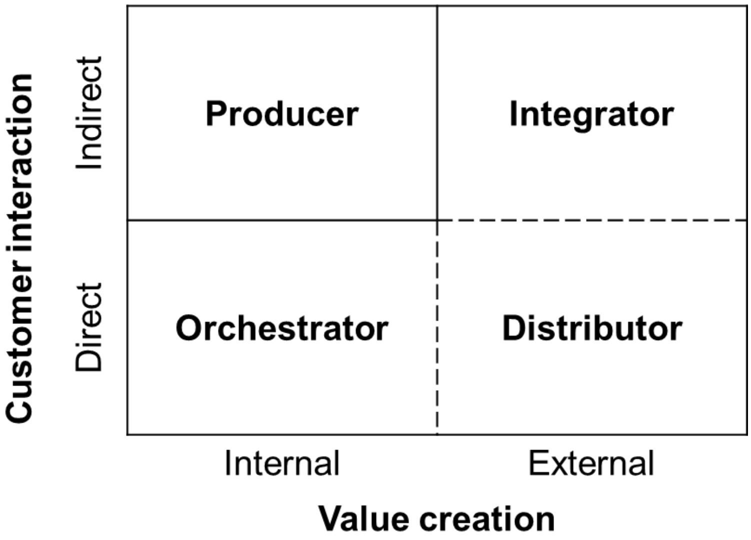

Figure IV.2-6: Strategic archetypes of platform ecosystems in banking

The archetype *orchestrator* complements its internal value creation by external services in the platform ecosystem. The strategic goal of the orchestrator is to maintain access to customers (status) and resources (power) as well as explore new product and service innovations. The focal value proposition of a platform ecosystem orchestrator is based on the bundling of components that serve as the input value to banking customers, whereby the value offerings are co-created with complements (Adner and Kapoor 2010). The orchestrator integrates banking functions as a subsystem into an app or mobile operating system and gives customers access to the ecosystem via third-party providers. It includes traditional roles, such as the customer account operator, platform roles such as the lending MSP, and the vital meta-roles of the product and, sales, and data hub, orchestrating several contextual third-party products and services. The orchestrator typically has direct interaction with customers. Additional matchmaking of the orchestrator can be realized via its sales hub functionalities. This development might become particularly evident by the entry of non-bank Fintech platforms, such as GAFA, from outside the banking industry, or entail traditional economy services to access the ecosystem. The ecosystem orchestrator chooses its boundaries to simultaneously open up towards outside third-party complements while coordinating the entire ecosystem. This type of selective openness guarantees access to novel resources (Alexy et al. 2013; Boudreau 2010; Henkel et al. 2014). However, the orchestrator also demands proprietary resources, such as the role segment of product developers (Alexy et al. 2018).

The archetype *distributor* focuses on external value creation following the mediation business model type. The primary goal of the distributor is to maintain access to customers (status). The distributor acts as a broker at the customer interface and connects customers to other well-connected industry actors, such as the sales MSP or sales hub. Hence, a sales MSP or sales hub could bypass or mediate the traditional bank occupying the sales manager role in disintermediation.

The archetype *integrator* is built upon an external value creation, as it relies on the business model type of integration. The integrator primarily wants to maintain access to important resources in the ecosystem (power), providing resource integration functionalities. Typically, the integrator does not interact directly with customers but provides integration capabilities to other institutions. In this context, different business models can be distinguished. Banking-as-a-service enablers (e.g., Solarisbank) provide the necessary resources to branded resellers (e.g., non-banks) or enhanced service providers (e.g., neobanks such as Revolut). Other white-label service providers only provide an API infrastructure (e.g., Bankable, Mambu, or Plaid). We find similar resulting structures for banking to those in the telecommunications industry (Pousttchi and Hufenbach 2009). The transaction hub entails platform roles such as the IT service MSP, the infrastructure provider, or external data MSP.

Finally, the archetype *producer* creates value primarily based on internal developments, such as transactions or product areas. The primary goal is to exploit existing resources and to participate in exploring new resources. If a provider becomes disintermediated or an entire industry becomes re-intermediated, it is displaced from the customer interface. The producer does not interact with customers directly in most cases but can become part of the value creation of external partners via contractual sourcing (i.e., horizontal bundling) or standardized APIs (i.e., lateral open access). The producer creates and operates the service, while a third party orchestrates, integrates, or distributes the service to the customer. An industry actor that follows the archetype of the producer would become a complementary product or service specialist, such as payments, investments, lending, or transactions, which is the domain of niche Fintech and traditional banks. These providers do not rely on the external building blocks of integration or mediation.

In sum, the relationships in terms of customer access have evolved with the producers being primarily at the outer periphery of the three platform-based archetypes, the integrators at the inner periphery, and the orchestrator and distributor as the re-intermediating industry cores in terms of customer access. Some powerful players may combine several archetypes in a hybrid platform ecosystem, combining innovation and transaction platforms (Gawer 2021).

4.2.2 Reference model instantiation

We instantiate the reference model from the third phase in the following. During desk research, we identified four decision fields and their influence factors that shape the banking industry and future business models: politics and regulation, competition, innovation and IT, and management. A total of 15 key uncertainties were identified as leading characteristics for scenario development (Table IV.2-4).

One central area is the future regulation of embedded and open finance use cases. The regulation of dominant market actors influences future ecosystem developments. Another area of uncertainty is the strategic thrust of the market players and their realized competitive advantages. Furthermore, the development of technological innovations including digital infrastructures is uncertain. It is also questionable how innovatively banks will react to the cost pressure on their business. Technological capabilities might also be used as an instrument to differentiate the product offering, govern the network, and control the access to the infrastructure, especially by the orchestrators. Future management dependencies between the ecosystem participants will impact their business relationships as well as the resulting primary strategic archetype of a traditional bank.

Table IV.2-4: Scenario decision fields and key uncertainties for future banking

Decision field	Key uncertainties	Exemplary sources
Politics and regulation	Unforeseen developments in banking regulation, especially payment and identity services (U1)	Brandao-Marques et al. 2020; Clemons and Madhani 2010; European Parliament 2015; European Commission 2021; Garber et al. 2021; Jacobides et al. 2016
Competition	Strategic competitive goals (U2)	Mistry 2019; Pickford 2019
	Entry and market power of competitors (U3)	Browne 2020; Gomber et al. 2018; Hatami 2016; Kazan et al. 2018
	Selection of cooperation partners (U4)	Alt and Puschmann 2016; Drasch et al. 2018
	Competitive advantages (U5)	Chiorazzo et al. 2018
Innovation/IT	Technological industry evolution (U6)	Beck et al. 2018; Du et al. 2019; Ha et al. 2012; Jakšič and Marinč 2019; PwC 2020a; Zachariadis and Ozcan 2016
	Infrastructure changes (U7)	Kazan et al. 2018; Kazan and Damsgaard 2016; Pagani 2013; Quest et al. 2021; World Economic Forum 2016
	Cost structure (U8)	Campbell and Frei 2010; Shamshur and Weill 2019
Management	Differentiation potential (U9)	Liu et al. 2011; Oberländer et al. 2021
	Customer ownership (U10)	Kazan et al. 2018; Son and Leswing 2021
	Network governance (U11)	Blakstad and Allen 2018; Zachariadis and Ozcan 2016
	Economies of scope (U12)	Gozman et al. 2018; Kohlmann and Alt 2011
	Flexibility to market changes (U13)	Allan 2020; Bramberger 2019; Vives 2019
	Dependency of partners (U14)	Bazarhanova et al. 2020; Kazan et al. 2018; Zachariadis 2020
	Strategic archetype (U15)	Alt and Puschmann 2016; Gozman et al. 2018; Kazan et al. 2018

We analyze the development opportunities for traditional banks in the platform economy based on these categories. For each characteristic, we identified several instances that form the respective rows in the morphological box (Ritchey 2011). The selection of one or more characteristic instance(s) for each criterion and the combination of the characteristics form a scenario (Pousttchi and Hufenbach 2011).

We distinguish three scenarios based on the future development of payment and identity services across the government and private sectors. Firstly, traditional banks could provide platform ecosystems for both regulated and unregulated payment and identity use cases ("strong bank" scenario). The government could therefore govern the relevant infrastructure but outsource the delivery of identity and payment services to banks (European Commission 2021; Quest et al. 2021). For example, such a top-down model is pursued by BankID in Sweden and Norway, but even there, the banks' market power has already been limited (Bazarhanova et al. 2020). This scenario would not generate large-scale network effects based on cross-sectional data analytics. Customer access to mobile payment services has already been occupied by GAFA actors, which makes the occupation of both use cases combined rather unrealistic. GAFA could likely build many unregulated use cases around the occupied mobile payment interface (Pousttchi and Hufenbach 2014). Future solutions need to meet customer expectations through customer-oriented advantages, making it difficult for regulators to limit the widespread demand.

