AFFECTIVE RESPONSES DURING EXERCISE AND SITUATED EXERCISE-RELATED DECISION-MAKING

Theoretical and Methodological Advancements Towards a Better Understanding of Exercise Behavior

by

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Dissertation

Faculty of Human Sciences

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Acknowledgement

The motivation for the topic of this dissertation originated from the feeling I repeatedly experience while working out: How can more people experience this exhilarating feeling and choose to exercise with ease and joy?

This motivation helped me to continue with this dissertation when the ease and joy left me, but even more important were the people who supported me to push the limits!

You know who you are - thank you!

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1 Preface

This thesis entitled “Affective responses during exercise and situated exercise-related decision-making” contains the synopsis of my dissertation, as required by the Faculty of Human Sciences at the University of Potsdam. Based on research conducted at the Department of Sport and Health Sciences, Sport and Exercise Psychology, University of Potsdam, this dissertation comprises of three publications. It presents a framework for the relationship between the three publications and elaborates on the underlying theoretical considerations and the resulting implications. The publications are briefly described and the main results are summarized. Finally, methodological and theoretical implications are presented.

"Knowing is not enough; we must apply. Willing is not enough; we must do."
Johann Wolfgang von Goethe

2 Situated processes in exercise behavior: Outline of the research program

The question "Why do individuals fail to maintain an exercise routine?" is not a new one. To illustrate this long-known yet still unresolved problem, let me start with an example that may be familiar to many individuals: First of January, you started the new year with good intentions to exercise more. This time, you are sure it will work out. You are motivated, you have a clear, smart goal, social support, and the best of intentions - what should go wrong? For a couple of weeks, things go according to the plan. Sometimes, you have to convince yourself, but you keep exercising. But then, life happens. First, you cannot manage to get yourself up just once, then once turns into twice, and before you realize it, you are spending your evenings on the couch more often than at the gym. What happened?

The reasons for this can be manifold, but they have one thing in common: *in-the-moment* of choice, a behavioral alternative was preferred over exercising. These choices[1] are referred to as *situated decisions*, meaning that each choice is contextualized within an individual's environment, including processes evoked by all available behavioral alternatives as well as one's current affective state.

The worldwide high prevalence of inactivity coupled with evidence from meta-analyses indicates that previous theory-based interventions have not been successful in increasing exercise behavior in a sustainable and meaningful way (Brand & Ekkekakis, 2021; Gourlan et al., 2016). One possible reason for this might be a one-size-fits-all approach that relies on universal socio-cognitive factors (e.g., goals and self-efficacy) but neglects the

[1] While the terms choice and decision have been used interchangeably in the literature, this work distinguishes between 'choice' as being faced with a multitude of options and 'decision' as the final selection (Cambridge Online Dictionary, 2023). The resulting behavior will always be the consequence of at least some deliberate decision-making, while the choice process, reaching to that decision might not be. The term 'situated decisions' has been introduced by Brand and Schweizer (2015) as a proper noun and will therefore be used accordingly.

influence of individual affective processes in situated decisions (Brand & Ekkekakis, 2021; Lachman et al., 2018).

Exercise psychology is concerned with the psychological factors that predispose individuals to avoid or engage in exercise behavior and the impact of exercise on mental health and well-being (Box et al., 2021). This dissertation identifies current challenges within this field (Chapter 3) that may contribute to why much of the variance in exercise behavior remains unexplained and why previous interventions have been largely unsuccessful (Ekkekakis, 2017). The publications in this synopsis address these challenges by incorporating existing methodological and theoretical approaches within exercise psychology and extending them in selected areas. These approaches include examining momentary affective states, situated processes and exercise behavior, on the one hand, and providing alternatives to self-reported measures and more comprehensive modeling and accounting of individual variability, on the other hand. Thus, the value of the three publications lies in targeting specific research gaps and expanding current boundaries within the field of exercise psychology. Future research can benefit from new methodological approaches and theoretical insights regarding the modeling and measurement of affective and situated processes, as well as the conceptualization and operationalization of exercise behavior.

Specifically, this dissertation aims to investigate individual (affective) processes connected to exercise experiences that reappear in situated decisions when faced with the choice to exercise while in a state of inactivity. One theory particularly concerned with the concept of situated decisions is the Affective-Reflective Theory of Physical Inactivity and Exercise (ART; Brand & Ekkekakis, 2018). Based on the Dual-Mode Theory (DMT; Ekkekakis, 2003) and empirical findings on the affective consequences of exercise (e.g., Williams et al., 2008), ART assumes that affective experiences made during exercise leave traces in memory and influence subsequent exercise behavior.

Publication one (Chapter 4.1) addresses how self-reported affective responses during exercise covary with signals of the body (facial actions) while taking into account intra- and interindividual variations in these measures. In addition to commonly used experiential self-reports (Feeling Scale: Hardy & Rejeski, 1989; Borg Scale: Borg, 1998), automated facial action analysis was applied to continuously measure changes in facial configurations.

The ART focuses on the moment when these affective experiences are assumed to reappear as an automatic affective valuation; for example, when an individual is confronted with the choice to exercise, i.e., a situated decision. Publication two (Chapter 4.2) focuses particularly on the concept of situated decisions and the processes occurring in-the-moment of choice. Through the use of eye-tracking and mixed-effects modeling, the influence of intraindividually varying processes (e.g., situated processes related to the specific behavioral options) are distinguished from interindividual processes that are rather stable within an individual (e.g., reflective evaluations of exercise).

While publication two focuses on the processes that occur in-the-moment of choice, less is known about how these translate into overall exercise behavior. Individuals must repeatedly choose exercise over other behavioral alternatives - such as going to the movies - in order to develop and maintain long-term exercise behaviors. Therefore, establishing a long-term exercise routine involves more than just a change in overt behavior; it also requires a change in psychological processes underlying repeated exercise-related decision-making (Dunton et al., 2022). To date, there is a lack of measures that operationalizes exercise behavior on a theoretical basis, i.e., as the result of situated decisions.

Publication three aims to fill this research gap by developing an open-source based adaptive research tool to measure *Decisional Preferences in Exercising* (DPEX) where participants have to indicate their preferences in a series of choices between an exercise and a non-exercise behavioral alternative. To test the theoretical underpinnings, correlations of the DPEX with overall exercise behavior and past exercise experiences were tested.

In the following, I first outline the challenges exercise psychology is currently facing (Chapter 3) and then discuss how the theoretical approaches and empirical work of this dissertation address them (Chapter 4). From this, methodological and theoretical implications will be drawn (Chapter 5), followed by a conclusion (Chapter 6).

3 Exercise behavior: Current challenges

Exercising can be defined as a “subset of physical activity that is planned, structured, and repetitive and has as a final or an intermediate objective the improvement or maintenance of physical fitness” (Caspersen et al., 1985, p. 126). From a behavior change perspective, it is important to distinguish physical activity - which includes all kinds of physical movements such as walking for transportation - from exercise, as exercising requires more effort to implement in daily life.

The World Health Organization (WHO) recommends individuals engage in at least 150-300 minutes of moderate intensity activity or at least 75-150 minutes of vigorous intensity, or an equivalent combination (Guthold et al., 2018). Numerous studies have provided substantial evidence for the health benefits of engaging in regular physical activity. Physical activity not only aids in preventing overweight and obesity (Jakicic et al., 2019; Lee et al., 2010) but also plays an important role in preventing noncommunicable diseases such as cardiovascular disease, cancer, diabetes (Anderson & Durstine, 2019) and mental health (Schuch & Vancampfort, 2021). While the beneficial effects of regular exercise are generally accepted and widely known (Fredriksson et al., 2018), 27.5 % of adults and 81 % of adolescents do not meet the WHO-recommended level of physical activity and exercise (Guthold et al., 2020). These self-reported data may even underestimate the problem of physical inactivity, as objective assessments with accelerometers suggest a prevalence of adequate physical activity between 3.2 % (Tudor-Locke et al., 2010) and 9.6 % (Tucker et al., 2011) in the United States. Despite the wealth and sophistication of approaches to promote exercise (e.g., Ntoumanis et al., 2018), these activity levels have been stagnating or even increased in high-income countries (from 27.1 % in 2001 to 37.2 % in 2022) (Guthold et al., 2020).

In the following, I will expand upon reasons why research has not been effective in developing successful long-term interventions. To this end, I present previous theoretical approaches and current research gaps. Specifically, the misconception of the human as a rational decision-maker, the uniqueness of exercise as a variable somatic-affective experience that influences situated decisions, and methodological shortcomings are discussed.

3.1 A critical evaluation of the rational decision-making assumption

Major theories of health behavior change, including those applied in exercise psychology, were strongly influenced by the "cognitive revolution" (Simon, 1991), placing a strong emphasis on individual differences in mental concepts such as goal-setting or self-efficacy to change behavior (Rhodes et al., 2019). Well-known proponents of the social-cognitive and humanistic frameworks, such as the theory of planned behavior (TPB; Ajzen, 1991) and self-determination theory (SDT; Deci & Ryan, 2012), assume that behavior change is achieved by altering an individual's belief or knowledge. Exercise psychology, the science of the effects of exercise on mental health, and the underlying mechanisms (e.g., psychological processes) of why people exercise, first emerged in the late 1960s, when the cognitivist perspective was the dominant framework. Following the conceptualization of the human as a rational decision-maker, a standard public health approach for changing exercise behavior aims to provide correct, complete, and compellingly presented information about the benefits of exercising and how to implement them (Ainsworth & Macera, 2018; Pate et al., 1995). However, considering that about 40 % of premature deaths in the United States are the result of personal lifestyle decisions (e.g., eating, exercise), individuals may not always be rational decision-makers (Keeney, 2008). This is supported by meta-analyses showing that constructs based on the social-cognitive or humanistic framework explain only 33 % of the variance in physical activity, and have not been able to increase the amount of exercise or physical activity in a meaningful and sustainable manner (small-to-medium effect sizes, between $d = 0.25$ and $d = 0.37$; Gourlan et al., 2016). This proportion may even be upwardly biased, as most studies employed self-reported measures of both the predictor (e.g., self-efficacy) and the outcome (e.g., exercise behavior), possibly inflating the size of the correlation due to a common method bias (Podsakoff et al., 2003).

A common theme among recent attempts that critically assess and extend the current theoretical approaches seems to be that previous theories of behavior change in exercise psychology have overemphasized the role of rational decision-making while disregarding the importance of affective processes in motivation (Brand & Ekkekakis, 2018; Cheval & Boisgontier, 2021; Conroy & Berry, 2017; Strobach et al., 2020; Williams et al., 2019). This has led to the development and increasing popularity of dual process theories in exercise psychology, such as the ART, stating that in addition to a more rational and deliberate process, behavior is influenced by automatic affective processes.

3.2 The role of reactivated affective processes in exercise-related situated decisions

Exercise differs from other health behaviors (such as eating) in that it evokes potentially unpleasant physical states with variable affective responses that can lead to homeostatic perturbations (Rhodes & Nigg, 2011). Quigley et al. (2014) described exercise as “perhaps the most-well-characterized way to manipulate peripheral physiological arousal producing an affective change” (p. 229). This experience plays a crucial role when an individual is faced with the choice to exercise or remain in a state of inactivity, as the somatic experience of exercise is assumed to reappear as an automatic affective process in this moment (Brand & Ekkekakis, 2021). There is accumulating evidence that automatic affective processes play an important role for future exercise behavior in addition to rational processes (e.g., Brand & Ekkekakis, 2018; Conroy & Berry, 2018). However, past systematic reviews and meta-analyses have revealed only small-to-medium effects for the relationship between automatic processes and exercise behavior (Chevance et al., 2019; Schinkoeth & Antoniewicz, 2017). One possible explanation is that most studies measured general automatic processes towards exercise across a wide range of possible activities rather than processes towards specific exercise types. Two studies that actually examined specific exercise types concluded that individuals do indeed have exercise type-specific automatic processes (Antoniewicz & Brand, 2014; Limmeroth & Braun, 2022). In addition, most of the existing studies predicted a rather distal behavioral criterium (e.g., self-reported exercise behavior or step count) from these basic information processes. Exercise-related automatic affective processes are theorized to influence exercise behavior through a continuous interplay with reflective evaluations in situated decisions (Brand & Ekkekakis, 2018). At this moment, not only are the stored experiences with exercise relevant, but also the current affective state and how we feel about the behavioral alternative. To better understand the individual processes for particular behavioral alternatives in different situations, experimental paradigms that capture situated processes happening in-the-moment of choice are needed.

The idea of situated decisions has already been recognized by the ART, but yet to be empirically tested in exercise psychology. This is partly due to a lack of suitable measures and statistical methods that are able to capture momentary intra- and interindividually varying processes. This methodological gap will be discussed in the following section.

3.3 From self-report measures and stable dispositions to process tracing methods and individual variability

In general, exercise psychology has a strong emphasis on self-report measures and cross-sectional approaches that allow conclusions about rather stable dispositions (e.g., traits such as personal beliefs or attitudes) to explain differences in individuals' exercise motivation (e.g., Biddle et al., 2007; Teixeira et al., 2012). This favors the investigation of cognitive variables (e.g., self-efficacy) but has limited ability to capture the dynamic variability of somatovisceral and automatic affective processes (e.g., current affective states).

When it comes to measuring affective processes, in addition to the general disadvantages of self-report measures (such as social desirability bias), relying on only one measure can be problematic. Besides the risk of a common method bias (Podsakoff et al., 2003), self-reported measures can induce cognitive or reflective processes thereby violating according to Ekkekakis (2013) “the most crucial defining attribute” of core affect. Core affect is defined as “a neurophysiological state consciously accessible as a simple primitive nonreflective feeling” (p. 104; Russell & Feldman Barrett, 2009) accompanied by activity in the autonomic nervous system, as well as facial and vocal changes (Russell, 2003). Core affect is a dynamic phenomenon that unfolds and changes over time (Ekkekakis, 2013). Self-reported measures are limited to momentary states and, thus, cannot provide a continuous measurement of the entire affective experience. Quigley et al. (2014) recommend that more than one measurement modality should be used to measure instances of affective states because subjective reports, physiological measures, or behavioral observations may reflect different aspects of the construct.

It has been increasingly recognized that to get a realistic picture of affective responses to exercise, it should be measured continuously during the exercise bout, not just before and after it (Ekkekakis et al., 2008). Studies that took this into account revealed a reliable dose-response pattern (i.e., a negative quadratic decline of affect with increasing intensity) with marked inter- and intraindividual differences (Ekkekakis et al., 2011). Statistical analyses investigating these changes, however, have usually followed a general linear modeling approach with repeated-measures analyses of variance (RM-ANOVA; e.g., Box & Petruzzello, 2020). Instead of modelling individual trajectories, this approach aggregates data at the group level. This can be misleading when individuals differ in terms of their direction of change (e.g., one experiences more positive affect, whereas the other experiences more negative affect) and does not allow for the inclusion of continuous predictors. A wide range of studies have shown that individuals exhibit substantial variability in their responses and that both inter- and intraindividually varying variables influence how we feel during exercise (Bourke et al., 2021). This underscores the need for statistical methods, such as mixed-effects modeling, to simultaneously model these influences.

Similar considerations apply to the measurement of exercise-related choice processes. So far, research on exercise-related decision-making has largely focused on decision outcomes rather than the processes leading up to the decision (e.g., Antoniewicz & Brand, 2016; Harris & Bray, 2021). In health behavior research in general, it has been argued that a more process-focused approach is needed to understand how various processes (e.g., cognitive and automatic affective processes) interact in the moment that a choice is made (Berkman, 2018). Exercise psychology research requires measures that can capture continuous processes during decision-making to reflect the underlying (automatic affective) processes. At the same time, statistical methods that are able to model individual choices across different situations (idiographic approach) are needed in addition to identifying patterns of differences between individuals (nomothetic approach).

With regard to the measurement of physical and exercise behavior aside from self-reported measures, objective measures (e.g., accelerometers) have also been applied. However, in the past, these have shown only low levels of agreement with self-report measures and may reflect only a certain aspect of a person's actual behavior (Armstrong & Bull, 2006). One reason for this may be the way in which exercise behavior has been conceptualized and operationalized to date. Commonly used measures are one-dimensional continuous variables (e.g., weekly amount of exercise) that cannot adequately reflect the complex multidimensional nature of this behavior (Seelig & Fuchs, 2011). In order to examine how exercise behavior can be changed long-term, measures that are based on a theoretical conceptualization of exercise are needed.

To summarize, exercise psychology has largely focused on a social cognitive approach and rather stable interindividual dispositions, disregarding the uniqueness of exercise behavior as a somatic experience that produces variable affective responses and the influence of situated processes. This illustrates the need in exercise psychology for theoretical and methodological advancement with regard to the consideration of a) exercise producing highly variable affective processes as signals of the body, b) situated processes during exercise-related decision-making, and c) the development of a theoretical conceptualization and operationalization of exercise behavior based on (a) and (b). Applying to all of these shortcomings, statistical methods that are able to model those processes more accurately instead of relying on aggregated data need to be established in exercise psychology research.

4 The dissertation program: Affective responses during exercise and situated exercise-related decision-making

In the following, the conceptual and theoretical considerations that led to the three publications are presented. Then, the publications are briefly summarized and followed by a discussion of methodical and theoretical implications. Table 1 presents an overview of all three publications regarding the purpose and research question, design and methods and the main results of each study.

Table 1

Overview of the Dissertation Program

Publication	Journal	Purpose & Research question	Design & Methods	Main results
1st Publication Affect and exertion during incremental physical exercise: Examining changes using automated facial action analysis and experiential self-report	PLOS ONE	Applied automated facial action analysis and experiential self-report to examine the covariation of AV and RPE with facial actions during exercise 1. How do changes in AV covary with changes in RPE? 2. Which facial actions are characteristic for changes in AV and RPE? 3. Do individuals show a homogenous or variable pattern of change?	*N* = 113 participants performed an incremental cycling protocol - AV and RPE were repeatedly measured with self-reports - Changes in facial configuration were continuously recorded and classified into facial actions by an algorithm - MEM with random effects for subjects	1. Negative quadratic trend in AV with increasing RPE 2. Changes in AV covary with changes in nose wrinkle, changes in RPE covary with changes in jaw drop 3. Substantial intra- and interindividual variability in facial actions as well as subjective experiences
2nd Publication Exercise or not? An empirical illustration of the role of behavioral alternatives in exercise motivation and resulting theoretical considerations	Frontiers in Psychology	Applied eye-tracking to capture situated processes during exercise-related decision-making 1. How is gaze behavior related to interindividual differences? 2. How do intraindividually varying processes and interindividual variables interact during exercise-related decision-making?	*N* = 101 participants performed a behavioral alternatives task, indicating preferences between exercise and non-exercise in a series of choices - Gaze behavior was measured at trial-level - AAV, RE and EB were measured at individual-level - MEM with crossed random effects for subject and trials	1. No difference in gaze behavior with individual differences in AAV, RE and EB 2. Intraindividually varying gaze behavior and interindividual difference in AAV, RE and exercise behavior independently explained choice behavior
3rd Publication Exercise as the sum of our choices between behavioral alternatives: the Decisional Preferences in Exercising Task (DPEX)	Psychology of Sport and Exercise (submitted)	Development of an adaptive research tool that operationalizes EB as the result of repeated situated decisions between an exercise and an alternative option 1. Are DPEX scores significantly associated with exercise behavior and past exercise experiences? 2. Can the DPEX be used to simultaneously model inter-and intraindividually varying processes?	*N* = 451 participants completed the DPEX, in addition - 451 completed the IPAQ - 212 completed an exercise e-diary over the next 14 days - 142 completed the AFFEXX - MEM with crossed random effects for subjects, exercise and non-exercise items	1. High correlations with past and future exercise behavior as well as with past exercise experiences 2. Non-regular exercisers were more likely to choose exercise when they took more time

Note. AV = affective valence, RPE = rate of perceived exertion, MEM = mixed-effects modelling, AAV = automatic affective valuation, RE = reflective evaluation, EB = exercise behavior, DPEX = decisional preferences in exercising

4.1 Affective responses during exercise

Exercise psychology has increasingly recognized that the importance of core affective processes during exercise have been underestimated in recent years (Ekkekakis et al., 2020; Maltagliati et al., 2022). Core affect as an underlying ever present non-reflective feeling is conceptualized on two orthogonal dimensions ‘affective valence’ (AV; feeling pleasure vs displeasure) and ‘arousal’ (high vs. low) (Russell, 1980). Reliable evidence supports the hedonic assumption that a positive change in AV during exercise is a significant predictor (with small to medium effect sizes) of subsequent exercise behavior (Rhodes & Kates, 2015; Williams et al., 2008). According to the DMT (Ekkekakis, 2003) and substantial empirical evidence (Ekkekakis et al., 2011), there are three metabolic domains that produce distinct patterns of affective responses. When individuals exercise at moderate intensity (below the ventilatory threshold; VT), most report a pleasant feeling. The domain between VT and the respiratory compensation point (RCT; heavy intensity) is characterized by response variability, with some individuals reporting negative feelings and some reporting positive feelings. When the intensity of exercise increases to the severe domain (above the RCT), almost all individuals report negative feelings. Empirical studies examining individual differences in affective responses during exercise often form groups to explain why some individuals might experience an increase while others might experience a decrease in affective valence during exercise (e.g., Alvarez-Alvarado et al., 2019; Box & Petruzzello, 2020). This aggregation of data ignores important variability in affective response, which may result in more homogenous response patterns than actually exist.

The variance in affective response is the result of a continuous interplay of cognitive factors (e.g., self-efficacy) and interoceptive factors (e.g., muscular or respiratory cues) that shift systematically as a function of exercise intensity (Ekkekakis, 2003). Studies examining cortical hemodynamics during exercise have shown that there is reduced oxygenation in the prefrontal cortex at heavy and severe intensities (Rooks et al., 2010), a brain area that is involved in many cognitive functions (Fuster, 2002). This supports the assumption that, at severe intensities, the affective response can no longer be regulated by prefrontal control functions and more directly reflects the physiological conditions of the body (Ekkekakis & Brand, 2019). Hartman et al. (2019) suggested that at high intensities, ratings of affective valence are closely connected to the concept of perceived physical exertion (RPE; "the feeling of how heavy and strenuous a physical task is", Borg, 1998, p. 11) and may even convert into one.

The aforementioned studies used self-reported measures to assess AV and RPE during exercise. While there have been initial attempts to associate RPE with single facial actions during exercise (e.g., de Morree & Marcora, 2010), no study to date has used automated technology to continuously monitor changes across the whole face and relate them to self-reported changes in AV and RPE.

4.1.1 Publication 1: Affect and exertion during incremental physical exercise: Examining changes using automated facial action analysis and experiential self-report

Publication one addresses the shortcomings in exercise psychology of relying on one method (self-report) to assess affective processes during exercise by testing whether new technologies - such as automated facial action analysis - can be applied to identify facial actions that reflect changes in AV and RPE. In addition, publication one uses mixed-effects models (MEM) with random effects for subjects to examine individual trajectories in core affective valence and perceived exertion along with continuous changes in facial actions.

A total of 113 sports and exercise students (M_{age} = 21.6, SD_{age} = 2.9; 52 women and 61 men) performed an incremental exercise protocol until voluntary exhaustion, while their faces were continuously recorded on video. Automated facial action analysis (AFFDEX; McDuff et al., 2016) was used to detect any movement in 34 facial landmarks and classify them into 20 facial actions using an algorithm based on millions of facial configurations (e.g., upward movement in lip corners is classified as "smile"). AV (Feeling Scale; Hardy & Rejeski, 1989) and RPE (Borg Scale; Borg, 1998) were self-reported every two minutes during the exercise protocol.

Linear MEMs predicting changes in AV with RPE confirm previous results that affective valence shows a negative quadratic decline with increasing intensity (Ekkekakis et al., 2011). Introducing random slopes for RPE revealed that participants showed significant variability in their affective trajectories, meaning that individuals reported a steep decline in AV with increasing RPE while others reported no change or only a slight change. Models testing the covariation of AV and RPE with facial actions revealed that nose wrinkle was indicative of a decline in AV (but not in RPE) and jaw drop of a decline in RPE (but not in AV). Mouth open was significantly associated with both AV and RPE. Random slopes for facial actions also revealed significant variability, meaning that participants differed in their facial actions for a similar reported feeling.

4.1.2 Methodological and theoretical advancements

From a methodological perspective, this study presents advancements in at least two areas. First, this is one of the first studies to continuously monitor whole face changes during exercise. Identifying facial actions as an alternative to self-report measures has the advantage of avoiding common method-bias and allows for continuously monitoring changes during the exercise experience. In contrast to other facial action analyses such as facial electromyography (fEMG) automated facial action analysis does not require equipment attached to the individual, is not limited to a selection of facial actions, and does not require a human encoder. However, automated facial action analysis is prone to disruptions and requires precise facial positioning with strongly expressed facial movements and specific technical equipment. It is therefore suitable for studying psychological processes during exercise in a laboratory setting but limited in scope. Second, this is the first study using MEM to model individual trajectories in AV and RPE. This allowed for the decomposition of variance at intra- and interindividual levels in addition to the integration of continuous predictors.

On a theoretical level, demonstrating a negative quadratic decline in affective responses with increasing exercise intensity confirms assumptions of the DMT and previous empirical evidence (Ekkekakis, 2003; Ekkekakis et al., 2011). However, random slopes revealed that the individual trajectories did not differ at only heavy intensity, and therefore presents a slightly different pattern than DMT would suggest. These findings suggest that variability in AV in response to equally experienced exhaustion is the norm rather than the exception.

The identification of two separate facial actions, that selectively reflect changes in RPE and AV supports the assumptions that RPE and AV are related but distinct constructs (Hardy & Rejeski, 1989). The finding that jaw drop is specific to RPE is consistent with the assumption that RPE entails a stronger physiological component (Bok et al., 2022). The increase in jaw drop can be interpreted as a signal of the body that increased oxygen uptake is necessary. The finding that nose wrinkle is indicative of changes in AV supports the assumption that AV is likely to reflect psychological processes, as nose wrinkle has repeatedly been associated with negative affective states in psychological research (Rozin et al., 1994).

The intensity of the facial actions increased with a higher workload during the exercise bout. This suggests that the signals of the body reflecting internal states become stronger as one approaches physical exhaustion. This is consistent with research showing that at severe intensities, affective responses may more directly reflect bodily states, since the individual is less able to execute cognitive control due to decreased oxygenation in the prefrontal cortex (Hartman et al., 2019). Thus, at high intensities, facial actions may offer a more unfiltered picture of the body's physiological state. As facial actions also entail communicatory functions, they may serve as a warning signal that physiological overload is imminent. These results suggest that, at severe intensities, homeostatic perturbations (which are hypothesized to enter consciousness via changes in affect) are also expressed through facial actions as signals of the body.

4.2 From affective responses during exercise to situated decisions in exercise psychology

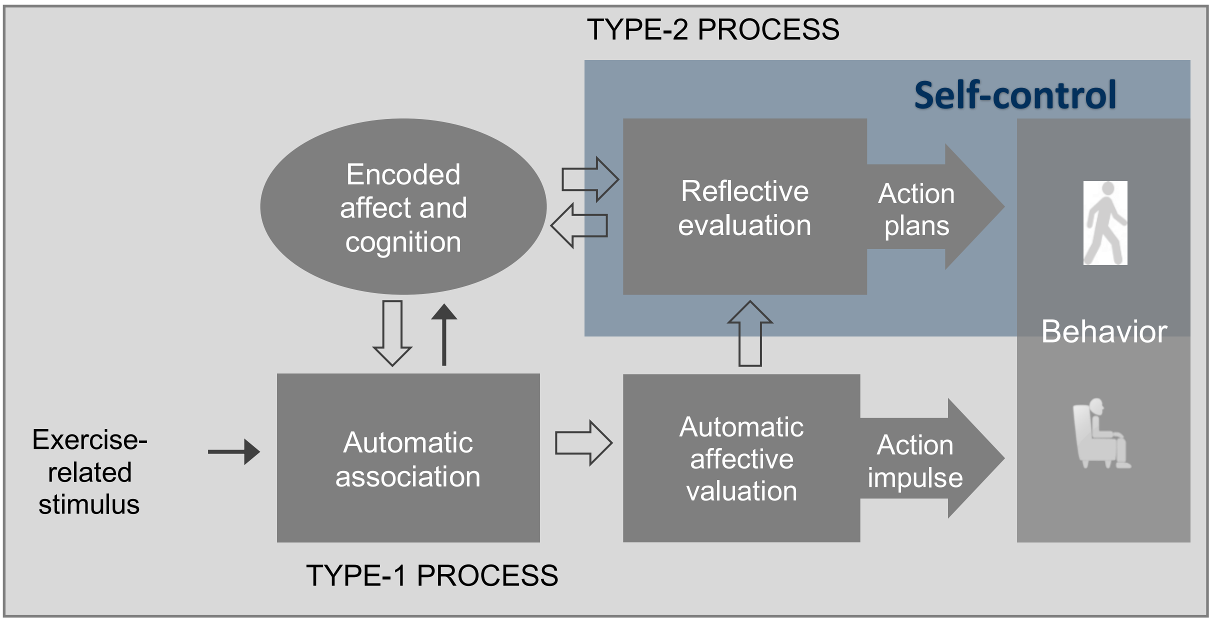
ART incorporates the assumptions of DMT on affective responses during exercise into a theoretical framework to explain why individuals become either active or remain in a state of inactivity. According to ART, affective responses during exercise leave traces in memory that are (re)activated in-the-moment an individual is confronted with the choice to exercise or to remain in a state of inactivity.

The idea that what we feel when we are faced with a choice is based on previous experience has roots in the somatic marker hypothesis (Bechara & Damasio, 2005). A somatic marker is formed by the repeated pairing of a behavior (e.g., exercise) and its accompanying internal state (e.g., pain). It is stored as a memory trace, inherently tagged with a pleasant or unpleasant valence, and reactivated in-the-moment when confronted with the choice to execute the behavior. This activated valence is imbued with an action impulse to either approach behaviors that are positively valenced or avoid behaviors that are negatively valenced. Lewin described these forces acting on the individual in-the-moment of choice as *driving* and *restraining forces* (Lewin, 1951). According to Lewin, psychological processes are “always to be derived from the relation of the concrete individual to the concrete situation” (Lewin, 1935, p.41). Taking into account the totality of a situation renders it imperative to ask not only what drives an individual to behave in a certain way, but also what restrains them from doing so.

These ideas from Lewin were transferred into exercise psychology and the theoretical assumptions of ART, specifically to the situated processes that take place at the exact moment an individual is confronted with the choice of exercise while being in a state of inactivity (Figure 1). ART assumes that whenever an individual is faced with the choice to exercise, core affective feelings (e.g., pleasure and displeasure) experienced by the individual during previous episodes of exercise are automatically activated as an automatic affective valuation. Neuroimaging studies support the assumption of dissociable neural pathways underlying the elicitation of affective and autonomic responses during predeliberative stages of processing (Ekkekakis & Brand, 2021). The amygdala plays a key role in supporting memory for affectively arousing experiences and when activated enhances or hinders the encoding of incoming stimuli (and thus also exercise-related choices) (Canli et al., 2000). A positive valuation and connected action impulse may drive an individual to change their current state of inactivity. Instead, a negative valuation may act as a restraining force (avoidance impulse) from changing the present state of inactivity. If sufficient self-control resources are available, reflective processes may follow and influence the decision.