Secondly, there could be a government-led solution of identity and payment schemes as it is currently followed in Belgium ('itsme') and Canada ('Verified.me') (Quest et al. 2021). Traditional banks could create high relevance for private customers as a trustworthy partner in regulated use cases, such as administrative, healthcare, and insurance services, where banks could provide rich digital identity functions and participate as the ecosystem orchestrator in a consortium (Quest et al. 2021). However, banks would likely remain complementor in unregulated use cases. Hence, traditional service providers may form a consortium, but it is questionable how competitive the result will be. Forming a consortium is difficult due to the traditional direct competitive situation of the banks, especially in Germany (savings banks, cooperatives, and private banks). Hence, it is rather unlikely that traditional banks will break down silos to work in a joint consortium that involves third parties in a platform ecosystem (Ozcan and Santos 2015). A competition-neutral actor like the local or supranational government as an initiator is most promising to achieve this. Another option, as the reference model shows, would be to have each partner spin up its network via white label services based on a common data and transaction hub.

Thirdly, the private sector could take over customer access for regulated and unregulated payment and identity use cases ("weak bank" scenario). The government would only set the guiding principles in this scenario (Quest et al. 2021). For the GAFA case, the banking competition policy and regulation continue to draw on self-governed negotiation by market rules, such as the regulatory enforcement of open interfaces in the EU. In this scenario, traditional banks would certainly have less say and influence (i.e., power and status). We summarize the "weak bank" scenario in Figure IV.2-7.

The “weak bank” reference model is graphically instantiated in Figure IV.2-8. The traditional bank retains the red-colored traditional roles as well as participates in the ecosystem of the orchestrator. Near-bank Fintech also participate in the orchestrator's ecosystem by providing specialized banking innovations, such as lending MSP services. The yellow roles are occupied by non-bank Fintech, typically a GAFA actor obtaining the meta-roles of the dominant ecosystem orchestrator. The transaction hub could be fulfilled by a consortium of green-colored near-bank Fintech or specialized niche banks that provide the platform ecosystem orchestrator with transaction settlement facilities. We demonstrate the corresponding value co-creation evolving around a strong ecosystem orchestrator in an identity and payment service context in the following.

Characteristics	Instances					
Competition policy and regulation (U1)	Self-governed negotiation by market rules	Mandatory rules for transaction processing	Regulation of horizontal cooperation of market-dominating companies	Independent custodian for customer data	Other forms of platform regulation	
Strategy (U2)	Exploration (access to innovation)	Power (control of resources)	Status (customer access)	Exploitation (focus on core business)		
Competitors (U3)	Bank	IT service provider	Fintech (near-bank)	Fintech (non-bank)		
Cooperation (U4)	Bank	IT service provider	Fintech (near-bank)	Fintech (non-bank)		
Competitive advantages (U5)	Process-oriented cost advantages	Customer oriented advantages	Technology-oriented advantages			
Technological evolution (U6)	Cloud computing	Business process outsourcing	Ongoing standardization (API)	Distributed ledger (blockchain)	Data analytics (AI)	Other
Infrastructure changes (U7)	Added services	Process integration	Open banking	New interfaces	None	
Cost structure (U8)	Cost for banking infrastructure (CAPEX, OPEX)	Transaction costs	Costs for outsourcing and monitoring	Costs for product and content development	Costs for marketing and sales	
Differentiation potential (U9)	Products and services	Customers	Brand			
Customer ownership (U10)	Bank	IT service provider	Fintech (near-bank)	Fintech (non-bank)	Other (e.g., state)	
Network Governance (U11)	Full coverage of value network (low specialization)	Partial coverage of value network (average specialization)	Concentration on core competencies (high specialization)			
Economies of scope (U12)	Vertical linkage	Horizontal bundling	Lateral openness	None		
Flexibility to market changes (U13)	High (dynamic, loosely coupled)	Low (stable, tightly coupled)				
Dependency of partners (U14)	High (direct access to transactions)	Average (indirect access to partners and customers)	Low (open access to ecosystem)			
Strategic archetype (U15)	Bank as Orchestrator	Bank as Integrator	Bank as Distributor	Bank as Producer		

Figure IV.2-7: Scenario "weak bank" from a traditional bank's perspective

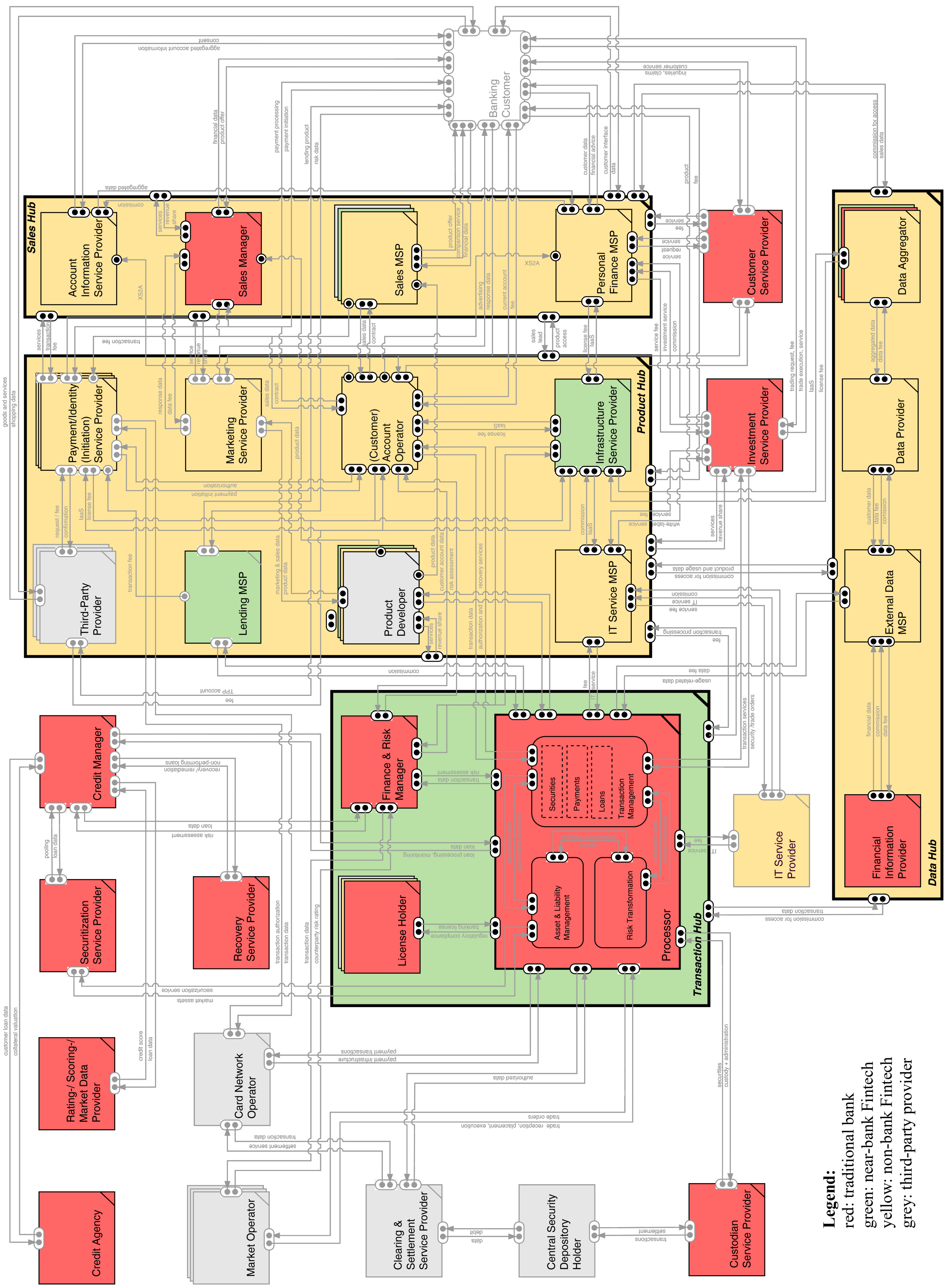

Figure IV.2-8: Model instantiation "weak bank"

4.2.3 Value co-creation in the future platform ecosystem

The ecosystem orchestrator and traditional bank business models coincide in a common ecosystem. In an ecosystem map, we discussed value co-creation as a recursive set of interactive value propositions (Payne et al. 2008). On this basis, we included typical values and capabilities in value creation maps of orchestrator and bank as well as elaborated on their value stream activities. The ecosystem map provides the springboard for the multi-perspective business model analysis. It binds all stakeholders or participants together, including their value propositions, roles, and relationships. A value creation map presents the value creation logic of the business models of each enterprise participant in the ecosystem. The value stream entails values and activities for value creation, including the value co-creation inputs from customers and complementors. It facilitates the transfer of value-based modeling to process models (Hotie and Gordijn 2019). Industry reference models can be included in capability modeling. VMP allows reusing the modeled value propositions and their values by mapping them to the VDML data model. Value co-creation requires the generation, recombination, and sharing of resources (Beirão et al. 2017). The ecosystem orchestrator facilitates the "merged dialogical process," including the customer and complementors (Grönroos and Voima 2013, p. 143). While the integration task of the ecosystem orchestrator entails the combining, standardizing, and sharing of resources, the actual value is realized through value co-creation and appropriation with the ecosystem participants (Wang 2021). This includes joint promotion, distribution, and development tasks (Saarijärvi 2012). Hence, the ecosystem orchestrator encourages complementors who enjoy high customer favorability to support value creation (McIntyre et al. 2020). However, complementor dedication likely varies (Hurni et al. 2021). Becoming a leader of a co-created platform service in the short term could, for instance, limit complementor engagement in the long term (Saadatmand et al. 2019). The ecosystem orchestrator adapts the platform core and the boundary resources through experimenting, searching, and updating, while the participation in the ecosystem is governed through controlling, rewarding, and promoting participants (Wang 2021).

4.2.3.1 Ecosystem map

Our workshops analyzed the business model logic for banking in the platform economy. Our workshops were informed by the literature on platform ecosystems (e.g., Chen et al. 2022; Mini and Widjaja 2019; Schreieck et al. 2021; Wang 2021), value co-creation (e.g., Grönroos and Voima 2013; Oertzen et al. 2018), the reference model development (e.g., Alt and Puschmann 2016, p. 130; BIAN 2020), and practitioner documents for the specific context (e.g., Garber et al. 2021; Open Banking Implementation Entity [OBIE] 2021; Quest et al. 2021).

Several actors participate in the ecosystem. Figure IV.2-10 in the appendix shows the ecosystem map around the orchestrator and the value propositions exchanged between the participants. The PSD2 implementation allows combining several service providers on the shared infrastructure of a digital platform (OBIE 2021). Accordingly, the ecosystem orchestrator implements the co-creation process with the complementors, such as product developers, traditional banks, insurance companies, car sellers, and the administration, as well as integrates suppliers, such as the processor of transactions. The orchestrator can build collaborative infrastructure around digital payment and identity services and monetize them according to the services they offer. This includes attainable fees or commissions from third-party providers (relying parties), central customer access to offer their services, and associated revenues from mediation, which are offset by related costs for operating the identity and payment services (Garber et al. 2021; Quest et al. 2021). The ecosystem orchestrator pursues, for instance, customer authentication, account information, payment initiation, and financial balance validation, including validated third-party providers (Garber et al. 2021; OBIE 2021; Quest et al. 2021). In the EU, qualified electronic signature (QES) entails electronic identification, authentication, and trust services (eIDAS) replacing the written form requirement.

4.2.3.2 Platform ecosystem orchestrator

The central goal of the ecosystem orchestrator is to increase customer interaction on its platform. In particular, winning complementors is challenging for the platform orchestrator due to digital platforms' chicken-or-egg dilemma (Parker et al. 2016, pp. 79 ff.).

Our discussions with the platform orchestrator revealed that potential complementors typically scrutinize the number of potential partners in another market player's platform ecosystem before joining. These actors usually share the promise that they could build their ecosystem and act as platform orchestrators themselves and thus do not want to share their customer base. However, many ecosystems from traditional economy providers are not relevant enough for private customers, given the small number of use cases typically involved. Thus, combining banking services with primary use cases from third-party providers increases relevance for customers more than an ecosystem that only focuses on banking products. In other words, each of these evolving platform ecosystems is too specialized to achieve customer scale effects. At the same time, the orchestrator has the problem of winning additional partners to increase the relevance of its ecosystem. Therefore, an ecosystem orchestrator with a solid customer base in the payment and identity service context could win partners more easily given transparency and trust.

The orchestrator provides a personalized customer service experience and promotes continuous content evolution. The applications on the platform determine a certain stickiness of the ecosystem (Tiwana 2014, p. 220), determining the average duration of customer interactions. As a result, customers leave an intense customer data footprint, which is the essential input factor for data-driven services, positively influencing the platform's usage (Gregory et al. in press). The customer data can be further used to increase the visit conversion rate of the ecosystem orchestrator. The cycle of data acquisition and utilization increases the platform's attractiveness for customers. The orchestrator activities include gaining dynamic customer insights, rapid response to customer needs, operational knowledge transfer, and integration and customization (Friend et al. 2020). This requires real-time, event-centric IS capabilities (Ramaswamy und Ozcan 2014; Schreieck et al. 2021). The orchestrator can commission the generated total transaction volume across the partners. The provision revenues might quickly cover the governance, development, and overhead costs, increasing profits for the given provision rate and the overall market value. However, traditional players are not mastering advanced data analytics in the virtuous cycle to scale the platform.

4.2.3.3 *Platform ecosystem complementors*

Complementors could realize commission-free revenues through their own traditional business or participate in the platform ecosystem's transactions. Banks could generate revenues through authentication, verification, and actual realization of digital business transactions (Quest et al. 2021). Based on the governance model, a complementor might pay a specific referral rate for the mediated business from the ecosystem. The orchestrator mediates, for example, identity credentials that are used by a third-party complementor (i.e., relying partner). Customer solvency data is one example. A traditional bank could serve as a relying party in the customer process and benefit from improved customer onboarding and risk management of the ecosystem. Depending on its capabilities, the orchestrator could, however, also predict secure credentials from the customer relationship data in future.

Complementors can achieve a competitive advantage by increasing their products' standalone and network value (Cenamor 2021). The customer standalone product value can be improved by designing innovative solutions. Banks could realize fees for the technical implementation of identity and payment services as infrastructure service providers, e.g., integrating APIs (Quest et al. 2021). Standalone products and services of the complementors will probably lose customer favor as the platform ecosystem's network effects and value-added services increase, so the incentive to participate in ecosystems becomes greater. The product network value depends on the number of customers (i.e., the installed base) and their interactions with the complementary product (Cenamor 2021). These innovations are based on the boundary resources of the orchestrator that is interested in pushing its ecosystem's overall value. Based on the aspired business values, i.e., revenue streams and costs, complementors, therefore, must weigh how much to invest in their standalone products as well as into platform product offerings. Complementors could multi-home their services on several platforms, strengthening their competitive position (Tavalaei and Cennamo 2020). They could invest broader in several product categories first and focus their limited resources on volume complements later (Rietveld and Eggers 2018). The investments and creativity of the complementors, the governance of the regulator and the orchestrator (interested in high-value complementors), and customers will determine the actual profits realized via the platform business. The identified business model tensions (Dessaigne and Pardo 2020) demand critical exchange, shared appraisal, and mutual respect (Keeling et al. 2021). Overall, platform orchestrators and complementors cooperate at the component and compete at the product level in selective coopetition (Cozzolino et al. 2021).

Evident economic implications for complementors from traditional industries could be stagnating or decreasing revenues through traditional touchpoints, but also additional revenues through digital platform-enabled products (cf. Fang et al. 2021). A comparison between JPMorgan Chase and Lendingclub reveals still a huge gap in the total volume of retail loans originated ($39.6B to $1.7B in Q2/2021; JPMorgan Chase & Co. 2021, p. 5; LendingClub 2021), suggesting that more elaborated platform ecosystem businesses might also boost near-bank Fintech in the lending space. Reintermediation could, on the one hand, make their offerings more influential to customers, but they could also be rendered obsolete (or acquired) by technologically advanced non-bank Fintech, which might rely instead on the trustworthy brand core of traditional banks in partnering. Our analyses demonstrated this tension.

We summarize the resulting value co-creation mapping to the VDML data model in Table IV.2-5.

Table IV.2-5: Value co-creation mapping of value propositions, roles, values, and activities

Value proposition (ecosystem map)	**Roles (reference model)**	**Values (value creation map)**	**Activities (value stream map)**
Management *(Traditional bank)*	- credit manager - securitization and recovery SP - finance and risk manager - investment SP	- profit - costs and revenues - installed base	- traditional bank management (information, portfolio, finance, policy, product, and partnership, accounting) - product innovation management (platform product development, complementary products and services)
Management *(Ecosystem orchestrator)*	- sales/product/data hub - customer account operator - IT service MSP	- market value - profit - platform generativity - equity, control, autonomy, modularity of complementors - development and governance costs	- develop platform core (enhancing user experience, screening complementors, coring functionality, regularizing product updates, experimenting, testing, monitoring policies and processes) - provide boundary resources (interfaces, manage access and external relationship control, consultancy services) - develop IT infrastructure (standardizing, orchestrating platforms and apps, multi-homing, information management)
Ecosystem product offering *(Ecosystem orchestrator)*	- sales/product/data hub - payment and marketing SP - account information SP	- customer experience, price, personalization, engagement, legitimation, perceived risk/trust - content evolution, stickiness - process integration capability	- provide sales and marketing (contact customer, provide offering, identify cross-selling potential, mobile marketing) - pursue co-creation (identify service connections, integration) - provide products and services (payment services, assess risk, customer finances, provide billing, customer support)
Platform business orchestrator *(Private customer)*		- number of visits per period - customer footprint data - visit conversion rate	- provide co-creation (co-develop, rate, access services, provide credentials, send and receive payments, follow marketing campaigns)
Bank ecosystem products *(Traditional bank)*	- product developer - credit manager - investment SP	- product-market fit - complementor customer experience, multi-homing - product network value - content richness/novelty - complementor creativity - ecosystem revenue, provision costs, participation fee	- provide product and service offerings - capture, track, resolve, and report on customer services - administer and manage loan and investment products
Platform business bank *(Ecosystem orchestrator)*	- product/data hub - infrastructure SP	- provisions and referral fees - boundary resources	- sharing program code/expertise/ knowledge - provide risk assessment - clearing, accounting, provide rewards
Lending services *(Lending MSP)*	- lending MSP	- product-market fit - complementor customer experience - product network value - ecosystem revenue, provision costs, participation fee - complementor creativity, content evolution, multi-homing,	- enable matching lending and risk strategy, ML-based creditworthiness checks
Platform business lending MSP *(Ecosystem orchestrator)*	- product/data hub - infrastructure SP	- provisions and referral fees - boundary resources	- sharing program code/expertise/ knowledge, clearing, accounting
Special banks and Fintech products *(Special banks and Fintech)*	- investment SP - credit manager - payment SP	- product-market fit - complementor customer experience, product network value - complementor creativity, content evolution - ecosystem revenue, provision costs, participation fee	- provide referral data - check creditworthiness, loan collateral - prove tradability, pooling, trade, booking, contracting, - fulfillment, archival, documentation
Platform business special banks and Fintech	- product/data hub - infrastructure SP	- provisions and referral fees - boundary resources	- sharing program code/expertise/ knowledge