Figure 1

A Graphical Illustration of the ART



Note. Adapted from "Affective-Reflective theory of physical inactivity and exercise. Foundations and preliminary evidence," by R. Brand & P. Ekkekakis, 2018, *German Journal of Exercise and Sport Research,* 48(1), p.56.

Multiple empirical studies support the claims of the ART by showing that exercise-related stimuli are associated with various types of automatic reactions including the activation of automatic associations (Rebar et al., 2016; Schinkoeth & Antoniewicz, 2017) and (somato-)affective reactions (e.g., Schinkoeth et al., 2019; Schinkoeth & Brand, 2020). Similarly, a variety of studies support the influence of self-control and reflective processes on exercise behavior (e.g., Best et al., 2014; Rhodes & Nigg, 2011).

However, research is limited on the action impulse, or what is happening at the exact moment of choice. Previous studies examining exercise-related choices have focused on the relationship of automatic affective processes and exercise behavior (e.g., Antoniewicz & Brand, 2014; Schinkoeth et al., 2019) or the outcome of an exercise-related choice (Antoniewicz & Brand, 2016). A more process-focused approach that concentrates on processes happening at the exact moment of choice is required to better understand how intra- and interindividual factors (i.e., when and who is more likely to choose exercise) influence exercise-related decisions. Taking into account Lewin's considerations about behavior change (changing your state from inactivity to exercise) the likelihood to change momentary behavior not just depends on the desired action (e.g., exercising) but on the totality of the situation which also includes the available alternative choices (e.g., lying on the couch) (Lewin, 1943). Brand and Schweizer (2015) introduced the concept of situated decisions in exercise psychology and provided a first paradigm (Situated Decision to Exercise Questionnaire; SDEQ) to assess participants' tendency to choose an exercise activity in different situations described by vignettes. However, using a self-report questionnaire, the SDEQ focused on reflective processes and interindividual differences. What is missing thus far is empirical research on the situated processes at the exact moment an individual is confronted with the choice between behavioral alternatives.

4.2.1 Publication 2: Exercise or not? An empirical illustration of the role of behavioral alternatives in exercise motivation and resulting theoretical considerations

Publication two addresses the shortcoming of neglecting the situated processes occurring in-the-moment when confronted with an exercise-related choice. It uses MEMs to account for the dynamic interplay of processes both between and within participants, as well as between and within each choice (i.e., each trial). Therefore, publication two tests an experimental paradigm specifically designed to capture and investigate the processes happening in-the-moment of choice (i.e., situated processes) that may vary from choice-to-choice and are specifically tied to the available behavioral alternatives.

A total of 101 participants ($M_{\text{age}} = 23.6$, $SD_{\text{age}} = 3.6$, 52 men and 49 women) performed a behavioral alternatives task in which they had to indicate their preference between an exercise and a non-exercise alternative in a series of choices. During the task, gaze behavior (*fixations* and *first gaze*) was automatically recorded using the Gazepoint GP3 eye-tracker. Before the task, automatic affective valuations of exercise were measured with an affective misattribution procedure (Payne et al., 2005). After the task, the participants were asked about their reflective evaluations towards exercise ("How do you feel about exercising?") on a 7-point Likert scale and their overall exercise behavior with the International Physical Activity Questionnaire – Short Form (IPAQ-SF; Craig et al., 2003).

MEM with crossed random effects for subject and trials revealed that during exercise-related choices, participants in general did not show an automatic bias in their first gaze or looked longer at the exercise or non-exercise alternative. However, individuals showed more fixations on the alternative they are about to choose. Interestingly, gaze behavior was not related to interindividual differences in automatic affective valuations or reflective evaluations, meaning that individuals with either positive automatic affective valuation or reflective evaluation towards exercise did not fixate on the exercise alternative longer (despite being more likely to choose exercise).

4.2.2 Methodological and theoretical advancements

From a methodological point of view, publication two invents an experimental paradigm to capture situated processes in-the-moment of choice. In this study, eye-tracking was applied, which has been used extensively in psychology research as a process tracing method to better understand processes during decision-making (Glaholt et al., 2011; Norman & Schulte-Mecklenbeck, 2009). This experimental paradigm also offers the opportunity to assess additional process tracing measures, such as heart rate variability or galvanic skin response, which might provide further insight into the processes occurring during exercise-related decision-making (Hardy & Rejeski, 1989).

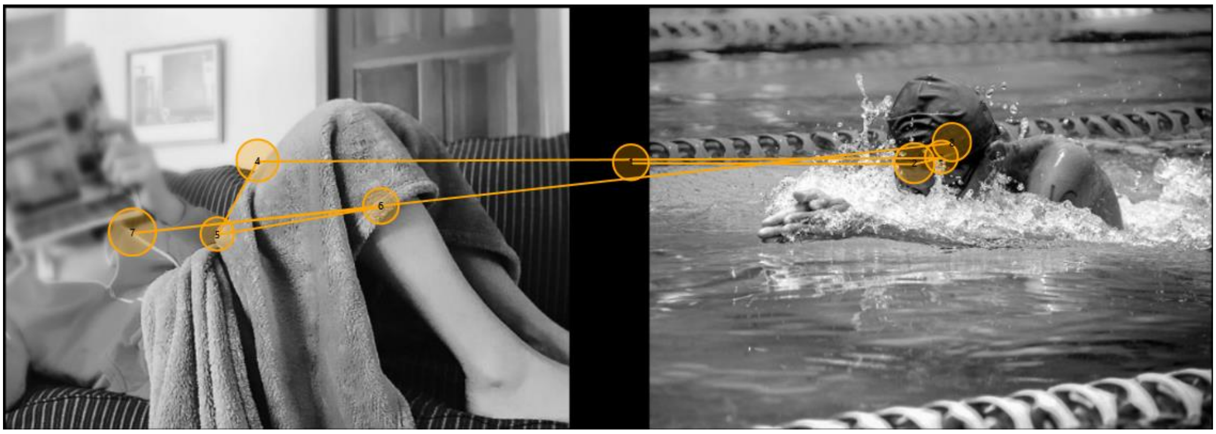
By using a computerized approach, common-method bias to commonly used self-reports in exercise psychology, such as the IPAQ (Craig et al., 2003), is avoided. The applied statistical approach (MEM with crossed random effects) supports a process-focused approach as it allows the inclusion of variables that change within each trial, over the course of the experiment and between individuals. Without specified random effects for trials, the common approach would have been to compute two scores per subject (e.g., the average rating for all exercise pictures and the average rating for the non-exercise pictures) and analyze these scores using a RM-ANOVA or a paired-samples t-test. This not only produces biased standard errors, and thus an increased type-I error rate, but also limits the possibilities for analysis (Judd et al., 2012).

From a theoretical point of view, publication two sheds light on the processes that occur in-the-moment of choice and how they might interact. The results indicate that in-the-moment of choice, situated processes associated with the concrete behavioral alternatives predict choice behavior independently of more stable dispositions, such as general preferences. This implies that over and above a general preference for exercise, situated processes triggered by the specific available behavioral alternatives impact individuals decision-making processes. This decision contingency emphasizes the relative nature of choice behavior. Preferences may differ depending on whether we evaluate an option directly or choose between two options (Pfister et al., 2017).

Although ART has assumptions about the psychological processes triggered by an exercise-related stimulus, it is not clear how the behavioral alternative is integrated in the choice process. There is growing empirical evidence from behavioral neuroscience that during decision-making, the brain integrates information from all options under consideration, assigns a value to each, and, when the integrated evidence exceeds a threshold, the most valued option is enacted (Rangel et al., 2008). The experimental paradigm from publication two is used to illustrate how such a process might occur in the context of exercise-related choices (Figure 2). Gaze behavior is used in a metaphorically sense to illustrate the approach and avoidance impulses emanating from the individual.

Figure 2

Gaze Behavior Pattern of a Participant when Faced with the Choice Between Lying on the Couch or Going for a Swim



Note. This figure is taken from iMotions software, displaying the shifts in an individual's gaze behavior in the Behavioral Alternatives task.

An individual faces the following situation (see Figure 2): Originally, she had planned to exercise this evening, but now finds herself lying on the couch with a good book. Then the thought of her original plan to go swimming enters her mind. According to ART, this thought triggers either a positive or negative automatic valuation based on previous experiences. Due to her generally positive experiences with swimming, she senses a positive feeling, inherently imbued with an impulse towards the exercise activity. This approach impulse is metaphorically symbolized by a gaze towards the exercise alternative (see Figure 2). However, after a long day at work, she is exhausted, and thinking about staying on the couch also triggers a pleasant feeling. This feeling evoked by the behavioral alternative in turn acts as a restraining force away from the exercise behavior. The connected avoidance impulse becomes apparent in the experimental paradigm though a gaze shift towards the non-exercise picture (see Figure 2). The shift between the behavioral alternatives continues, symbolizing the inner conflict of the individual. After a long, exhausting day, cognitive control resources are running low, and her thoughts shift more towards the non-exercise alternative (symbolized by more and more fixations on the non-exercise picture, see Figure 2). At some point, when one of the opposing forces prevails, which is symbolized by gaze dominance on this alternative, a decision is reached.

In line with Lewin's emphasis on the totality of a situation, the situated processes towards the exercise option and towards the behavioral alternative influence why an individual may or may not change his or her current state in a certain situation (Lewin, 1943). The theoretical conceptualization of exercise-related decision-making should take this contingency of the decision into account, as well as how it translates into an individual's overall exercise behavior. Publication three aims to develop a test based on this conceptualization and examines its relation with exercise-related variables.

4.3 Exercise as the sum of situated decisions based on past exercise experiences

Publication three takes the concept of situated decisions and translates it into a widely applicable tool that measures decisional preferences in exercising (the DPEX). While previous models of individuals' decisions to exercise have shed light on the reason-based and deliberate nature of the behavior, the fact that exercise needs to be executed on a repetitive basis to be successfully sustained has not received much attention. Brand and Schweizer (2015) first introduced the concept of situated decisions in exercise psychology. They provided evidence that situated decisions can be conceptualized as a functional link between automatic and reflective evaluations of exercise with exercising behavior. Publication two translated this idea into a computerized behavioral alternatives task. However, this task is not well suited for research or practical usage because of its technical complexity, a tie to specific software, and rigidity in the stimulus material used. To provide a widely applicable tool, it should be simple to implement (e.g., should not require a great deal of technical effort), flexible in the stimulus material (e.g., within the framework of the given categories), have precise instructions for use, and publicly available code for open-source software. Taking the theoretical considerations into account, the DPEX should reflect the repetitive nature of exercise choices between behavioral alternatives and be related to both past exercise experiences and past and future exercise behaviors. To test possibilities for further application, this tool should be able to differentiate between exercisers and non-exercisers and enable further investigation of intra- and interindividually varying processes.

4.3.1 Publication 3: Exercise as the sum of our choices between behavioral alternatives: The Decisional Preference in Exercising Test (DPEX)

Publication three addresses the shortcomings of solely relying on self-reports or objective measures to study exercise behavior by developing a computerized tool based on a theoretical conceptualization of exercise behavior. MEM with random effects for subjects, exercise items and non-exercise items were used to calculate the test score. This type of measurement and statistical analysis allows us to capture processes that are specific to each individual and each available alternative presented without the need to artificially aggregate the data.

A total of 451 participants (M_{age} = 28.88, SD_{age} = 15.21, 204 men and 247 women) took part in a series of studies to develop and validate the theoretical underpinning of the DPEX. The DPEX is designed to require participants to choose between an exercise and a non-exercise activity across a multitude of choices. The activities are displayed as black and white images on a computer screen, while participants have to indicate their preference with a key response. Combinations are randomly assembled from two definable stimuli pools (exercise vs. non-exercise). Owing to the adaptive test design and open-source code, the stimulus pools and presentation times can be specified to researchers' needs. For test scoring, a random effect scoring method was used to extend the generalizability of the stimulus material. The resulting DPEX-REM (random effects model with crossed random effects for participants, exercise and non-exercise items) score predicts the probability of choosing exercise over non-exercise alternatives.

The DPEX-REM score showed high correlations with self-reported exercise behavior as measured with the IPAQ-SF (Craig et al., 2003) and with an app-based exercise-e-diary over the following 14-days. These findings suggest that the DPEX is not only associated with self-reported past exercise-behavior but can also predict future exercise behavior. Furthermore, the DPEX-REM score was highly associated with all subscales of the Affective Exercise Experiences questionnaire (AFFEXX; Ekkekakis et al., 2021), especially with the attraction-antipathy scale, that is the motivational outcome variable theorized to stem from affective experiences.

Receiver operating curve analysis supported these findings by demonstrating good accuracy in discriminating between exercisers and non-exercisers. Exploring reaction times showed that regular exercisers were faster when making exercise choices (compared to non-exercise choices), whereas non-exercisers were faster in making non-exercise choices (compared to exercise choices).

4.3.2 Methodological and theoretical advancements

The DPEX is one of the first research tools to conceptualize exercise behavior based on theoretical considerations. Due to its ease of use and public availability, it can be widely used and presents an alternative to existing self-reports. It allows the implementation of additional measures such as heart rate variability or facial expressions, which are used in decision research as process tracing methods and have also been proposed in exercise psychology to approach a somatic correlate of the automatic affective valuation (Schinkoeth et al., 2019).

Using a MEM with crossed random effects for subjects, exercise and non-exercise items offers several advantages. Despite the general advantages of MEM (being able to handle unbalanced data, tests of continuous variables, modelling nested data structure), specifying crossed random effects for each item category (exercise and non-exercise) and subjects provide advantages, that specifically support features of the DPEX. One of the main aims was to develop a tool that does not require extensive pretesting of the stimulus material and is not limited to the specific pictures of the activities that were sampled. Modeling exercise and non-exercise images as random effects, enables us to generalize the results to a larger population of exercise and non-exercise activities (Baayen et al., 2008). In addition, variance and covariance components were calculated for both subjects and each item category (exercise and non-exercise). This provides information on how much a certain subject or item deviates from the average, and offers the opportunity to integrate possible predictors explaining these individual deviations. For example, subjects with a preference for group exercise may be associated with exercise items representing group activities.

From a theoretical point of view, the development of the DPEX rests on the idea that people usually do not simply start exercising; instead, they are often faced with choosing between a variety of behavioral alternatives. Publication three provides empirical evidence for the assumption that exercise behavior is constituted by the sum of situated decisions between behavioral alternatives influenced by past experiences with exercise. Conceptualization and operationalization of exercise behavior should go beyond individual decisions and the most distal behavioral outcome (e.g., number of steps or self-reported exercise over a certain time period). Instead, incorporating the concept of repeated situated decisions across a variety of situations into future research on the antecedents of exercising seems feasible.

The finding that it was more likely for non-exercisers to choose exercise when taking more time suggests that when making decisions that are not in line with their usual behavior, individuals have to resolve a conflict. The automatic response might have been to choose the non-exercise option, but by taking more time, additional resources could be activated and bring more attention to why the exercise option might the better choice. In addition, when specific behavioral alternatives do not match someone's general preferences (e.g., someone who likes to exercise but does not like volleyball), this may lead to hesitation and the individual not making their usual choice. A cautious interpretation of this data suggests that fast decisions could be indicative for the "default" automatic response, while slower reaction times indicate that additional (cognitive) processes may be activated, that are more slowly and deliberative in nature. This is in line with the assumptions of the ART, stating that someone with a negative automatic affective valuation might experience a conflict when confronted with the choice to exercise. Under the condition of sufficient self-control resources, reflective evaluations that are slower and more deliberate in nature may be activated, and conflict can be resolved in favor of the decision to exercise.