Value proposition (ecosystem map)	**Roles (reference model)**	**Values (value creation map)**	**Activities (value stream map)**
(Ecosystem orchestrator)			- data transfer, credit and conformity check, fee determination, clearing, accounting - provide rewards
Product development services *(Product developers)*	- product developer	- complementor creativity, multi-homing, - ecosystem revenue, development costs, fees	- develop product extensions, added services, interfaces, maintain and assess coverage
Platform business developers *(Ecosystem orchestrator)*	- product/data hub - infrastructure SP	- content evolution - boundary resources	- sharing program code/expertise/ knowledge - operate the data and process interface, clearing, accounting - provide rewards
Regulatory services *(State/regulator)*	- market operator	- membership subscriptions, license fee	- confirm validity of customer identity - assess risks, monitor fraud and compliance issues (trust framework, test service, monitor policies and processes) - operate payment/identity networks
Regulatory compliance *(Ecosystem orchestrator)*	- product/data hub - infrastructure SP - finance and risk manager	- regulatory compliance, number of frauds, bursted revenue share	- real-time data and transaction transfer
TPP offering *(Third-party providers)*	- third-party provider	- product-market fit - complementor customer experience - product network value - complementor creativity, content evolution - ecosystem revenue, provision costs, participation fee	- provide referral data, provide value added services, review claims
Platform business TPP *(Ecosystem orchestrator)*	- product/data hub - infrastructure SP	- provisions and referral fees - boundary resources	- sharing program code/expertise/ knowledge - integrate added services, clearing, accounting - provide rewards
Sales MSP services *(Comparison portal)*	- sales MSP	- product-market fit - complementor customer experience - product network value - complementor creativity, content evolution - ecosystem revenue, participation fee	- offer comparison and brokerage services
Platform business sales MSP *(Ecosystem orchestrator)*	- sales hub - infrastructure SP	- provisions and referral fees - boundary resources	- sharing program code//expertise/knowledge - integrate added services, clearing, accounting, provide rewards
Identification services *(Identity SP)*	- infrastructure SP	- fraud minimization, regulatory compliance, cost per transaction - ecosystem revenue	- authenticate identity credentials - prove authenticity, fulfill regulatory compliance (as-a-service) - manage compliance, monitoring
Transactions ID orchestrator *(Ecosystem orchestrator)*	- product/data hub	- provision costs, participation fee - boundary resources	- clear identification requests, transfer data
Settlement business orchestrator *(Processor)*	- transaction hub - processor, license holder, finance and risk manager	- perceived risk, risk minimization, cost per transaction - ecosystem transaction revenue	- transaction settlement (capture, verify and process transaction data) - operate the technical infrastructure - fulfill supervisory duties (detect non-compliant transaction activities)
Transactions orchestrator *(Ecosystem orchestrator)*	- sales/product/data hub	- total transaction costs	- clear transactions, transfer data

5 Evaluation

We validated our reference models with seven interview partners (I) from traditional banks and Fintech (Hevner et al. 2004). The interviewees held a managing director position in the respective institutions or associations. The average interview duration was two hours. Specific actor constellations substantiated the discussion. The feedback was constructive and positive: *"I see the market developments sufficiently represented. I cannot think of any other case that could not be represented" (I1). "For the new market players, the model allows an apt mapping. It exactly illustrates the problem situation we're in right now with this model" (I2). "With the role model, I ask myself, who can fill which role best" (I3).* The interviewees underpinned the comprehensibility and construction adequacy of the reference models: *"The models are extremely coherent. They map where there are or will be critical changes and simplify the rest" (I5). "We can distinguish different types of banks in the model" (I6). The feedback from business experts indicates the comprehensibility and clarity for the target model user group: "The models adequately represent the complexity of the banking business, including the financing product area that is central to us" (I7).* The discussion of alternative model structures in payment and open banking finally strengthened the significance and comparability of the reference modeling. The design decisions and necessary compromises have been discussed in-depth, especially regarding regulations. The interviewees confirmed the appropriate level of generalization of the models: *"I think this is a great overall model. It is complexly put together, but still clearly laid out" (I2). "I like very much how banking was broken down" (I3).* The appropriateness to the actual business problems of the banks was highlighted several times: *"There are a lot of market power threats that can be pointed out" (I1). "It is a matter of defining interfaces, looking for partners who can bring in new business on platform ecosystems" (I2). "You can distinguish bank products, bank-related products as well as non-bank added values. The latter are assimilated into specific roles in the hubs" (I3). "The models show potentially complementary and conflicting roles" (I6). "As an executive, I have to ask myself, what assets I can hand off" (I3). "I see a central benefit in structuring our thinking between the real and digital world" (I4).*

Thus, the e3-value models are suitable for modeling the relational and abiotic components and stimulating our thinking on the future ecosystem's biotic component. From our experience, the reference models can serve as a basis for strategy development in a concrete use case. The reference model provided the workshop leader a basis for talking to practitioners about roles and activities and translating these into business model artifacts. Hence, they fuel the modeling of business model views, such as in VDML (Frank 2014). The VDML models allowed us to reflect on questions such as: Which actors will participate in the platform ecosystem, what the revenue models could look like, and what kind of activities and capabilities are necessary to enable the ecosystem participants' value co-creation. Hence, the interview partner from the ecosystem orchestrator pointed out that stimulating the ecosystem thinking was a practical implication of the reference model instantiation. We could draw on the reference model to qualitatively examine novel factors influencing their business model and derive system requirements that enable the aspired business and customer values. Notably, the biotic component is modeled in more detail using the VDML. The ecosystem map, for instance, enabled the mapping of concrete values to the value propositions exchanged. The graphical modeling, however, was too inflexible for assigning all roles to the actors in the ecosystem map, so mapping the roles and values to the data model in the business model view seemed more appropriate. The subsequent mapping requires additional time so that additional asynchronous modeling phases are needed to complete the analysis. More institutional contexts could be incorporated in VDML models across multiple phases and alternatives.

6 Conclusion

6.1 Implications for research

The study extends the knowledge of platform economy impact on traditional industries for researchers. We contribute to the theoretical discourse on how digital platforms give firms leverage to shape the value architecture to their advantage (Cusumano et al. 2019; Gawer and Cusumano 2014; Tan et al. 2020). Our results provide evidence that value architectures in B2C industries, such as banking, are evolving from a focus on the core business to access to innovation and resource control, eventually striving towards network-centric access to customers. These findings indicate how late entrants could benefit from prior infrastructuring and platformization to achieve network centrality (Constantinides et al. 2018). The contribution also fuels the "control or enable" debate with empirical insights from the banking context (Hagiu and Wright 2019).

Our contribution is threefold: Firstly, we develop three role-based reference models for banking in the platform economy. We provide a terminological apparatus in the subject area of platform ecosystems in banking that enables general statements about the class of traditional banking and Fintech companies based on roles and value exchanges and the influence of DT on these (Fettke and Loos 2004). We introduced the concept of meta-roles and role segments to describe central entities of digital platform ecosystems. Secondly, we contribute to enterprise modeling in digital platform ecosystems, extending the role-modified e3-value modeling approach with additional value mappings in VDML. The methodological approach was exemplified to show its capability of fulfilling the prerequisites for modeling platform ecosystems (Betz and Jung 2021; Tsai et al. 2021). Thirdly, we provide theoretical advancements such as generic patterns and strategic archetypes in the platform economy for banking.

6.2 Implications for practice

Our findings offer direct insights useful for practitioners' strategy and business model development, such as new roles, functions, and transformation mechanisms, considering the competitive threat at the customer interface. As new actors could occupy central parts of value creation at the customer interface, the economic consequences of the platform economy are substantial. In Germany alone, 550 thousand people are employed in banks, and a “weak bank” scenario under dominance of GAFA actors at the customer interface would put numerous of these jobs at risk. Regarding the risks and opportunities of open banking, DT thus determines the economic perspective of traditional banks and, given their economic functions, it will also largely influence other industries in platform ecosystems.

Our results indicate that the future competitiveness will depend mainly on how sustainably traditional banks respond to the challenges of the platform economy. They could participate in the ecosystem either as part of a consortium of traditional economic actors or as a vital complementor. The main threat for traditional banks is that non-bank Fintech meta-platforms may choose to integrate third-party complements from near-bank Fintech if these attract a large fraction of the platform end-users (Eisenmann et al. 2008), especially in the standardized retail banking business. One evident economic effect of a GAFA ecosystem would be the erosion of the incumbent's margins which can also force a complementor to merge or even exit a market. As traditional universal banks are threatened with being stuck as a producer, both a strategic reorientation and finding a suitable mode between internal and external value creation is required to occupy important roles of the future value architecture. Incumbent banks are particularly called upon to implement digital strategies with appropriate ecosystem and network moves to overcome technological backwardness in order to remain competitive and retain customers, even as complementors in the ecosystem. This entails ways to increase access to innovation, resource control and preserve network centrality, such as customer access.

However, a platform ecosystem orchestrator must ensure that the value of the core service increases, the number of customers who value both the platform and the complements is high, and, ultimately, that real economic value is derived from such interactions (Hagiu et al. 2020). A mixed-mode would be beneficial to balance between control of resources and enabling of partners (Hagiu and Wright 2019). While those parts of the value creation with higher margins and customer access could be kept in-house, services with high design costs (i.e., outside the core competencies) should be sourced externally to superior third-party providers (Baldwin and Hippel 2011). Our models entail the roles, functions, and underlying value exchange relationships. The success depends not only on strong digital leadership but also on bank-friendly regulations, such as fewer regulatory obligations, to innovate products and services genuinely. As solo efforts are difficult, cooperation is important, especially in data and transaction management. Unfortunately, prior market developments, such as those in mobile payment platforms, have shown that coopetition among incumbent players is a difficult avenue (Ozcan and Santos 2015).

6.3 Limitations and future research

Despite its strengths, the study also has limitations. This research is based on a large number of international case studies and abductive theorizing. The artifacts have also been evaluated by practitioners, while implementing them demands syntactic service integration (Alt and Puschmann 2012; Alt, Ehmke et al. 2019). Digital platform and blockchain economies could interact in the future, which is an opportunity for further research, especially in the interbanking area. Thus, additional models could be developed for different regulatory conditions. Future EM research should evaluate the outcomes of the method application. The reference model can be instantiated for different contexts; however, we did not provide a lexicon for non-banking activities, such as those pursued by third-party providers from other industries, as we focused on contextual banking functions. Based on the business model logic in the data model, further research could explore the financial aspects of value co-creation relationships for banking. Hence, researchers could to study the economic implications based on quantitative simulations of the EM artifacts. Business model outcomes can be simulated quantitatively based on concrete business data, formulas about the modeled cause-effect relationships, and required scenario assumptions. Performance indicators could measure the generated benefits for collaborative business ecosystems (Graça and Camarinha-Matos 2017). While examining the impact of platform governance requires additional phases and alternative models, various revenue models of a platform ecosystem are possible (Täuscher and Laudien 2018); this stimulates further research.

Appendix

Table IV.2-6: Traditional roles in the banking reference model

Role name	**Functional description**
Transactions	
Processor	captures, verifies, and processes transaction data for payments, loans, and investments, as well as transforms risk and manages assets and liabilities
License Holder	involves supervisory duties: transaction records, operations, processes, and annual reports
Finance & Risk Manager	tracks the resolution of detected non-compliance finance activities and instances
IT Service Provider	supplies the processor with vital IT resources (e.g., standardized or customized hardware and software) for the operation of the IT systems and cross-functional support of all activities
Interbanking	
Clearing and Settlement Service Provider	fulfills a correspondent bank agreement between the bank and another bank or an automated clearing house (etc.) and handles the clearing and settlement of payments
Custodian Service Provider	administers the custodial holding of securities held by a customer, which includes making the necessary adjustments for sales and acquisitions as well as initiating the processing dividends, other corporate events, and reporting obligations
Payment Network Operator	operates the payment card network and orchestrates the activities related to the inclusion of new acquirers and issuers, their terms and conditions, and their status
Market Operator	captures the general capability to trade a principal position in the wholesale markets
Financial Information Provider	provides processes, filters, and individualizes financial market information and delivers them electronically to its customers
Products	
Product Developer	maintains and assesses coverage and relative performance/profitability of the full range of offered products and product combinations/bundles
Rating-/ Scoring-/ Market Data Provider	classifies the creditor into creditworthiness grades according to a credit logic/scoring, which indicates the creditworthiness/capability of a consumer
Credit Agency	determines the initial and ongoing values of the customer loan collateral (valuation)
Credit Manager	administers and manages loan products, takes over the credit business for other banks
Recovery Service Provider	deals with the recovery and realization of non-performing loans
Securitization Service Provider	administers the securitization process of loans, mortgages, etc.
Customer Account Operator	handles administrative activities, including the orchestration of consumer checking/demand deposit accounts with a typical range of services and fees
Payment Service Provider	manages the technical network connections and payment methods
Investment Service Provider	captures activities in the professional asset management of various securities (shares, bonds, etc.) and other (e.g., real estate) to meet specified investment goals of investors
Sales, services, and marketing	
Sales Manager	captures, classifies, and tracks a sales lead with established clients for additional products or services and provides specialist advice to customers for products and services on offer
Marketing Service Provider	develops the plan for and oversees advertising campaigns, including budget and resource management, involved in the sales planning and promotion processes
Customer Service Provider	captures, tracks, resolves, and reports on customer servicing issues
Data management	
Customer Data Provider	aggregates and maintains a comprehensive set of customer reference details, including demographics, administrative, KYC related properties, status and activity summaries
Customer Data Aggregator	operates the interface for importing data feeds from customers

Table IV.2-7: New roles in the current banking reference model

Role name	Functional description
Transactions	
IT service MSP	provides processing interfaces (data provision and retrieval) realizes cloud service integration and customization
Products	
Infrastructure Service Provider	provides streamlined end-to-end process technologies that are accessible via APIs for different products/services, e.g., customer authentication flows to downstream roles enables banking businesses to fulfill digital and, given a bank license, also compliant white-label financial services to their B2B customers that build their scalable banking products and services
Account Information Service Provider (AISP)	collects account information electronically on behalf of the customer/account holder directly from the account-holding financial institution provides consolidated and user-friendly information and overviews for the customer from multiple bank accounts (money management tools) enables customers to quickly and securely share financial information with a lender or broker (loan application tools)
Lending MSP	captures all activities related to digital platform offerings, which enable hybrid lending strategies and match borrowers and investors risk preferences
Investment MSP	brokers between customers and investment brokers provides investment strategies (social investing platforms)
Sales, services and marketing	
Sales MSP	offers comparison and brokerage services for either a wide range of banking products or with a focus on one specific product category, brokers between the customer and the traditional bank
Personal Finance MSP	realizes individual offers for customers based on analyses of account transactions provides support in managing, structuring, and planning finances of private/corporate customers includes tools for analysis of account turnover to improve liquidity management for private customers
Data management	
External Data MSP	provides a variety of valuable data from various sources integrates financial data of companies and public authorities in a data pool

Table IV.2-8: Meta-roles in the future banking reference model

Role name	Functional description
Transactions	
Transaction hub	provides the technical infrastructure for settlement of products and services (e.g., payment hubs) to a group of participating partners handles commission and billing of services across all participating partners
Products	
(Open banking) Product hub	provides open interfaces for contextual products and services, such as lending or investment hub services, operates the central customer account manages and aggregates third-party partnerships and ecosystem governance
Sales, services, and marketing	
Sales hub	provides the central interface to the customer, typically over an app or mobile OS, recommends suitable products and services or mediates them in advisory and comparison services as well as manages personal finances across different accounts offers an ecosystem of sales and service providers for contextual banking services
Data management	
Data hub	- manages data access across all partners, i.e., transaction, product, and sales hubs handles commission and billing of data services across participating partners

Table IV.2-9: Exemplary case list for strategic network moves in banking

Bank	Case	Role	Network move
ING	Yolt aggregator and payment	Personal Finance MSP, Payment SP	Acquisition
	Payvision	Sales MSP	Alliance formation
	Lendico	Sales MSP	Acquisition
	Flowcast AI-based credit decision process	Rating-/Scoring-/Market Data Provider	Tie addition
	Cobase multi-banking platform	AISP, IT service MSP	Tie addition
DWS	AI Arabesque AI-based portfolio management	IT SP	Tie addition
	White-label investment platform WISE	Investment MSP	Acquisition
	Edison white-label robo advisor	Investment MSP	Acquisition
	Neo Skyline AI	Investment SP	Tie addition
Deutsche Bank	SimCorp fund services platform	IT SP	Alliance formation
	Deposit Solutions	Sales MSP	Alliance formation
	QPLIX platform	Investment SP, Personal Finance MSP, Financial Information Provider	Alliance formation
	Motion Code Technology launched with Mastercard	Authentication SP	Alliance formation
Deka	Deka Net	Sales MSP, Financial Information Provider	Acquisition
	Bevestor	Investment SP	Acquisition
DZ Bank	VisualVest	Investment SP, IT SP	Acquisition
	IDNow identity service provider	Authentication SP	Alliance formation
	Figo	Open API Provider	Alliance formation
	TrustBills auction platform	Sales MSP, Clearing and Settlement SP	Alliance formation
	VR Finanzguide	Financial Information Provider	Acquisition
Commerzbank	Digital platform ONE	Customer Relationship Manager, Customer Data Aggregator	Acquisition
	Cooperation with WeltSparen	Sales MSP	Alliance formation
	Payworks	Payment SP	Tie addition
	Margeta	Infrastructure SP	Tie addition
	Mambu	IT SP	Tie addition
	Iwoca	Sales MSP	Tie addition
	GetSafe insurtech	-	Tie addition
BBVA	Prosper open gig worker platform	Sales MSP	Acquisition
	Wollit	Personal Finance Manager	Tie addition
	Holvi	Customer Account Operator	Acquisition
China Merchants Bank	CMB App, CMB Life App	Customer Data Aggregator	Acquisition
	SWIFT Analytics	Financial Information Provider	Alliance formation
	OneSumX regulatory reporting	Finance and Risk Manager	Alliance formation
	Interbank Service Gateway platform	IT SP	Acquisition
	Tencent Cloud Services R&D	IT SP	Alliance formation
	CMB cash management solution	Finance and Risk Manager, IT SP	Acquisition