To summarize, by developing the DPEX, we provide researchers and practitioners with a tool that is easy to use, highly adaptive in its test configuration (i.e., stimulus material, presentation time, number of trials), and publicly available (open-source code and software). Based on theoretical considerations, the DPEX provides empirical support for the assumption that exercise behavior can be conceptualized as the sum of repeated decisions between behavioral alternatives influenced by previous exercise experiences. Random effects modeling provides an opportunity to better understand and study the processes underlying these decisions, rather than focusing primarily on decision outcomes.

5 General discussion

The research program of this dissertation integrates previous knowledge from the field of exercise psychology and addresses existing challenges in advancing the understanding of the psychological factors underlying exercise behavior. The publications address the need for alternatives to self-reported measures, the empirical investigation of situated processes, and a theoretically based operationalization of exercise behavior. Moreover, recent developments in affective science and psychology are taken into account, according to which variability should be modeled as a source of information rather than a source of error (Barrett, 2017; Judd et al., 2012). In this way, each publication addresses specific shortcomings in exercise psychology and not only expands insights, but also opens up future possibilities for research.

My first publication targeted affective responses during exercise, as these are increasingly recognized as important determinants of future exercise behavior (e.g., Maltagliati et al., 2022; Rhodes & Kates, 2015). By using automated facial action analysis, publication one was able to identify externally observable behavioral indicators for changes in AV and RPE during exercise. MEM revealed an overall quadratic negative decline in AV with increasing RPE, with substantial intra- and interindividual variability.

ART assumes that these affective experiences during exercising leave traces in memory and are reactivated when confronted with the choice to exercise. Publication two invented a new experimental paradigm examining situated processes in-the-moment of choice. The results suggest that intraindividually varying processes tied to specific behavioral alternatives independently influence exercise choices from processes that are rather stable within an individual.

To achieve sustained exercise behavior in the long run, exercise must be repeatedly preferred over other alternatives in a variety of situations. Publication three applied this conceptualization of exercise behavior to develop a research tool that approaches exercise behavior as the sum of situated decisions that are influenced by past exercise experiences and predict future exercise behavior.

Taken together, the empirical findings collected in this dissertation suggest that situated decisions influenced by highly variable previous exercise experiences play a decisive role in long-term exercise adherence. Both the affective processes during exercise and the situated processes during exercise-related decision-making were marked by substantial intra- and interindividual variability, indicating the importance of individual and context-specific influences. These multifaceted results strongly encourage the integration of situated processes into extant theories of exercise psychology. To better understand individual motivation, we need to focus on the processes in situations in which the relevant behavior is performed, that is during exercise and exercise-related decisions. In the following section, implications for future research and practice are discussed.

5.1 Implications

This dissertation commenced with the illustration that although exercise psychology has made progress in explaining exercise behavior by incorporating dual process models in theory, much of the variance in behavior remains unexplained and unchanged. To create further progress, it is necessary that individual variability in affective responses during exercise are given greater consideration, and that long-term exercise behavior is understood as the result of repetitive situated decisions influenced by a variety of psychological processes. This not only requires theoretical advancements but also innovative ways of measuring and analyzing these processes.

5.1.1 Affective responses during exercise

While DMT already posits that there is significant interindividual variability at heavy intensities (between the VT and RCT), the results of publication one show that affective responses to exercise are more variable than theory would suggest; subjectively experienced and bodily expressed. This implies that more attention should be paid to the fact that the same physiological stimulus can elicit a variety of individual responses. More emphasis should be placed on technologies that can capture continuous psychological and physiological changes during activity, as well as on statistical models (e.g., MEM) that can capture this variability and integrate continuous predictors to explain it. Recent advancements in mobile (e.g., app based) and wearable sensor technologies (e.g., smart shirts) offer new opportunities to capture individual affective responses across a variety of different activities and settings in real time (Dunton et al., 2023).

Identifying separate facial actions specifically tied to AV and RPE provides future research with alternative indicators to test manipulations of affective responses during exercise. For example, music has reliably been shown to improve affective responses during high exercise intensities. However, strategies such as music cannot be disguised, making such designs vulnerable to expectancy effects when participants are required to report their feelings. Assessing the efficacy of such in-task strategies using alternative methods, such as facial actions, adds to the validity of these strategies in altering affective responses during exercise. Moreover, a greater understanding of whether such strategies affect automatic responses can provide further evidence in support of their use. Furthermore, externally observable cues can help practitioners (e.g., teachers, coaches) to better assess an exerciser's perceived exertion and momentary affective state to increase the odds of pleasurable physical exercise.

5.1.2 Situated decisions in exercise

The impetus that diverts many individuals from the path of lasting change often emanates from in-the-moment choices, when well-intended exercise plans are discarded and individuals choose to remain ensconced on the couch instead. In this very moment, a conflict arises between opposing forces that act on in-the-moment decisions that ultimately constitute exercise behavior. Most theories of behavior change neglect this momentary conflict, nor do they target interventions on how to avoid or overcome it. Since this has been deemed as the “real place of power for achieving lasting change” (Segar, 2022, p. 3) it is essential to better understand the variety of processes that influence these situated decisions.

Results from publication two suggest that in addition to a general preference for exercise, it is important to determine which specific type of exercise and behavioral alternatives are available to choose. Thus, in order to shift the decision tendency towards the exercise alternative, it is not only about the motivational forces towards exercise, but also about what is opposed to it. Both alternatives can trigger driving as well as restraining forces that make it either more likely to approach or to avoid the respective behavior. To shift the decision tendency towards the exercise option, either driving forces toward exercise can be amplified (and restraining forces lessened) or driving forces towards the behavioral alternative can be dampened (and restraining forces amplified). As these forces are situated within our past experiences with exercise, positive affective experiences play a key role in strengthening the driving forces towards exercise and weakening the restraining forces. Importantly, these automatic affective processes seem to be tied to specific exercise settings or types (e.g., Limmeroth & Braun, 2022). Therefore, frequent positive experiences with a particular exercise type should lead to a more positive automatic affective valuation of that setting, “which in turn might influence behavioral choices and setting preferences” (Antoniewicz & Brand, 2014, p. 7). To better understand these behavioral choices, future research needs to consider that exercise behavior is a multifaceted phenomenon and that preferences as well as automatic affective processes can be situation- and activity-specific.

Heeding the conceptualization that exercise behavior results from a series of choices between exercise and behavioral alternatives, it is important to consider the role of the alternative, both in research and in practice. Behavioral economics coined the term of “choice architecture”, meaning constructing choices in a way that makes a particular outcome more likely (Carr & Epstein, 2020). If we know which behavioral alternatives are likely to restrain us from becoming active, we should try to avoid facing this choice in the first place. For example, if we know that as soon as we lie on the couch, we will not be able to get up, we should not expose ourselves to this conflict of opposing forces over and over again. Instead, we should establish choices in which exercise becomes the default response. At the same time, this implies for research that the value of any alternative is not fixed but depends on the context, which includes available alternative options (Carr & Epstein, 2020). This is taken into account by the DPEX, providing both practitioners and researchers with a tool that conceptualizes exercise behavior as the sum of situated decisions between exercise and a behavioral alternative.

Analyses using the DPEX as a functional link between basic information processing and the resulting behavior may allow a deeper understanding of the role of specific psychological processes (e.g., by manipulating response times). It can be used as an alternative proximate operationalization of exercise behavior to investigate the effectiveness of interventions seeking to address affective response during exercise to improve exercise behavior. Furthermore, it might be used as a diagnostic tool to better understand individual drivers and barriers towards exercise (e.g., for which type of activity a person is more likely to choose exercise or the alternative) or to classify individuals as not meeting the recommended amounts of exercise.

6 Conclusion

Research in exercise psychology over the past 50 years has revealed a variety of processes that influence exercise behavior. After interventions largely based on cognitive variables have failed to yield the expected success, dual process models that acknowledge the influence of automatic affective processes have become increasingly popular. The present work is located within this framework by shedding light on exercise-related affective processes and situated in-the-moment choices. The value of the three studies in this synopsis lies in the integration of existing knowledge from the research field of exercise psychology and its expansion by newly gained insights into theoretical knowledge. Current challenges were identified, and alternative innovative approaches to measuring and modeling were introduced.

Many individuals may fail to exercise regularly because they choose to do other things instead. Therefore, the commonly used one-size-fits all approach will not be successful until it explicitly targets individual barriers. These can be: “Why do I not like to exercise?” or “What would I rather do instead?” These findings need to be leveraged into existing theoretical and empirical frameworks to develop and test interventions designed to increase exercise behavior. For example, measuring and analyzing affective response using a variety of measures (physiological, psychological, behavioral) to better understand variations in how individuals feel during exercise is necessary. Based on this, more individualized interventions that manipulate affective responses during exercise should be developed and systematically tested to establish a causal link to the automatic affective processes that are reactivated when faced with the choice to become active. At this moment, what other processes are at play, how they interact with each other, and ultimately constitute an individual’s exercise behavior should be considered.

Thus far, exercise psychology has failed to acknowledge that variability in behavior and responses provides important information, rather than solely being regarded as measurement error. Scientific investigations should be explicitly designed to capture this variability, ideally using multiple measures in a situated, contextually variable manner (Barrett, 2022; Ekkekakis & Brand, 2019). This requires more complex approaches and analyses, such as disaggregating between- and within-person effects through MEM and using experience sampling in longitudinal designs (Ruissen et al., 2022), to combine an idiographic approach with the commonly used nomothetic approach (Conner et al., 2009). This will allow for a more personalized approach to promoting and maintaining exercise behavior, that incorporates individuals' choices and preferences as well as their context, rather than a one-size-fits all approach to exercise programs (Lachman et al., 2018).

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8 Declaration of authorship

I declare that I have authored this thesis independently, that I have not used other than the declared sources, and that I have explicitly marked all materials which has been quoted.

I hereby certify that the thesis I am submitting is entirely my own original work except where otherwise indicated. I am aware of the University's regulations concerning plagiarism, including those regulations concerning disciplinary actions that may result from plagiarism. Any use of the works by any other author, in any form, is properly acknowledged at their point of use.

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9 The publications as they were published or submitted

The three publications are listed below exactly as they were published or submitted. They are attached in serial order.

Timme, S., & Brand, R. (2020). Affect and exertion during incremental physical exercise: Examining changes using automated facial action analysis and experiential self-report. *PLOS ONE, 15*(2), e0228739. https://doi.org/10.1371/journal.pone.0228739

Timme, S., Brand, R., & Raboldt, M. (2023). Exercise or not? An empirical illustration of the role of behavioral alternatives in exercise motivation and resulting theoretical considerations. *Frontiers in Psychology, 14*, 1049356. https://doi.org/10.3389/fpsyg.2023.1049356

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Affect and exertion during incremental physical exercise: Examining changes using automated facial action analysis and experiential self-report.

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Abstract

Recent research indicates that affective responses during exercise are an important determinant of future exercise and physical activity. Thus far these responses have been measured with standardized self-report scales, but this study used biometric software for automated facial action analysis to analyze the changes that occur during physical exercise. A sample of 132 young, healthy individuals performed an incremental test on a cycle ergometer. During that test the participants' faces were video-recorded and the changes were algorithmically analyzed at frame rate (30 fps). Perceived exertion and affective valence were measured every two minutes with established psychometric scales. Taking into account anticipated inter-individual variability, multilevel regression analysis was used to model how affective valence and ratings of perceived exertion (RPE) covaried with movement in 20 facial action areas. We found the expected quadratic decline in self-reported affective valence (more negative) as exercise intensity increased. Repeated measures correlation showed that the facial action *mouth open* was linked to changes in (highly intercorrelated) affective valence and RPE. Multilevel trend analyses were calculated to investigate whether facial actions were typically linked to either affective valence or RPE. These analyses showed that *mouth open* and *jaw drop* predicted RPE, whereas (additional) *nose wrinkle* was indicative for the decline in affective valence. Our results contribute to the view that negative affect, escalating with increasing exercise intensity, may be the body's essential warning signal that physiological overload is imminent. We conclude that automated facial action analysis provides new options for researchers investigating feelings during exercise. In addition, our findings offer physical educators and coaches a new way of monitoring the affective state of exercisers, without interrupting and asking them.

Keywords: Exercise psychology; Motivation; Feeling scale; Emotion; Affectiva SDK.

1 Introduction

Exercise plays a significant role in reducing the risk of developing diseases and in improving health and wellbeing [1], yet despite knowing that exercise is good for them most adults in Western countries are insufficiently active [2].

Exercise psychologists have spent the last 50 years developing and testing theories about why some people are more successful than others in changing their behavior to promote their own health and exercise more regularly. After decades of focusing on social-cognitive factors and the role of deliberate reasoning in motivation (e.g. goal-setting and self-efficacy) researchers began to focus on the role of more automatic and affective processes in promoting change in health-related behaviors [3, 4, 5].

Affect has been defined as a pleasant or unpleasant non-reflective feeling that is always accessible and is an inherent aspect of moods and emotional episodes, but can be experienced independently of these states as well [6]. Affect can be described in the two orthogonal dimensions: 'affective valence' (how good or bad one feels) and 'arousal' (high vs. low) [7]. There is conclusive evidence that those who experience a more pleasant affective state during exercise are more likely to exercise again [8].

Dual-mode theory [9] explains how feelings during exercise are moderated by exercise intensity. According to the theory and supported by evidence [10], the affective response to *moderate* intensity exercise (below ventilatory threshold; VT) is mostly positive, but affective responses to *heavy* intensity exercise (approaching the VT) are more variable. Some individuals continue to report positive affect as exercise intensity increases, but others report more and more negative affect. When the intensity of exercise increases to the *severe* domain (when the respiratory compensation threshold, RCT, is exceeded), almost all individuals report a decline in pleasure [9, 10].

Ratings of affective valence above the VT are closely connected to the concept of perceived exertion. Borg [11, p. 8] defined perceived exertion as "... the feeling of how heavy and strenuous a physical task is". A recent article in *Experimental Biology* proposed that at high exercise intensities feelings of negative affect and perceived exertion may even convert into one, suggesting that the sensation of severe exertion enters consciousness via a decline in pleasure [12].

We believe that gaining a deeper understanding of the relationship between the affective response to exercise and perceived exertion is important not just from a research perspective, but also from a practical perspective. Practitioners (e.g. teachers and coaches) would greatly and immediately benefit from being able to assess an exerciser's perceived exertion and his or her momentary affective state to increase the odds of further effective and pleasurable physical exercise.

1.1 Measurement of exercise-induced feelings during exercise

Thus far exercise-induced feelings have been mostly measured with exercisers' self-reports [3]. The most commonly used psychometric measures of affective valence is the Feeling Scale (FS) [13], a single-item measure consisting of the question "How do you feel right now?" to which responses are given using an 11-point bipolar rating scale. Various studies have shown that displeasure increases with a quadratic trend under increasing exercise intensity, although with considerable inter-individual variability [10].

Perceived exertion, on the other hand, has often been measured with Borg's rating of perceived exertion (RPE) scale [11]. In this test participants are asked to indicate their actual state during exercise on a 15-point scale ranging from 6 *no exertion* to 20 *maximal exertion*. The scale is designed to reflect the heart rate of the individual before, during and after physical exercise. It would be assumed that an RPE of 13 corresponds approximately to a heart rate of 130 [14].