Bank	Case	Role	Network move
JP Morgan Chase	Co-branded credit card products	Card Provider	Tie addition
	ChaseNet	Payment Network Operator	Acquisition
	InvestCloud robo advisor	Investment SP, IT SP	Alliance formation
	Interbank Information Network IIN	Market Operator	Acquisition
	Multi-asset portfolio analytics solution for asset managers	IT SP, Finance and Risk Manager	Acquisition
	Persado marketing AI	Marketing SP	Alliance formation
Nedbank ZA	OML infrastructure services	Processor	Alliance formation
	Ecobank / Nedbank Alliance	AISP	Alliance formation
DBS	CUBE for regulatory compliance	Finance and Risk Manager	Tie addition
	Hyper Anna AI Bot	Financial Information Provider, Customer Data Aggregator	Tie addition
	Dov-E for mobile push notification services	Payment SP	Tie addition
Sberbank	Sbercloud	IT SP	Alliance formation
	Payment Solution for Social Messenger including a financial planning system	Payment SP, Personal Finance MSP	Alliance formation
	AI Telekom	External Data MSP	Alliance formation
	Fintech API	Infrastructure SP	Alliance formations
Westpac	Moven data analytics platform	Personal Finance MSP, Customer Data Aggregator, Payment SP	Alliance formation
	Assembly payments platform	Payment SP	Alliance formation
Rabobank	Rabo APIs	Infrastructure SP	Acquisition
	SurePay	Payment SP	Acquisition
	White-Label Treasury Platform TreasurUp	IT SP	Alliance formation
PingAn Bank	Payroll, CashierPal	Payment SP	Acquisition
	Automatic investment plan to funds	Investment SP, Personal Finance MSP	Acquisition
	Interbank E-Express	IT SP	Acquisition

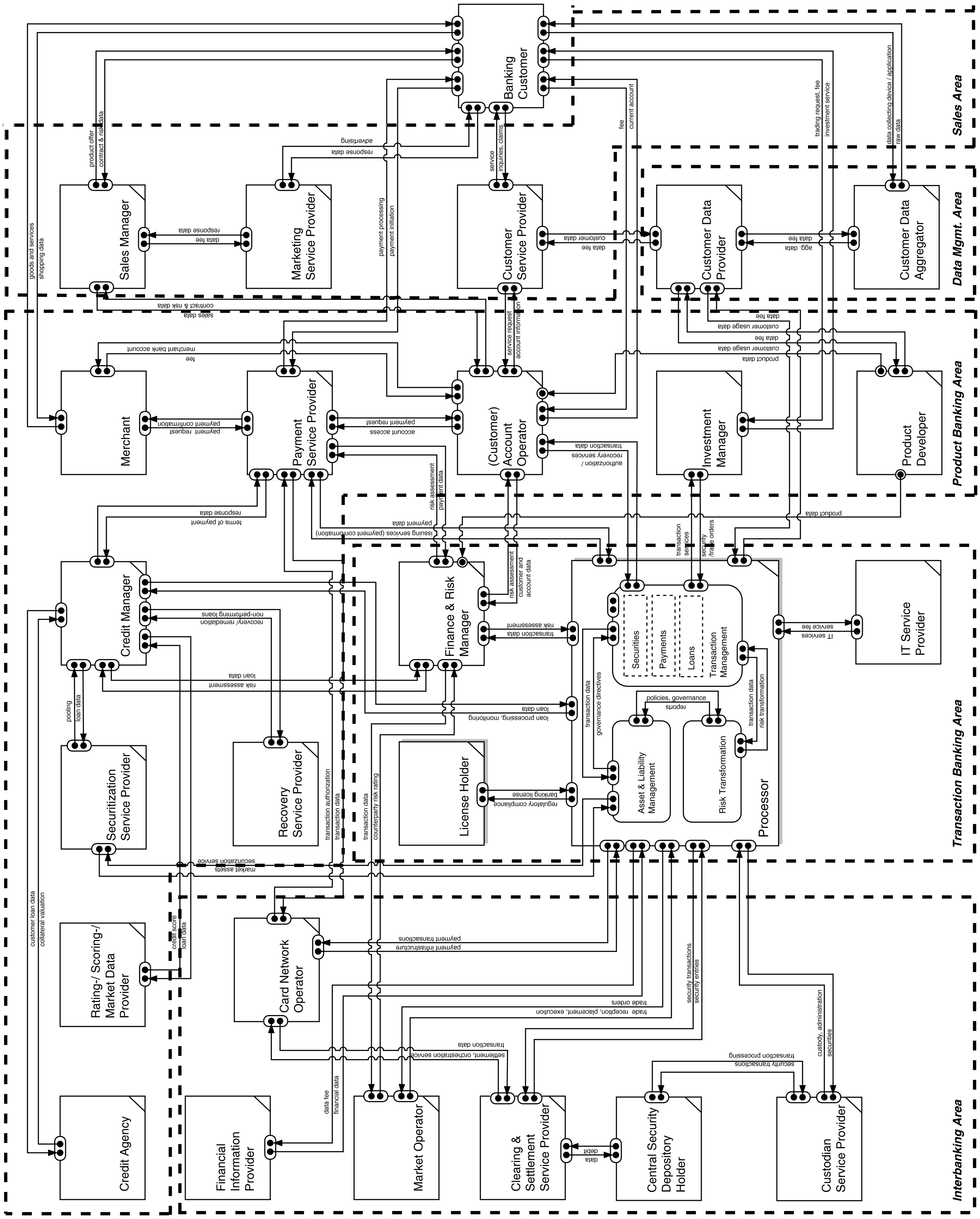

Figure IV.2-9: Traditional banking areas (bold dashed lines)