Focusing on two tasks simultaneously (exercising and rating one's own feelings at the same time) can bias the validity of the answer as well as the feeling states itself. It is known that the act of labeling affect can influence the individual's affective response [15]. Another limitation is that affective valence changes during exercise [10] and repeatedly asking people how they feel inevitably carries the risk that it will interrupt their experience and introduce additional bias to their answers. Monitoring changes in biometric data avoids these interruptions and can thereby provide an alternative way to learn about the feelings that occur during exercise.

1.2 Facial action (facial expression) analysis

Spectators and commentators on sport readily infer how athletes might feel from their facial movements during exercise. Some of these "expressions" might reveal information about an athletes' inner state. However, it cannot universally be assumed that observed facial movements always reflect (i.e., are expressive of) an inner state [16]. Facial actions can also be related to perceptual, social, attentional, or cognitive processes [17, 18]. Therefore, we refer to facial expressions as facial actions in order to discourage the misunderstanding that subjective inner states are unambiguously expressed in the face.

The majority of studies conducted so far has quantified facial action by using either facial electromyographic activity (fEMG) or specific coding systems, of which the Facial Action Coding System (FACS) is probably the most widely known [19, 20].

fEMG involves measuring electrical potentials from facial muscles in order to infer muscular contractions. It requires the placement of electrodes on the face and thus can only measure the activity of a pre-selected set of facial muscles. Another limitation of using fEMG is that it is affected by crosstalk, meaning that surrounding muscles interfere with the signals from the muscles of interest, making fEMG signals noisy and ambiguous [21, 22]. A few fEMG studies have demonstrated that contraction of specific facial muscles (corrugator supercilii, zygomaticus and masseter muscle) is correlated with RPE during resistance training [21, 23] and bouts of cycling [20, 24].

Furthermore there are coding systems. Many of them are rooted in the FACS, which is an anatomy based, descriptive systems for manually coding all visually observable facial movements [19]. Trained coders view video-recordings of facial movements frame-by-frame in order to code facial movements into action units (AUs). FACS is time-consuming to learn and use (approximately 100 hours to learn FACS and one to two hours to analyze just one minute of video content) [20].

Recent progress has been made in building computer systems to identify facial actions and analyze them as a source of information about for example affective states [25]. Computer scientists have developed computer vision and machine learning models, which automatically decode the content of facial movements to facilitate faster, more replicable coding. The computer systems display high concurrent validity with manual coding [26].

We are aware of only one study so far that has used automated facial feature tracking to describe how facial activity changed with exercise intensity [27]. The authors analyzed video-recordings of overall head movement and 49 facial points with the IntraFace software to classify movement in the upper and lower face. The study showed that facial activity in all areas differed between intensity domains. The movement increased from lactate threshold until attainment of maximal aerobic power with greater movement in the upper face than in the lower face at all exercise intensities.

1.3 This study

The aim of this study was to examine changes in a variety of discrete facial actions during an incremental exercise test, and relate them to changes in self-reported RPE and affective valence, i.e. feelings that typically occur during exercise. To the best of our knowledge it is the first study to involve the use of automated facial action analysis as a method of investigating the covariation of these variables.

We have used an automated facial action coding system with the Affectiva Affdex algorithm at its core [28]. It includes the Viola Jones Cascaded Classifier algorithm [29] to detect faces in digital videos, and then digitally tags and tracks the configuration of 34 facial landmarks (e.g., nose tip, chin tip, eye corners). Data is fed into a classification algorithm which translates the relative positions and movements of the landmarks into 20 facial actions (e.g., *mouth open*). Classification by Affectiva Affdex relies on a normative data set based on manual initial codings of human FACS coders, and subsequent machine learning data enrichment with more than 6.5 million faces analyzed [30]. Facial actions as detected by Affectiva Affdex are similar [31] but not identical to the AUs from the FACS. Facial actions consist of a single facial movement or a combination of several movements (e.g., facial action *mouth open*: lower lip drops downwards as indicated by AU 25 *lips part*; facial action s*mile* as indicated by AU 6 *cheak raiser* together with AU 12 *lip corner puller*).

Connecting with dual mode theory [9] and research pointing out the importance of positive affect during exercise for further exercising [8], facial action metrics might provide useful biometric indicators for evaluating feeling states during exercise at different intensities. We took a descriptive approach to analyze which facial actions co-occur with affective valence and perceived exertion during exercise. This approach enables us to contribute conceptually to the examination of the relationship between the constructs of perceived exertion and affective valence (e.g. to determine if they are one or two distinct constructs and whether this depends on physical load) [12], whilst avoiding bias caused by repeatedly interrupting subjects' experience of exercise to obtain self-reports.

In order to account for expectable high inter- and intra-individual variability in both the affective response to exercise [3] and in facial actions [16], we used multilevel regression modeling to analyze our data; as far as we know, we are the first in this research area to use this method of data analysis.

2 Method and Materials

The Research Ethics Committee of the University of Potsdam approved the study and all procedures complied with the Helsinki declaration. All participants gave their signed consent prior to partaking in the experiment. The individual in this manuscript has given written informed consent (as outlined in PLOS consent form) to publish these case details.

2.1 General setup

Study participants completed an exercise protocol involving exercising at increasing intensity on a cycle ergometer until they reached voluntary exhaustion. Whilst they were exercising their face was recorded continuously on video. Both affective valence and perceived exertion were measured repeatedly every two minutes. Changes in facial action were then evaluated with the help of software for automated facial action analysis and related to the self-report data. Advanced statistical methods were used for data analysis, accounting for the generally nested data structure (repeated measurements are nested within individuals).

2.2 Participants

We tested a group of 132 healthy individuals, aged between 18 and 36 years ($M_{\text{age}} = 21.58$, $SD_{\text{age}} = 2.93$; 53 women). All of them were enrolled in a bachelor's degree course in sport and exercise science. The group average of (self-reported) at least moderate physical activity was 337 minutes per week. Students with a beard or dependent on spectacles were not eligible to participate. Data from 19 participants were unusable due to recording malfunction ($n = 6$), poor video quality ($n = 6$; more than 10% missing values because the software did not detect the face) or due to disturbing external circumstances ($n = 7$; people entering the room unexpectedly; loud music played in the nearby gym). This resulted in a final sample of 113 study participants.

2.3 Treatment and measures

2.3.1 Exercise protocol

The participants performed an incremental exercise test on an indoor bike ergometer. Required power output was increased by 25 watt increments every two minutes, starting from 25 watts until the participants indicated that they had reached voluntary exhaustion [32]. The protocol was stopped when the participant was unable to produce the required wattage any more. If a participant reached 300 watts, the final phase involved pedaling at this level for two minutes. Thus the maximum duration of the exercise was 26 minutes. All participants performed a five-minute cool-down consisting of easy cycling.

For a plausibility check whether self-declared physical exhaustion would be at least close to the participants' physiological state heart rate during exercise was monitored in about half of the participants (n = 54). A Shimmer3 ECG device with a sampling rate of 512 Hz was used for that. These participants started with a one-minute heart rate baseline measurement before the exercise.

2.3.2 Affective valence and perceived exertion

The FS (a single item scale: response options range from -5 *very bad* to +5 *very good*) [13] was used to measure affective valence, and participants rated their level of exertion using Borg's Rating of Perceived Exertion (RPE; a single-item scale; response options range from 6 *no exertion* to 20 *maximal exertion*) [11]. FS and RPE were assessed every two minutes during the exercise task, at the end of each watt level. For this purpose the two questionnaires (FS first and RPE second) were displayed on the monitor in front of the participants (see below) and they were asked to give their rating verbally to the experimenter.

2.3.3 Automated facial expression analysis

The participants' facial actions during the exercise task were analyzed using the software Affectiva Affdex [28] as implemented in the iMotions^{TM} platform for biometric research (Version 7.2). Faces were continuously recorded with a Logitech HD Pro C920 webcam at a sampling rate of 30 fps during performance of the exercise task. The camera was mounted on top of the ergometer screen (0.4 m in front of the face with an angle of 20 degrees from below) and connected to the investigator's laptop.

Affectiva Affdex continuously analyzed the configuration of the 34 facial landmarks [31] during performance of the exercise task (Fig 1). It provided scores for 20 discrete facial actions (e.g., *nose wrinkle, lip press*) from all over the face (all facial actions detected by Affectiva Affdex are listed in Table 1, in the results section) [31]. The algorithm performs analysis and classification at frame rate. This means that at a time resolution of 30 picture frames per video second (30 fps), our analyses were based on 1.800 data points per facial action per 1 minute. Recent research has shown that Affectiva Affdex facial action scores are highly correlated with fEMG-derived scores, and that Affectiva Affdex outperforms fEMG in recognizing affectively neutral faces [33].

Each data point that Affectiva Affdex provides for a facial action is the probability of presence (0 - 100%) of that facial action. We aggregated these raw data, for each facial action separately, to facial actions scores (time percent scores) indicating how long during a watt level on the ergometer (i.e., within 2 minutes) a facial action was detected with the value 10 or higher. For example, a facial action score of 0 indicates that the facial action was not present during the watt level, whereas a score of 100 indicates that it was present all the time during that watt level. Fig 1 illustrates examples of facial actions and the analyzed facial landmarks.

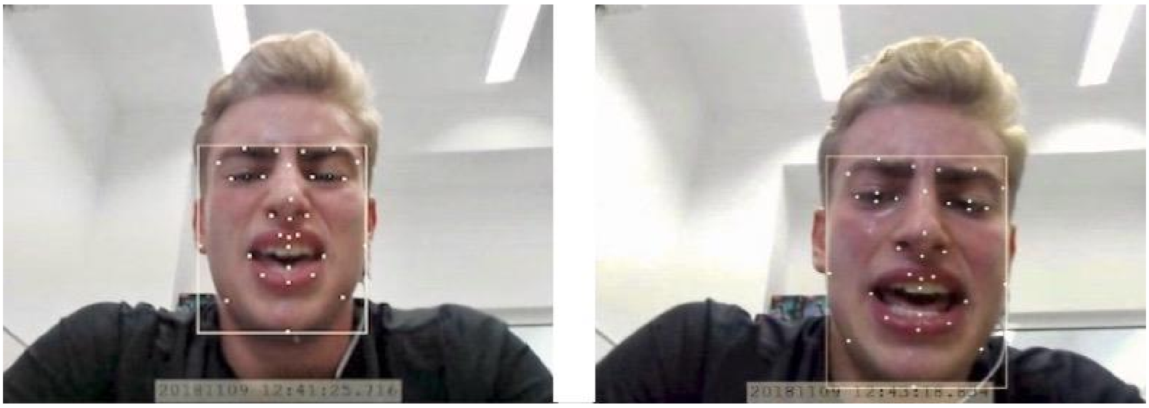

Fig 1. Examples of facial actions during exercise. Mouth open and nose wrinkle (left picture), jaw drop (right picture). The position of the 34 analyzed facial landmarks are marked with yellow dots.

2.4 Procedure

After the participants arrived at the laboratory they were informed about the exercise task and told that their face would be filmed during the task. They were also given a detailed description of the two scales (FS and RPE), what they are supposed to measure and how they would be used in the study.

Participation was voluntary and all participants completed data protection forms and were checked for current health problems. Participants performed the exercise task on a stationary cycle ergometer in an evenly and clearly lit laboratory in single sessions. An external 22” monitor was positioned 1.5 m in front of the participant; this was used to display instructions during the exercise session (instruction on watt level for 100 s always at the beginning of each watt level; the two scales, FS and RPE, always for 10 s at the end of each level). Throughout the trial, no verbal encouragement or performance feedback was provided and the researcher followed a standard script of verbal interaction. During the exercise session the researcher remained out of the participants’ sight and noted the participant’s verbal responses when FS and RPE responses were solicited. The periods during which participants were reporting their ratings were cut from the video for the facial action analysis.

2.5 Statistical approach, modeling and data analysis

Multilevel models were used to assess the anticipated increase in negative affect during exercise and to examine the relationships between facial action, affective valence and perceived exertion. We had multiple observations for each participant (20 facial action score(s), FS, RPE), so that these repeated measurements (level 1) were nested within individuals (level 2). The main advantages of multilevel models are that they separate between-person variance from within-subject variance, so that estimates can be made at individual level as well as at sample level [34]. Because they use heterogeneous regression slopes (one regression model for each participant) multilevel statistics enable analysis of dependent data and a potentially unbalanced design (series of measurements with different lengths); two conditions that would violate test assumptions of traditional regression and variance analysis.

Our first model tested whether affective valence (FS) showed the expected quadratic trend [10] with increasing perceived exertion (RPE; time-varying predictor). In this model, RPE and derived polynomials were centered at zero and used as a continuous covariate for prediction of change in affective valence (FS).

To investigate which facial actions were associated with affective valence (FS) and with perceived exertion (RPE) we carried out separate analyses of the degree of covariation of FS and RPE with each facial action. First we looked at repeated measure correlations, which take the dependency of the data into account by analyzing common intra-individual associations whilst controlling for inter-individual variability [35]. Then we predicted affective valence (FS) from facial action whilst controlling for the influence of RPE, considering each facial action in a separate model. In parallel analyses we predicted RPE from facial action whilst controlling for the influence of FS. The significance of the fixed effects of facial actions were tested using chi-square tests for differences in -2 log likelihood values. A model with facial action as a predictor was compared with a reduced model without facial action. We compared all models in which FS or RPE was predicted by facial action, using the Akaike Information Criterion Corrected (AICC) and Weight of Evidence (*W*) [36]. Pseudo R_x^2 (within-subject level) was calculated to estimate the proportion of variance explained by the predictor [36].

Finally, to test whether FS and RPE made unique contributions in explaining variance in facial action, we calculated separate multilevel models in which specific facial actions were predicted by FS and RPE. This allowed us to partial out the separate amounts of explained variance of FS and RPE in the respective facial action.

We used the lme script from the nlme package (version 3.1-139) [37] to estimate fixed and random coefficients. This package is supplied in the R system for statistical computing (version 3.6.0) [38].

3 Results

3.1 Manipulation checks

As expected, participants reached different maximum watt levels in the exercise session and so the number of observations varied between participants. In summary, we recorded 1102 data point observations for the 113 participants, derived from between 5 and 13 power levels per participant.

Mean maximum RPE in our sample was 19.29 (SD = 1.01) and the mean heart rate in the final stage before exhaustion was 174.61 bpm (SD = 16.08). This is similar to previously reported reached maximal heart rate in incremental cycling tasks (e.g. HR_{max}: 179.5 ± 20.2 bpm, in [39]). The correlation between heart rate and RPE was very high, $r = .82$, $p < .001$. We believe it is valid to assume that most of the participants were working at close to maximum capacity at the end of the incremental exercise session in our study.

3.2 Multilevel trend analysis of FS with RPE

An unconditional null model was estimated to calculate the intraclass correlation for affective valence (FS) ($\rho_I = .33$), supporting the rationale of conducting multilevel analysis [34]. Next we introduced centered RPE (RPE_0) as a time-varying covariate to test the trend of FS with increasing RPE_0.

The model with a quadratic trend ($b_1 = -0.01$, $p = .65$; $b_2 = -0.02$, $p < .001$) provided a significantly better fit to the data compared to the linear model, χ^2 (1) = 93.39, $p < .001$. The inclusion of random slopes (χ^2 (2) = 141.46, $p < .001$) and random curvatures further improved the model fit significantly, χ^2 (3) = 28.39, $p < .001$. The full model, with RPE_0 and $(\text{RPE\_0})^2$ as fixed effects and random intercepts and slopes, explained 67.12% of the variance in FS.

Thus our results confirm previous results, indicating that FS showed the expected negative quadratic trend [11] with increasing intensity (RPE). Fig 2 illustrates the finding, which can be made particularly obvious by means of multilevel regression analysis: The high interindividual variability in the decrease of affective valence (more negative) under increasing perceived exhaustion is striking.

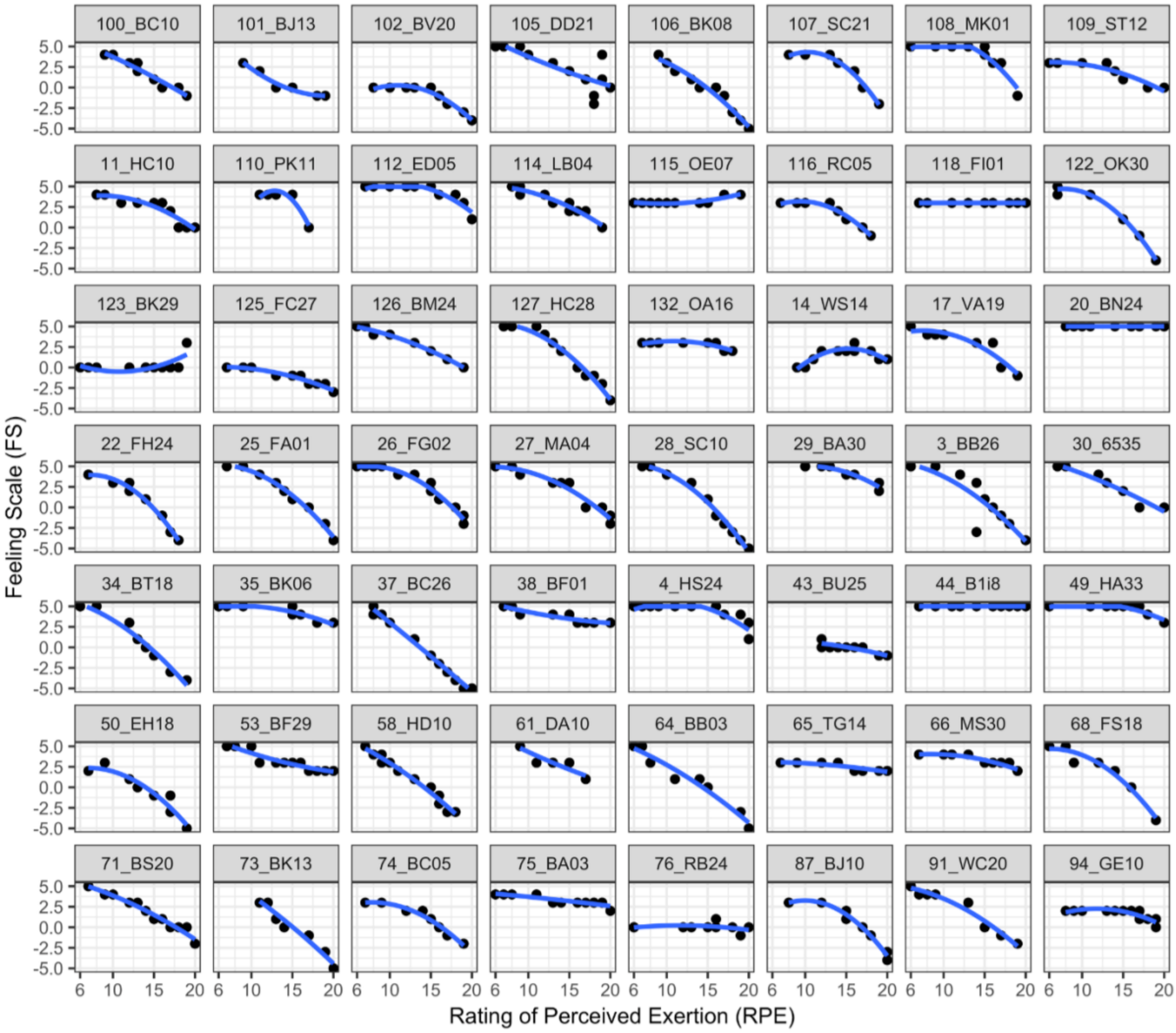

Fig 2. Quadratic relationship between FS and RPE at individual level. Data from a random selection of half of the participants (*n* = 56) are presented to illustrate the intra- and inter-individual variability in affective response to increasing exercise intensity. Intraclass correlation shows that 33% of the variance in affective valence (FS) is due to inter-individual variability.

3.3 Repeated measures correlations

3.3.1 Covariation of FS and RPE with facial action as intensity increases

First correlations between each facial action and FS and RPE were calculated (Table 1). Repeated measures correlations revealed that *mouth open* (r = -.55, p < .001), *jaw drop* (r = -.40, p < .001) and *nose wrinkle* (r = -.34, p < .001) showed the highest correlations with affective valence (FS). *Mouth open* ($r = .70$, $p < .001$) and j*aw drop* ($r = .51$, $p < .001$) also showed the highest correlation with perceived exertion (RPE), followed by *lip pucker* ($r = .32$, $p < .001$). FS and RPE were highly correlated ($r = -.74$, $p < .001$). These results indicate that both FS and RPE were associated with *mouth open* and *jaw drop*.

Table 1. Repeated measures correlation of all facial actions with FS and RPE

Facial Action	**FS**	**RPE**
mouth open	-0.55*	0.70*
jaw drop	-0.40*	0.51*
nose wrinkle	-0.34*	0.29*
lip pucker	-0.32*	0.32*
upper lip raise	-0.31*	0.27*
lid tighten	-0.30*	0.26*
eye closure	-0.29*	0.30*
smile	-0.26*	0.25*
lip stretch	-0.21*	0.18*
cheek raise	-0.19*	0.21*
lip press	-0.19*	0.15*
dimpler	-0.17*	0.13*
brow furrow	-0.14*	0.17*
eye widen	0.14*	-0.27*
lip corner depressor	-0.13*	0.13*
lip suck	-0.10*	0.01
inner brow raise	-0.10*	0.07
brow raise	-0.07	0.16*
chin raise	-0.07	0.03
smirk	-0.07	-0.06

FS, Feeling Scale; RPE, Rating of perceived exertion
*p < .001

3.4 Multilevel Analyses

3.4.1 Predicting FS from facial action whilst controlling for RPE

To identify which facial action best explains variation in FS during an incremental exercise session we calculated separate multilevel models for each facial action (left column of

Table 2). RPE was included in these models as a control variable with random intercepts and slopes. The model with *nose wrinkle* as the predictor showed the best fit (AICC = 2770.08, *W* = 1). Parameter estimates ($b = -0.09$, $p < .001$) indicate a linear decrease in FS with increasing *nose wrinkle*. Adding *nose wrinkle* as a fixed effect significantly improved the model fit ($\chi^2(1) = 12.37$, $p < .001$) compared to the reduced model (RPE predicting FS). Adding *nose wrinkle* to this model as a random effect further improved model fit significantly, $\chi^2(3) = 32.89$, $p < .001$. *Nose wrinkle* explained 15.51% of the within-subject variation in FS. *Smile* showed the next best fit (AICC = 2780.83, W = 0), with parameter estimates ($b = -0.03$, $p < .001$) indicating a linear decrease in FS as *smile* increased, explaining 3.47% of the within-subject variation in FS. All other facial actions showed an even worse model fit (left column of Table 2).

All in all, these results indicate that when controlling for the effects of RPE, *nose wrinkle* explains a significant proportion of the variation in affective valence and more than any other of the facial actions.

Table 2. Comparison of multilevel models in which one facial action predicts FS (left column) or RPE (right column).

	FS				RPE			
model	**K**	**AICC**	**Delta AICC**	**W**	**K**	**AICC**	**Delta AICC**	**W**
reduced[a]	7	2807.19	37.11	0	7	4192.92	57.86	0
mouth open	11	2796.18	26.10	0	11	4135.06	0	0
jaw drop	11	2810.51	40.43	0	11	4184.02	48.96	0
nose wrinkle	11	2770.08	0	1	11	4197.21	62.14	0
lip pucker	11	2805.21	35.13	0	11	4197.64	62.58	0
upper lip raise	8[b]	2796.12	26.04	0	11	4199.05	63.99	0
lid tighten	11	2788.75	18.67	0	11	4200.74	65.68	0
eye closure	11	2810.74	40.66	0	11	4198.96	63.90	0
smile	11	2780.83	10.75	0	11	4200.38	65.32	0
lip stretch	11	2811.84	41.76	0	11	4197.89	62.82	0
cheek raise	11	2796.27	26.19	0	11	4199.80	64.74	0
lip press	11	2808.03	37.95	0	11	4198.29	63.23	0
dimpler	11	2813.96	43.88	0	11	4197.60	62.53	0
brow furrow	11	2803.04	32.96	0	11	4200.38	65.32	0
eye widen	11	2811.23	41.15	0	11	4188.29	53.23	0
lip corner depressor	8[b]	2807.60	37.52	0	11	4200.32	65.25	0
lip suck	11	2814.52	44.44	0	11	4201.08	66.02	0
inner brow raise	11	2809.52	39.44	0	11	4200.38	65.32	0
brow raise	11	2813.85	43.77	0	11	4200.81	65.75	0

chin raise	11	2813.14	43.06	0	11	4200.92	65.86	0
smirk	11	2804.41	34.33	0	11	4197.28	62.22	0

FS, Feeling Scale; RPE, Rating of perceived exertion; K, number of parameters; AICC, Akaike information criterion corrected; W, weight of evidence. Models predicted FS (left column) resp. RPE (right column) with each facial action as a fixed and random factor while controlling for the influence of RPE resp. FS.
[a]The reduced model describes the respective outcome variable predicted by the respective covariate (left column: RPE predicting FS, right column: FS predicting RPE).
[b]The models with upper lip raise and lip corner depressor as a predictor of FS failed to converge. Therefore, a more parsimonious model without the facial action as a random factor was calculated, resulting in a smaller number of parameters (K).

3.4.2 Predicting RPE from facial action whilst controlling for FS

To determine which facial action explains the most variation in RPE during the incremental exercise session we calculated a series of analyses in which RPE was predicted by all different facial actions in separate multilevel models (right column of Table 2). FS was included in each model as a control variable with random intercepts and slopes.

Here *mouth open* showed the best model fit (AICC = 4135.06, $W = 1$), followed by *jaw drop* (AICC = 4184.02, $W = 0$). Parameter estimates for both *mouth open* ($b = 0.03$, $p < .001$) and *jaw drop* ($b = 0.02$, $p < .001$) indicate a linear increase in RPE with increasing facial action.

Adding *mouth open* as a fixed effect to the reduced model (FS predicting RPE) significantly improved model fit (χ^2 (1) = 65.85, $p < .001$) and this model explained 16.28% of within-subject variance in RPE. Adding *mouth open* as a random effect did not further improve model fit, χ^2 (3) = 0.15, $p = .99$.

Adding *jaw drop* as a fixed effect to the reduced model (FS predicting RPE) significantly improved the model fit (χ^2 (1) = 16.84, $p < .001$) and this model explained 5.37% of within-subject variance in RPE; adding *jaw drop* as a random effect did not further improve the model fit, χ^2 (3) = 0.20, $p = .98$.

All other facial actions showed a worse model fit (right column of Table 2), none explained more than 2.68% (*eye widen*) of the within-subject variation in FS.

Taken together these results indicate that *mouth open* and *jaw drop* explained significant variation in perceived exertion, and more than all other facial actions. Both facial actions involve movements in the mouth region; *jaw drop* is the bigger movement, as the whole jaw drops downwards, whereas *mouth open* only involves a drop of the lower lip [31].

3.4.3 Predicting facial action from FS and RPE

In order to separate the proportion of variance in the above identified facial actions (i.e. *mouth open* and *jaw drop*; *nose wrinkle*) explained by RPE and FS we calculated three separate multilevel models with each of these facial actions as the dependent variable and RPE and FS as time-varying predictors.

Mouth open was significantly predicted by both, RPE (b = 2.53, p = < .001) and FS (b = -1.34, p = .003). Introducing random slopes for RPE significantly improved model fit, χ^2 (2) = 7.12, p = .03. RPE accounted for 41.21% of the within-subject variance in *mouth open* and significantly improved the model compared to a reduced model without RPE as a predictor, χ^2 (3) = 99.32, p < .001. FS accounted for 11.42% of the within-subject variance in *mouth open* and significantly improved model fit compared with the reduced model without FS as a predictor, χ^2 (1) = 10.50, p = .001.

Nose wrinkle was significantly predicted by FS (b = -0.32, p = .003), but not by RPE (b = 0.06, p = .13). Introducing random slopes for FS and then RPE in separate steps significantly improved model fit; FS: χ^2 (2) = 152.07, p < .001, and RPE: χ^2 (3) = 21.78, p < .001. FS explained 21.10% of the within-subject variance in *nose wrinkle* and significantly improved model fit compared to the reduced model without FS as a predictor, χ^2 (4) = 122.11, p < .001.

Jaw drop was significantly predicted by RPE (b = 1.06, p < .001), but not by FS (b = -0.49, p = .12). Introducing random slopes for RPE significantly improved model fit, χ^2 (2) = 14.54, p < .001. RPE explained 35.83% of the within-subject variance in *jaw drop* and significantly improved model fit compared to a reduced model without RPE as a predictor, χ^2 (3) = 59.02, p < .001.

4 Discussion

The aim of this study was to examine whether and how single facial actions change with exercise intensity and how they were related to affective valence and perceived exertion. The study is innovative with regard to at least two aspects. First, we used automated facial action analysis technology to observe change in 20 discrete facial areas covering the whole face in a large sample of study participants. Second, the use of multilevel models allowed us to account for differences in change across individuals (nested data structure). We found that both affective valence and perceived exertion were significantly associated with *mouth open*. After controlling for the influence of RPE, *mouth open* was no longer significantly associated with affective valence, but the relationship between *mouth open* and RPE remained significant after controlling for the effect of affective valence. All in all, during exercise *nose wrinkle* was specifically characteristic of negative affect (i.e., less pleasurable feelings with increasing perceived exertion) and *jaw drop* of higher RPE. Fig 1 illustrates examples of these relevant facial actions.

4.1 Affective responses at different levels of perceived exertion

Several studies have investigated the change of affective responses during exercise with repeated measurement designs [10]. We think that this makes the separation of the intra- and inter-individual variability in data analysis inevitable. However, to the best of our knowledge there is currently no published study in which trajectories have been analyzed using the according multilevel regression approach. On the basis of dual-mode theory [9] and previous findings we hypothesized that there would be a negative quadratic trend [10, 40] of the affective response with increasing exercise intensity. Multilevel analysis confirmed this hypothesis and also demonstrated that there was high inter-individual variability in reported affective valence during exercise (Fig 2). This demonstrates the, in our view, necessity of using multilevel analysis when examining the decline in affect (more negative) during exercising with increasing intensity.

Previous studies were able to demonstrate the existence of inter-individual variability in affective valence by describing that e.g. 7% of participants reported an increase in affect ratings, 50% no change and 43% a decrease during exercise below the VT [41]. The statistical approach presented here extends this approach and allows to perform research that quantifies the influence of moderators of the exercise intensity-affect relationship to explain inter-individual differences in affective responses to exercise at given intensity level.