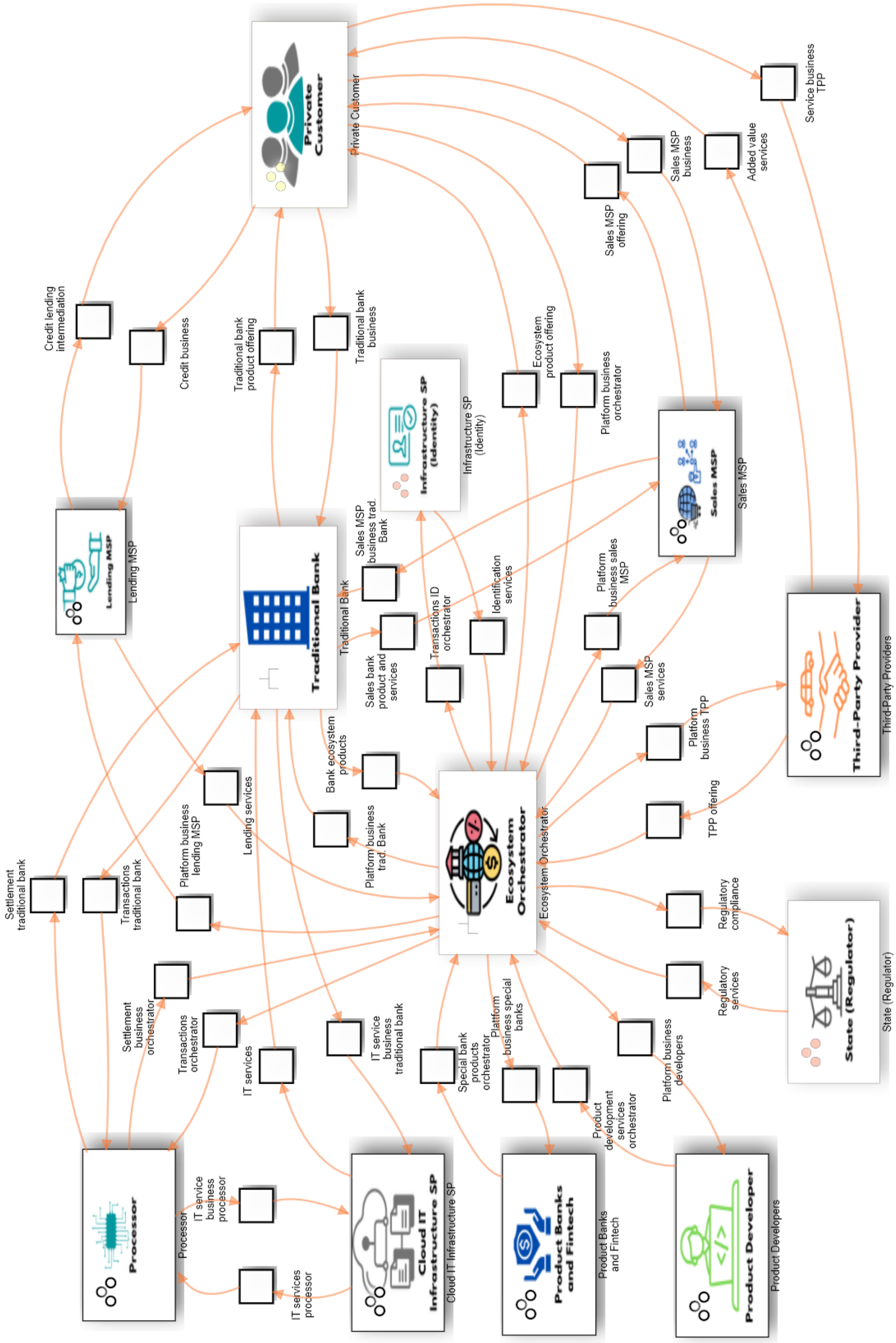

Figure IV.2-10: Ecosystem map of the banking platform ecosystem

V Conclusion

V.1 Synthesis of results

In the following, I summarize the key findings of my dissertation in response to the research questions on the digital transformation (DT) of incumbent organizations.

Regarding the first set of research questions (*i.e., the DT causes*), I identified the influencing factors and digital paths to banking products and services for CDM in digitalization (*Paper II.1*). I revealed changing customer expectations in the Fintech environment and new access paths to banking, which point more strongly to recommendation marketing and the influence of the social environment in the digital realm. In doing so, I elaborated on a resulting novel decision-making mechanism which leads to the shortening of the buying process and takes the customer directly to the decision-making stage by providing precisely matching product and service offerings.

I uncovered the preferences of German banking customers by using the example of checking accounts (*Paper II.2*). Our results indicate an overall traditionally oriented customer behavior. A large traditional product-innovative customer segment was identified that would opt for digitalized (i.e., data-driven) checking account offerings. I demonstrated the preferred mix of traditional and digital service attributes, which indicates that, in addition to digital product innovations, human banking expertise remains in demand among German customers. I highlighted the new Fintech provider's increasing importance, providing purely digital product access, digital product innovation, and a strong customer service experience for the Fintech customer segment. The results show a lower pragmatism, i.e., usefulness orientation, of these customers and the impact of subjective norms on the Fintech customer segment. The value orientation was identified as a preference-forming influencing factor that advances traditional attribute characteristics concerning traditionally oriented customer segments. Trust was identified as a contributor to the choice of traditional providers and as a prerequisite for the use of digital account services. Market mavenism points to the value of professional banking expertise rather than pure digital innovativeness. The growing necessity of banking product digitalization among the largest traditional product-innovative segment and the fintech customer segment can be concluded from the detailed characterization of customer segments, as well as the more fine-grained analyses.

I identified a set of characteristics as drivers for the changing business models and market power of providers in DT in the study of smart product-service systems (PSS) (*Paper II.3*). These systems, for example, lead to the hierarchization of products and services and create an intermediation effect based on data collection and analysis, and coupling control, especially in B2C industries such as banking. Smart home devices with interfaces for voice (i.e., conversational) banking are a typical example. The descriptive analysis has revealed an overall low maturity of smart PSS for B2C business models so far. Overall, I identified an evolution from the stand-alone smart PSS for sales purposes, the complementary bundling and cross-selling smart PSS, the external ecosystem solution providers, and remote usage and monitoring smart PSS to the intermediary product as a point of sales and advertising smart PSS. The paper's outcome serves both scholars and practitioners as a tool for analyzing the compatibility of empirical smart PSS configurations and business model patterns.

Regarding the second set of research questions (*i.e., the effects of DT*), digital strategies of financial service providers could be classified along with their level of firm performance (*Paper III.1*). The different standard types uncover the asymmetric relationships between the degree of DT (i.e., digital maturity level) and firm performance, leading to a strategic competitive disadvantage for smaller and less digitally mature financial service providers. By contrast, international developments show that platform ecosystems are used as a lifeline on the path to proprietary product and business model innovations. Hence, they represent a transitional state to the innovative digital pioneers. In this context, the phenomenon of facade digitalization was substantiated, which consists of structurally disadvantaged banks. These banks have increasingly converted their interaction with customers to digital sales channels (such as mobile apps) but have not associated any new business models and revenue sources with them and have not yet comprehensively digitalized the underlying processes and systems. The findings also show that many financial services providers are implementing a more data-driven digital strategy via introducing a chief digital officer (or equivalent) role. However, incumbents are not yet structurally comparable with Fintech, even among the innovative financial service providers, since the transition to a digitalized core has not been fully achieved.

The further analyses show the occurrence of the productivity and profitability paradox, which cannot be resolved as long as there are no success effects of value creation and value proposition dimension in savings banks (*Paper III.2*). Although these banks have structurally downsized facing digitalization, they have not become more productive and profitable due to DT measures over time. Hence, a primary customer interaction-focused approach without implementing a holistic digital strategy reduces firm profitability instead, as demonstrated by the longitudinal panel regression analysis of the business development of German savings banks.

In this regard, the introduction of novel digital technology for customer advisory is linked to an increasing standardization and automation of banking (*Paper III.3*). In the analysis, the reorganization of customer advisory services at savings banks showed reduced task variety and increased job autonomy associated with the sales and service co-creation approach. Here, I uncovered the threefold impact of IT support in customer interaction on salespeople's job satisfaction in savings banks. My analyses showed the direct positive impact of the core banking solution on job satisfaction, provided it positively supports customer interaction from the customer advisors' perspective. Given that increasing standardization as part of the DT harms the perception of job meaningfulness and, subsequently, diminishes job satisfaction among customer advisors, I found that supportive IT can dampen or even eliminate this negative effect. In addition, IT support in customer interaction can lead to a better perception of feedback from the job and improve job meaningfulness and satisfaction. IT support in customer interaction in face-to-face settings, as common in banks with lower levels of digital customer interaction, also positively impacts customer proximity, which, in turn, increases job meaningfulness and satisfaction. Process flows, data availability, and advisory interfaces were identified as key drivers of IT support in customer interaction. Given the widespread and well-studied relationship between job satisfaction and job performance, the analysis indicates that digital technology implemented in appropriate workflows plays a crucial role in harmonizing the economic (cost-oriented) and organizational (value-oriented) interests for future banking.

Regarding the third set of research questions (*i.e., the solution paths in DT*), I developed a consolidated taxonomy of data-driven business models (*Paper IV.1*). This taxonomy highlights the building blocks of data-driven business model innovation for incumbents in DT across the three dimensions of value creation, value proposition, and customer interaction. Overall, I identified a low maturity of data-driven business model change in B2C industries such as banking.

Concerning the second key technology, digital platforms, I demonstrated the effects of the platform economy on banking (*Paper IV.2*). To this end, a reference model of banking along three phases was developed based on the literature, established banking industry frameworks, and international case studies. The model shows the essential roles and activities of centralized, platform-based banking along with options for incumbent action at the B2C customer interface. Based on the role models, I highlighted future actor constellations of value co-creation in platform ecosystems. I exemplified the implications of the market entry of Bigtech actors using the example of B2C payment and identity platform ecosystems. In this regard, the business model opportunities and risks for traditional banks could be modeled, deriving four strategic archetypes. The artifacts have been discussed and evaluated with industry representatives. The findings highlight the potentials of data analytics and platforms for preserving and stimulating the business of incumbent banks in DT.

V.2 Contributions

Overall, my dissertation sheds light on the tensions between incumbent banks' old and new value creation paths in DT. The individual paper contributions have been highlighted in the articles. I summarize six research contributions in the following.

Firstly, the dissertation contributes to research in the area of customer behavior in DT, moving beyond the technology acceptance model. Online consumer reviews were systematized for this purpose and the purchase decision process was derived with the effects of digitalization. The findings provide researchers with a basis for studying specific intermediation effects in the future. Using an experimental design, I uncovered the impact of influencing factors and the underlying segments among German customers for checking accounts, a typical example of a trustworthy banking product. The quantitative analysis of service attributes and personal influencing factors combined in an experiment also makes a methodological contribution to IS research.

Secondly, the thesis contributes to sparse research in the area of incumbents' DT strategies. A set-theoretical research method was applied in the contexts of business model and digital strategy analyses and for standard type derivation. I established facade digitalization as one standard type that lacks a holistic strategic response to DT. Arguably, the facader standard type could also be present among incumbents from other B2C industries, as it enables the fastest possible response to the immediate challenges of DT for customer interaction but does not entail a sustainable long-term digital strategy. This type of analysis can also be used to determine other strategic types in the future.

Thirdly, the thesis also highlights the specific challenges faced by small and medium-sized firms, such as the savings banks, which have tended to be underrepresented in DT research so far. Notably, the findings reveal the contradictory impact of digitalization on central business figures for this particular banking group.