4.2 Affective responses and facial action

In our study affective valence was most highly correlated with the facial action *mouth open* when using simple repeated measures correlations (Table 1). However, affective valence was highly correlated with RPE, which was in turn highly correlated with *mouth open*. In order to determine what facial actions account for components of variance in specific constructs it is necessary to take into account the multicollinearity of the constructs. We did this by controlling statistically for variance in one construct (e.g. RPE) when analyzing the effect of the other (e.g. affective valence). When the influence of perceived exertion was taken into account, affective valence was most strongly associated with the facial action *nose wrinkle* (Table 2). This is consistent with previous research showing that nose wrinkling may indicate negative affect. For example, newborns [42] and students [43] respond to aversive stimuli (e.g., a sour liquid [42] or offensive smells [43]) by wrinkling their nose. Perhaps pain is the context most relatable to high-intensity exercise. Studies of pain have identified nose wrinkling as an indicator of the affective dimension of pain [44], which is highly correlated with, but independent from, the sensory dimension [45].

Nose wrinkle has also been specifically associated with the emotion disgust [15]. However, the same facial action has been observed in various other situations (e.g. while learning) [46] and emotional states (e.g., anger) [47] and is not always observed concomitantly with reports of disgust [48]. *Nose wrinkle* may be indicative of negative affect more generally, rather than of a specific emotional state therefore.

Nose wrinkle explained more variance in affective valence than any other facial action, but given that this is the first study to have examined changes in facial action and affect during the course of an incremental exercise test and was performed with a sample of healthy adults, we suggest limiting the conclusion to the following: *nose wrinkle* is a facial action indicating negative affect in healthy adults during incremental exercise. To draw more general conclusions, for example, that *nose wrinkle* is the characteristic expression of negative affect during exercise, further research is needed. It would need to be demonstrated, for example, that this facial action reliably co-occurs with negative affect and that this co-occurrence prevails across several exercise modalities (e.g., running, resistance training).

4.3 Perceived exertion and facial action

The facial actions that were most highly correlated with perceived exertion, when controlling for the effect of affective valence were *mouth open* and *jaw drop* (Table 2). On one hand, this is in line with research showing that activity in the jaw region is correlated with RPE [24]. At first sight, this may not go well with the findings from the fEMG study [22] that suggested that perceived exertion during physical tasks is mainly linked with corrugator muscle activity. It is important to note, however, that fEMG only measures activity in the muscles to which electrodes were attached (apart from noisy crosstalk), and that it cannot capture the dynamics of the whole face [49].

On the other hand, it is worth pointing out that we observed a correlation between RPE and *brow furrow* (which partly reflects corrugator activity). This correlation was smaller than the two correlations between RPE and *jaw drop* and *mouth open* however (Table 1). First and foremost, it must be noted that as physical exertion increases, the exerciser is likely to breath heavier. The change from nose to mouth breathing is certainly to be interpreted against the background that more air can flow faster through the mouth. The observed change in facial action (i.e. increased *mouth open* and *jaw drop*) therefore most likely correlated with the physiological need for optimized gas exchange in the working organism. It is therefore particularly important to exploit the advantages of automated facial action analyses of the whole face and discrete facial actions to investigate the covariation of the various facial actions more closely.

4.4 Affective responses, perceived exertion and facial action

Both affective valence and perceived exertion were significantly associated with the facial action *mouth open* (Table 2). While *nose wrinkle* was specific in explaining significant amounts of variance in affective valence and *jaw drop* in perceived exertion, *mouth open* explained significant amounts of variance in both affective valence and physical exertion (the facial action *mouth open* is described as “lower lip dropped downwards” in the Affectiva developer portal; *jaw drop* is “the jaw pulled downwards” with an even wider and further opening of the mouth [31]). This pattern of results might be interesting for the conceptual differentiation of affective valence and perceived physical exertion.

The two concepts, affective valence and physical exertion, are certainly closely linked [12]. This is reflected in our finding that the two are significantly correlated with the same facial action – *mouth open*. However, when the relationship of affective valence with the facial actions was controlled for the influence of RPE, *mouth open* explained only 1.19% of the within-subject variance in affective valence; *nose wrinkle* explained 15.51% on the other hand. These results suggest that mouth opening can be seen as a sign for the physical exertion portion in the experienced affect, whereas *nose wrinkle* indicates negative affect specifically.

Jaw drop (as the more extreme mouth opening), on the other hand, appeared not to be related to affective valence. *Jaw drop* could thus be assumed to be the more specific sign for (excessive) perceived exertion. Both the metabolic thresholds, VT and RCP, are related to perceived exertion. They are objective, individualized metabolic indicators of intensity, and are already associated with psychological transitions in dual mode theory [9]. Linking them to transitions in facial actions could be a future prospect and be something like this: While exercising at the VT might mark the transition between nose to (predominantly) mouth breathing and thus also the transition to more *mouth open*, exercising above the VT might mark a transition to more *jaw drop*. This kind of intensified breathing might covary with escalating negative affective valence – that is the evolutionary built-in warning signal that homeostatic perturbation is precarious and behavioral adaptation (reduction of physical strain) is necessary [12]. We have not analyzed the dynamics of the different facial actions in our study under this aspect, as this would not have been appropriate because we did not measure physiological markers for exercise intensity. But we suggest that future research should focus on exactly that.

4.5 Context- and individual-specific facial actions

This study can also be seen as a contribution to the current debate on what the face reveals about underlying affective states and whether universal, prototypical emotional facial expressions exist [16]. Our results support the notion that specific facial actions must be associated with affective states in a context- or individual-dependent manner in the first place. For example, *smile* (AU 6 + AU 12) is typically associated with the emotion "happiness" [50] and with positive affective valence [51]. This does not match our finding, and that of another study in the context of exercise [21], that *smile* can also be correlated with negative affective valence.

The use of biometric indices of facial action to measure psychological states requires that one takes into consideration that facial action is subject to high intra- and inter-individual variability [16]. Using multilevel analyses allowed us to take this into account. Due to the fact that some people show little or no movement in their faces, aggregational grand mean analyses such as a repeated measures ANOVA (which does not first model individual change) would be biased by this variation. Such analyses treat individual deviation from the grand mean as residual error, leading to the loss of important information about inter-individual differences. By taking individual trajectories into account, multilevel analyses allowed us to separate within-subject variance from between-subject variance and hence to adjust for obvious individual differences in facial action.

4.6 Limitations and recommendations for further research

Among the limitations of our study are the following: Basically we argued that automated facial action analysis could be an alternative for a more unobtrusive measurement of feelings during exercise. It is important not to lose sight of the fact, however, that simply knowing that you are being filmed can of course also change your behavior [52]. Another point is that although this study primarily focused on the correlations between facial actions and ratings of affective valence and perceived exertion, it would be advantageous to determine exercise intensity physiologically at the level of the individual participants in future studies (e.g., by the use of respiratory gas analysis in a pretest). This would have given us more confidence as to whether the majority of our participants have actually reached a state close to physical exhaustion at the end of the exercise protocol. Considering the participants' average RPE in their maximum watt levels and the comparison of the achieved heart rates with other studies on bicycle ergometers we think this is likely, but we cannot be sure of course. We further suggest that future studies should use more heterogeneous participant samples and a greater variety of sports and exercises to assure higher generalizability of the findings. Different modalities and different exercise intensities might produce specific facial actions. More heterogeneous samples are likely to produce more variance in affective responses, which may lead to further insight into the variation in facial reactions to exercise.

5 Conclusion

We conclude that both affective valence and perceived exertion can be captured using automated facial action analysis. Escalating negative affect during physical exercise may be characterized by nose wrinkling, representing the 'face of affect' in this context. The 'face of exertion', on the other hand, may be characterized by jaw dropping.

From a practical perspective, these results suggest that observing the face of an exerciser can give instructors important insights into the exerciser's momentary feelings. Facial actions can tell a lot about how the individual feels during exercise, and instructors could use individual facial cues to monitor instructed exercise intensity; to enhance exercisers' affective experience during exercise, which, at least for those who are not keen on exercise, is an important variable for maintaining the disliked behavior.

6 References

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Exercise or Not? An Empirical Illustration of the Role of Behavioral Alternatives in Exercise Motivation and Resulting Theoretical Considerations

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Abstract

Objective: Individuals' decisions to engage in exercise are often the result of in-the-moment choices between exercise and a competing behavioral alternative. The purpose of this study was to investigate underlying processes that occur in-the-moment (i.e., situated processes) when individuals are faced with the choice between exercise and a behavioral alternative during a computerized task. These were analyzed against the background of interindividual differences in individuals' automatic valuation and controlled evaluation of exercise.

Method: In a behavioral alternatives task 101 participants were asked whether they would rather choose an exercise option or a behavioral alternative in 25 trials. Participants' gaze behavior (first gaze and fixations) was recorded using eye-tracking. An exercise-specific affect misattribution procedure (AMP) was used to assess participants' automatic valuation of exercise before the task. After the task, self-reported feelings towards exercise (controlled evaluation) and usual weekly exercise volume were assessed. Mixed effects models with random effects for subjects and trials were used for data analysis.

Results: Choosing exercise was positively correlated with individuals' automatic valuation (r = .20, p = .05), controlled evaluation (r = .58, p <.001), and their weekly exercise volume (r = .43, p <.001). Participants showed no bias in their initial gaze or number of fixations towards the exercise or the non-exercise alternative. However, participants were 1.30 times more likely to fixate on the chosen alternative first and more frequently, but this gaze behavior was not related to individuals' automatic valuation, controlled evaluation, or weekly exercise volume.

Conclusion: The results suggest that situated processes arising from defined behavioral alternatives may be independent of individuals' general preferences. Despite one's best general intention to exercise more, the choice of a non-exercise alternative behavior in-the-moment may seem more appealing and eventually be chosen. New psychological theories of health behavior change should therefore better consider the role of potentially conflicting alternatives when it comes to initiating physical activity or exercise.

1 Introduction

Promoting exercise is one of the most critical public health priorities, considering being insufficiently active increases the risk of death by 20 - 30 % compared to being sufficiently active (World Health Organization, 2020). Understanding the psychological processes that guide the choice to be physically active is key to more effectively promoting regular exercise behavior. In the past 20 years, exercise psychology has been largely dominated by a focus on social-cognitive and humanistic/organismic frameworks that conceptualize behavior change as a mostly unidirectional process, such that a behavior is done based on mentally imagined goals (e.g., the idea of going for a run, which may have positive consequences or fit particularly well with our subjective values) (Ekkekakis & Brand, 2021; Rhodes et al., 2019). This framework is based on the assumption that individuals form expectations (e.g., that exercise is important and doable) from which the intention to exercise culminates (Rhodes et al., 2019). Intention as the primary antecedent of behavior is one of the cornerstones of the social-cognitive framework, yet empirical evidence reveals a consistent intention-behavior gap (Rhodes & de Bruijn, 2013). Possible reasons for this gap are negative exercise-related automatic tendencies that are contrary to the intention (Brand & Ekkekakis, 2021), such as negative automatic associations (Schinkoeth & Antoniewicz, 2017), affective valuations (Schinkoeth & Brand, 2020), habit or identity (Rhodes, 2017, 2021).

Only recently, dual-process models that emphasize the role of automatic processes in addition to controlled cognitive processes (e.g., forming an intention from expectations about the future), have been applied to exercise psychology. According to a recent review, dual-process models are ‘the most recent and understudied framework for understanding physical activity’ (Rhodes et al., 2019, p. 100). Moreover, there is at least one other characteristic of dual-process models that needs to be emphasized. The dual-process framework implies that automatically activated momentary processes are essentially predetermined by the situation and therefore also referred to as *situated* processes (Brand & Ekkekakis, 2018). They may conflict with behavioral plans and must be analyzed in terms of their importance for behavioral regulation.

Examples of dual-process theories that address the role of *situated processes* within exercise and physical activity behavior include the Affective-Reflective Theory of Physical Inactivity and Exercise (ART; Brand & Ekkekakis, 2018) and the Theory of Effort Minimization in Physical Activity (TEMPA; Cheval & Boisgontier, 2021). The two have been recently contrasted in a theoretical article with an argument that provides the foundation for the current study (Brand & Cheval, 2019). Both theories are grounded in the idea that in-the-moment when individuals have to make a choice between one behavior (e.g., do exercise) or a competing behavioral alternative (e.g., remain physically inactive), a *momentary conflict* can arise before a choice is made. According to the ART, there are situated automatic affective processes that have been learned through previous experiences with exercise that can prevent individuals from rationally considering becoming physically active (a negative affective valuation of exercise) or steer us toward it (a positive affective valuation of the behavior). The TEMPA assumes that a hard-wired evolutionary process is default, which accounts for an ever-present behavioral tendency to avoid and economize physical activity and may conflict with more rational considerations.

Multiple experimental studies support the perspective of dual-process theories that when individuals are confronted with an exercise-related stimulus an immediate psychological response (e.g., affective reaction or approach/avoidance tendency) is triggered (Rebar et al., 2016; Schinkoeth & Antoniewicz, 2017). Previous studies have typically measured automatic (e.g., Chevance et al., 2017) and controlled processes first (e.g., Kiviniemi et al., 2007), and then either correlated them with remembered usual exercise behavior (e.g., Bluemke et al., 2010) or used them to predict exercise behavior in subsequent weeks (e.g., Antoniewicz & Brand, 2016). Findings from these studies suggest that those who are more active tend to focus more on exercise stimuli. Despite previous literature on interindividual differences (e.g., automatic preferences) and distal behavior outcomes (e.g., usual exercise volume), less is known about potentially conflicting situated processes that occur in the moment an individual is asked to choose a behavior. For example, some may have a strong automatic preference for exercise, but when confronted with a competing non-exercise behavioral option, the behavioral alternative may seem even more attractive in that particular moment and eventually be chosen.

Harris and Bray (2019, 2021) examined single situated exercise decisions. Participants had to choose between an exercise vs a non-exercise task (e.g., seated "free time" with smartphone) after completing either a high- or low-cognitive demand task. The high cognitive demand task resulted in increased mental fatigue, which in turn decreased likelihood of choosing to exercise. These findings emphasize the importance of situated factors (e.g., mental fatigue) in an individual's in-the-moment choice whether or not to exercise.

In a recent study, Cheval et al. (2020) took situated processes into account by employing a paradigm in which eye-tracking was used to examine participants' gaze behavior while they viewed mutually exclusive behaviors. The authors found that physically active individuals were generally more likely to focus their attention on physical activity stimuli than on stimuli representing a sedentary alternative. The study presented here builds on these findings, but examines situated gaze in a more complete behavioral situation: We monitored participants' gaze behavior when they have to *choose* between an exercise-related stimulus and a stimulus displaying a non-exercise alternative, and analyze their choices on the background of previously measured interindividual differences in self-reported exercise behavior, automatic valuation of exercise and self-reported feelings towards exercise.

In other fields, such as consumer psychology, process tracing methods are frequently used to capture situated processes in order to assess which factors play a role during behavioral decision-making (e.g., information search strategy). For example, eye-tracking has often been used to assess attentional processes during behavioral or consumer choices. Commonly used measures are *first gaze* (i.e., first fixated location) and number of *fixations* (i.e., temporally closely spaced fixated locations for a period of time). First gaze has shown a weak and inconsistent association with choice behavior. Schotter et al. (2010) demonstrated that participants were slightly more likely to choose the item they fixated on first. In contrast, Krajbich et al. (2010) found that the probability of fixating an item first was unaffected by their initially preferred ratings. A more homogenous pattern of results emerges for number of fixations. Previous research supports the idea that the more time we spend on an item, the more likely we are to choose it (Cavanagh et al., 2014; Krajbich et al., 2010). However, researchers disagree on whether this relation is causal, leaving open the question of whether we direct our attention on what we like or we will like what we focus our attention on (Orquin & Mueller Loose, 2013).

The present study aimed to extend insights on the processes occurring when individuals are confronted with competing behavioral alternatives. We administered eye-tracking in a computerized task where participants were asked to choose between an exercise and a non-exercise alternative in a series of hypothetical situations. Gaze behavior was tracked to examine how much attention was paid to each behavioral alternative in each situation of choice. This allowed us to measure both interindividual (e.g., who is generally more likely to look at exercise) and intraindividual processes (e.g., which of the behavioral alternatives is more likely to be fixated) and use them as proxies for the situated processes that would likely occur in real life situations.