Fourthly, the dissertation also contributes to the research stream on digitalized work settings. I disentangled the relationships between job characteristics, IT support in customer interaction, and employee job perceptions using the example of banking customer advisory. The findings highlight the threefold impact of digital technology on job satisfaction within digitalized job designs for banking.

Fifthly, the dissertation contributes to the evolving discourse around smart products and services and the taxonomy development research on data-driven business models.

Finally, the dissertation extends enterprise modeling research on platform ecosystems and value co-creation using the example of banking, modeling the platform economy impact on incumbents with the entry of Bigtech market actors. The role-based e3-value modeling is extended by meta-roles and role segments and linked to additional modeling views in VDML, enabling business model development and analysis for the platform economy.

V.3 Practical implications

Some important practical implications can be derived from the research results, which have been discussed in detail in the individual papers. I take up five key messages to bank practitioners as follows.

Firstly, digital intermediaries that establish smart products and services can occupy the central customer interface in banking based on ecosystem control and data analysis capabilities. Traditional banks are advised to be aware of the new digital decision paths of customers. Regarding this, traditional marketing and sales are at risk of failing if competitors reach customers directly and initiate tailored offerings in the digital realm (e.g., need/arousal when buying a car and subsequent offerings of loans for car financing).

Secondly, traditional banks must develop digitalized forms of banking services (value creation) and new revenue models (value capture) that meet the needs of the digital-affine customers, i.e., are integrated into customer journeys. Bank challengers participate in value creation via interfaces (cf. mobile payment and identity services). Therefore, the key lies in embedding banking services in the digital purchase decision paths as well, starting from the need and arousal of customers to processing the recognized demands via role-based business activities and processes in the ecosystem, including external partners.

Thirdly, strategic archetypes should correspond with bank strategic goals and competencies so that the roles chosen and value creation activities could contribute to the banking ecosystem. Hence, strategy development must take the overall ecosystem value into account. Such an ecosystem will extend beyond banking in the future and connect digital banking products to primary use cases of customers.

Fourthly, data-based products should be introduced to serve the segment of digital product-innovative customers. Data-driven business models could become the extended arm of customer advisory services, especially in the standardized retail banking business. Given the intense platform competition, customer service experience and professional expertise could firstly compensate for current disadvantages regarding data analytics capabilities due to lower interaction frequencies on emerging platform ecosystems.

Finally, traditional banks should not abandon traditional business model components, such as human on-site business capabilities. The personal advisory business continues to drive banking relationship earnings as professional expertise is still a valuable asset. A lot of customers still prefer a hybrid banking model including digital and human operations, therefore, customer advisory specialists should be supported by IT in customer interaction to integrate them into standardized workflows for customer co-creation in the digital age.

V.4 Limitations

Certain limitations and corresponding further research options result from the data availability and quality and the methodological approaches chosen.

Online consumer reviews are indicative of customer purchasing experiences for banking products in online environments. Hence, the online review data constitutes a representative subsample of possible digitalization influences primarily on purchasing decisions in the online environment. However, I also integrated online reviews for offline purchase experiences in banking.

The preferences stated were used in the discrete choice experiments to analyze, ex-ante, hypothetical future customers' purchasing decisions. The results should be confirmed in the future by conducting revealed preference studies or other ex-post studies on customer behavior in which the corresponding situational factors of real purchase decisions are explicitly taken into account. Similarly, further drivers, such as the purchase path to the product or the service usage behavior, should be investigated in the future.

Concerning the standard type derivation in fsQCA, multi-year case study data on DT strategies, i.e., observations over time, would be helpful to confirm and extend the robust standard types. A researcher's subjective influence can never be ruled out in case study analyses. I countered this issue by involving independent coders and using an interrater reliability assessment.

Furthermore, the panel regression analyses of annual reports are based on data derived by innovative text mining methods, which cannot replace data obtained via surveys (if these can be obtained over such long periods). However, despite the methodological limitation of automated data collection, which could impact the reliability of the analysis, the annual report data provides the potential advantage of increased validity due to the greater objectivity that the public disclosure in annual reports entails. The analysis should be reapplied to recent annual report data and market actors beyond the savings banks to confirm or expand the results.

Concerning the survey data obtained, good responder and common method biases can never be completely ruled out. However, I guaranteed the employees' anonymity and considered method variance issues ex-ante and ex-post. Moreover, the taxonomy development reflected the respective state of research and practice on smart products and services as well as data-driven business models. Future market developments could provide new categories.

Regarding enterprise modeling, abductive theoretical conjectures were developed for future market developments. Scenario planning helped encounter market development uncertainties. The prospective reference model is based on established industry frameworks in banking, the study of the relevant literature, case studies from the banking industry, including its relevant adjacent actors, and in-depth discussions with practitioners.

V.5 Future research

Future research options have already been highlighted in the respective contributions. Researchers should study the positive and negative impact of DT further along its progress (Vial 2019). Five central ideas are presented in the following based on the findings of the thesis.

Firstly, it is conceivable that an optimal mix of digital and non-digital value creation activities can be found for incumbents, given the different customer preferences identified for banking. Regarding this, future research should closely examine the strategic fit between business model configurations and customer behavior in platform ecosystems beyond banking. Scholars could test the multiplicity of DT strategies under various environmental conditions, including consumer-based factors. Research could examine the appropriate alignment of structural prerequisites, environmental factors, and DT management that will influence firm performance. Scholars could test whether the propositions established in the fourth paper hold for other industries and under which conditions. In this regard, standard types other than the established facader are probably conceivable in addition to banking.

Secondly, value co-creation research could study the mutual influence of roles and actors over time as modeled in the future banking platform ecosystem. Traditional IS alignment research assumed that the probabilities of all possible environment states are constant and known to the actor (Henderson and Venkatraman 1993). However, DT entails unknown and conflicting properties of the fast-changing external environment. Research agendas have been published on this (Benbya et al. 2019; Chan and Reich 2007; Coltman et al. 2015; Gerow et al. 2014; Niederman and Salvatore 2019). Cross-case analyses provide a related opportunity to study the value creation trajectories from banks and Fintech towards platforms ecosystems.

Thirdly, future research could elaborate on how DT strategies can best integrate stakeholder needs, wants, and interests. Value co-creation, for instance, requires collaborative work between the actors involved to realize functional, emotional, social, ecological, or traditional economic goals (Taylor et al. 2020). Customers might strive for convenience and innovative products, while society might opt for sustainable, accessible, and privacy-compatible services (Oesterle 2014). The legislator and governments might force regulation and public supply. As the banking customer advisory study showed, employees may have ambitions to achieve a work-life balance, including meaningful and satisfying work settings. Prior research has revealed the competing concerns within incumbent organizations (Svahn et al. 2017; Dehnert 2020a). In this context, it is intriguing to examine how incumbents can find consensus more effectively in the digital strategy development and implementation process, including goals, value creation activities, and technology. Future research could take a strategy-as-practice lens to focus on the activities across organizations to manage these concerns effectively (Barley 2007; Hughes and McDonagh 2021). In this regard, the leadership and control approach necessary to achieve value creation and appropriation in hybrid traditional and meta-organizations such as platform ecosystems is a related topic to explore further in IS research (Wiener et al. 2019; Dehnert and Santelmann 2021).

Fourthly, digital strategy implementation is an exciting follow-up field for research. Technological opportunities in digital strategy must be considered a central means to enhance value creation and capture. Digital infrastructures, such as platform and cloud architectures, are the fertile ground implemented in technology planning, connecting all value creation activities to data (Iansiti and Lakhani 2020, pp. 53 ff.). Hence, the interplay of conceptualizing and enacting digital strategy and the feedback loop to reconceptualize a strategy is interesting to study (Weiser et al. 2020). The structural DT paths developed in the third part of the dissertation should be examined in more detail for the evolving banking industry, such as developing data-driven business models and participating in platform ecosystems. Uniformity is critical because DT is a rather lengthy process that must be performed in parallel with existing operations. The sum of DT activities results in polysynchronicity, which DT management must translate into a coherent, uniform action program (Kunisch et al. 2017). Here, the fsQCA method is promising to analyze the multiple paths of DT at incumbents.

Finally, another research avenue is the study of technology and process integration based on my findings. I highlighted several new value creation roles and activities in future digital banking. Banks need to integrate digital technology in their processes to become their customers' preferred digitalized financial partner. This means, they have to tackle the inherent knowledge and complexity problems of DT (Townsend et al. 2018). Hence, further research needs to explore risk management, customer acquisition, and customer advisory in large scale data-driven banking. Robo advisory is one relevant product and service type that is currently based on financial mathematical models rather than large-scale data analytics. Another challenge for incumbents in DT is to link their physical and digital businesses (Adner et al. 2019; Recker et al. 2021; Wang 2021). Scholars should study customer journeys beyond single enterprises and the implementation of the value creation activities in processes towards hybrid customer interaction (Nüesch et al. 2015). Therefore, studying technology and process integration is highly connectable to our enterprise modeling artifacts for platform ecosystems in banking.

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Appendix

The original submission entailed an attached data medium with the thesis, figures, data sets, and the published articles. Also included were the co-authorship statements, proof of attendance at doctoral colloquia, and an author's affidavit and consent form.