According to the TEMPA, one could assume an initial bias towards the non-exercise alternative (Cheval & Boisgontier, 2021). With the ART conceptualizing the automatic response as a learned process (Brand & Ekkekakis, 2018) one would assume that individuals who (have learned to like and do) exercise more regularly will have an initial bias towards the exercise alternative. Based on findings from consumer psychology, we expected that individuals would be more likely to initially direct their gaze toward the chosen alternative and fixate this alternative more often. Whilst the current study emphasized the examination of gaze behavior as situated processes within individuals, we recognize that interindividual differences in automatic and controlled processes are also relevant to exercise behavior (e.g., Rhodes et al., 2019; Schinkoeth & Antoniewicz, 2017). In line with the constructs of the ART (Brand & Ekkekakis, 2018), we included examinations of the association of automatic valuation towards exercise, self-reported feelings towards exercise (controlled evaluation) and exercise behavior with gaze behavior on a subject-level as well. Based on previous findings (Cheval et al., 2020) we expect individuals with higher levels of self-reported exercise behavior (and more positive automatic and controlled (e)valuations of exercise) to display higher attentional focus (first gaze and fixations) on exercise-related stimuli. By simultaneously considering inter- and intraindividual varying processes when individuals are confronted with exercise-related choices, this study introduces a new approach to investigate situated processes in exercise psychology.

2 Materials and Methods

2.1 Participants

106 students from the University of Potsdam took part in this study. Participants were recruited through the university's participant pool. Five participants were removed from the analysis due to technical problems during data collection, resulting in a total sample of N = 101 participants (M_{age} = 23.6, SD_{age} = 3.6, 48.5% females). Most of the participants were enrolled in a sports science (n = 80) or psychology (n = 21) program. All participants provided written consent before the experiment, fulfilled the screening criteria (i.e., no confounding activities such as intensive exercise or alcoholic beverages beforehand), and reported having a normal or corrected-to-normal vision without color blindness. Participants were compensated for their participation with additional (non-obligatory) course credit. The study was conducted following the ethical standards laid out in the Declaration of Helsinki and the local institution's ethical guidelines. Data, analysis code, and stimulus material are available at https://osf.io/ubrj7/.

2.2 Measures

2.2.1 Behavioral Alternatives Task

For the behavioral alternatives task, we adapted the idea of the Situated Decisions to Exercise Questionnaire (SDEQ) by Brand and Schweizer (2015) in a computerized task presented with iMotions^{TM} software (version 8.0). After reading a prototypical everyday situation (vignette, e.g., a friend has asked you if you'd either like to work out with him tonight or have a lazy evening) five randomized pairs of pictures representing the conflicting behavioral alternatives exercise vs. non-exercise were presented. In each of the trials, participants were forced to choose one of the presented behavioral alternatives they would engage in (see Figure 1). Two vignettes each described situations where the activities would be done alone (vignettes 1 and

5) or together with others (vignettes 2 and 3), respectively. One vignette described an ambivalent situation where the individual could choose to do the behavior alone or in a group (vignette 4). Thus, participants completed 5 vignettes with 5 randomized pairs of pictures resulting in a total of 25 trials. The pictures were presented side-by-side on the left and right sides of the computer screen. The side of the screen was randomized for the exercise and non-exercise alternative. Choices had to be made within 10 seconds by clicking on either the ‘E’ (left behavioral alternative) or ‘I’ (right behavioral alternative) button on a keyboard.

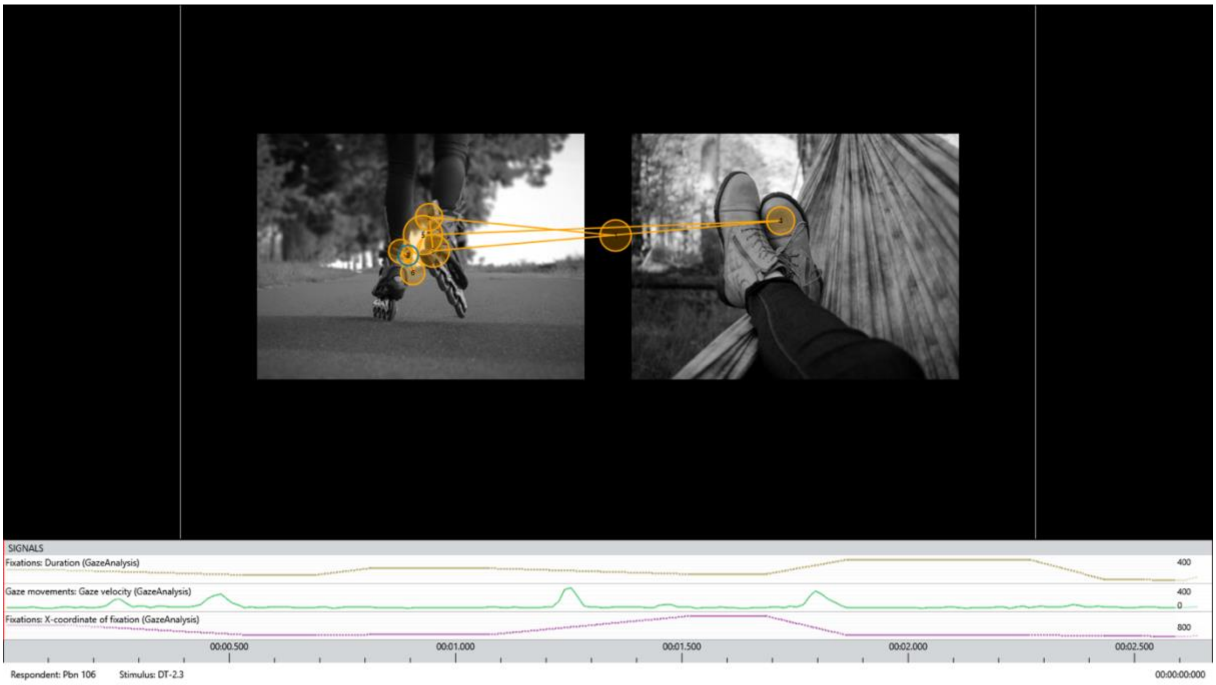

Figure 1 | Example of a decision trial with recorded fixations. Screenshot from iMotions software.

A 10-second time constraint with manual advance was set. To prevent participants from engaging excessively in deliberate thinking, they were asked to choose based on their initial thought as fast as possible. Between the trials, participants had to focus on a fixation cross for 5 s.

In total, 50 different pictures were used in the task: 25 representing exercise and 25 representing non-exercise. The exercise activities were selected according to the results of a representative survey on common sports and exercise activities among the Berlin population (Dierker et al., 2018). The results of that survey indicated biking, running, fitness, swimming, and hiking as the five most frequent activities. Since primarily moderate- or vigorous-intensity activities should be displayed in the current study, hiking was not considered; however, additional fitness activities were included based on exercise trends (e.g., CrossFit, rollerblading). For the non-exercise alternative, a broad range of alternatives were selected such as reading, listening to music, and lying in the park. Images were mainly provided by a license-free image database (pixabay.com), and four images were self-taken by the authors. All images were presented in grayscale (16 bit) with a minimum resolution of 1024 x 768 pixels and processed so that brightness distribution and contrasts were matched. The exercise and non-exercise images had to fulfill the following requirements: a similar perspective, the same number of individuals on the images with no visible facial expressions, no sexual stimuli, and no labels.

Intraindividual differences in gaze behavior and choice behavior for the behavioral alternatives were repeatedly measured and analyzed for each choice trial during the task.

Since these measures can differ from situation to situation within individuals, they were used as a proxy for situated processes.

2.2.1.1 Gaze Behavior

Gaze behavior (*first gaze* and *fixations*) was measured with the Gazepoint GP3 eye-tracker at a sampling frequency of 60 Hz. For each trial, a *first gaze* toward the exercising picture was coded as 1, whereas a first gaze toward the non-exercise picture was coded as 0. *Fixations* are a period during which the eyes are locked on a specific location in the visual field, measured by the eye tracker as a series of very close gaze points in time and range. The I-VT algorithm was used to classify eye movements above the velocity threshold of 30°/s as a fixation (Olsen, 2012). Number of fixations was separately computed for the exercising and the non-exercise alternative.

2.2.1.2 Choice

For each trial, choosing the exercise alternative (*choice*) was coded as 1, whereas choosing the non-exercise alternative was coded as 0.

2.2.2 Interindividual Differences

Interindividual differences in participants' automatic valuation of exercise was assessed before the task, whereas self-reported feelings towards exercise and exercise behavior were assessed after completing the task.

2.2.2.1 Automatic Valuation of Exercise

The affective misattribution procedure (AMP; Payne et al., 2005) was used as a proxy for an automatic-affective valuation of exercise. The AMP uses supraliminal presentations of primes (of the affective target stimuli, e.g., exercise) followed by a neutral Chinese ideograph. It is assumed that participants misattribute their spontaneous affective response to the primes for evaluation of the Chinese ideographs (Payne & Lundberg, 2014). Positive values indicate that ideographs following an exercise prime are more likely to be positively evaluated, and negative values indicate that ideographs following a non-exercise prime are more likely to be positively evaluated. In this study, an adapted version of the standard AMP (Payne et al., 2005) was presented with Inquisit 5.0 software. The same exercise and non-exercise pictures from the behavioral alternatives task were used as target primes, and grey squares were used as neutral primes. Primes were presented for 75 ms followed by a 125 ms black screen and by the presentation of the Chinese ideograph for 200 ms. Then, a grey mask picture was shown until participants evaluated the ideograph as "pleasant" or "unpleasant" by pressing the "E" or "I" key respectively on a standard QWERTZ keyboard. Participants were instructed to ignore the prime stimulus (Payne & Lundberg, 2014) and completed 100 randomly presented trials, lasting approximately five minutes total. The AMP score was calculated as the difference between the proportions of ideographs evaluated as pleasant after the exercise primes vs. the non-exercise primes divided by 100, resulting in a score between -1 and 1 (Payne et al., 2005). Positives scores indicated more ideographs following an exercise prime were evaluated as pleasant, whereas negatives scores indicated more ideograph following a non-exercise prime were evaluated as pleasant. The AMP score was z-transformed before further analyses. The internal consistency of the AMP in this sample (split-half; $\rho = 0.81$) is similar to that found in previous studies (> .80; e.g., Zenko & Ekkekakis, 2019). We chose the AMP as an implicit measure of automatic-affective valuation of exercise due to its inherent core affective and valuative properties. The AMP is based on the theoretical idea to elicit a spontaneous, automatic, affective judgement. This is conceptually close to the construct of automatic-affective valuation of exercise according to the ART (Brand & Ekkekakis, 2018; in contrast, for example, implicit association tests are based much more on the assumption of mental representations). Many studies from different research areas have already used the AMP to draw conclusions about automatic affective reactions to a wide range of behaviors, including drinking decisions (Payne et al., 2008), moral decisions (Hofmann & Baumert, 2010) and eating behavior (e.g., Hofmann et al., 2010). According to a meta-analysis (Cameron et al., 2012), the AMP can be used to predict behavior with an average effect size of $r = 0.35$. Few original studies in exercise psychology have used the AMP, but had comparable results (Antoniewicz & Brand, 2014; Karpen et al., 2012).

2.2.2.2 Self-reported Feelings towards Exercise

Self-reported feelings associated with exercise was used as a proxy for controlled evaluation of exercise. Participants indicated how they felt about exercising on a continuous 7-point scale ("absolutely negative" to "absolutely positive"). Scores for self-reported positive feelings were z-standardized. Research has shown that single-item measures to capture exercise-related feelings have reasonable validity, meaning that single-item measures measuring exercise-related feelings are highly correlated with multi-item measured of the same construct ($r = .56$ to $.70$; Brito et al., 2022).

2.2.2.3 Self-reported Exercise Volume

Self-reported exercise volume was measured through questions from the International Physical Activity Questionnaire (short form; Craig et al., 2003) as a proxy for a behavioral component. Participants were asked about their usual exercise behavior in their free time. Exercising was defined as activities that are deliberately pursued in a way that makes one breathe faster and break a sweat (e.g., swimming, jogging, going to the gym, tennis, soccer). Participants indicated their weekly frequency and duration of exercise sessions according to this definition. Average weekly exercise volume (sessions per week × duration per session) was calculated. One participant who reported an average duration of 360 minutes per session was excluded from all analyses of self-reported exercise volume.

2.2.3 Procedure

Participants were tested in single-person lab sessions lasting for approximately 45 min. The laboratory was dimmed with artificial lightning (i.e., no sunlight). Participants were seated 60 cm in front of a Benq Senseq FP222WA, 22" monitor. The monitor was connected to the investigator's laptop. The investigator could thereby monitor the experiment but was out of the participant's sight.

First, participants completed the AMP and then manually advanced to the behavioral alternatives task. Before initiating behavioral alternatives task, calibration of the screen-based Gazepoint eye-tracker was done by the iMotions^{TM} software. Participants were instructed to minimize head movements during eye-tracking recording. After successful calibration, participants completed the behavioral alternatives task. After the task, participants answered a follow-up questionnaire to control for possible confounders (e.g., excessive exercise before the experiment, demographics) and to assess the exercise-related controlled and behavioral component. Finally, participants were thanked and debriefed.

2.2.4 Data Analysis

The data were analyzed using generalized mixed models with the lme4-package (Bates et al., 2015) in R-software (R Core Team, 2021). Logistic mixed-effects models were used to predict the odds of first gaze (exercise vs. non-exercise) and linear mixed-effects to predict the number of fixations on the behavioral alternatives. Participants and trials were included as

crossed random effects to account for the crossed data structure and the non-independence of observations. Assuming a medium sized effect (based on a meta-analysis on the effect of visual attention on choice; Bhatnagar & Orquin, 2022), simulation studies revealed that in a fully crossed design with 25 trials 90 participants or more would result into 80% power (Westfall et al., 2014). To account for study attrition and data loss we aimed for a sample of at least 100 participants.
First, unconditional means models with the respective dependent variable (first gaze, exercise fixations, non-exercise fixation) were computed. Second, choice (1 = exercise, 2 = non-exercise) was added to model to test the relationship between gaze and decision behavior. Third, interindividual variables (i.e., automatic valuation of exercise, self-reported feelings towards exercise, and self-reported exercise volume) were separately introduced into this model to examine interindividual differences in gaze behavior.

3 Results

3.1 Choices in the Behavioral Alternatives Task

In the behavioral alternatives task, choosing the exercise alternative was more likely than choosing the non-exercise alternative (*OR* = 1.85, 95% CI [1.39; 2.47], $p < .001$). In other words, there was a 65% chance of choosing exercise across all decision trials and participants. Choosing the exercise alternative in the behavioral alternatives task correlated with self-reported exercise volume ($r = .43$, 95% CI [.20, .53], $p < .001$), with self-reported positive feelings towards exercise ($r = .58$, 95% CI [.43, .70], $p < .001$) and with the automatic valuation of exercise as measured with the AMP ($r = .20$, 95% CI [.00, .38], $p = .05$). Correlations and descriptive statistics of all main variables are presented in Table 1.

3.2 Gaze Behavior

3.2.1 First Gaze

There was no significant difference in whether participants fixated the exercise or the non-exercise alternative first (*OR* = 1.29, 95% CI [0.89, 1.88], $p = .18$), suggesting there was no initial bias towards the non-exercise alternative. However, the initial gaze fixation was more likely on the alternative that was then chosen by the participant (*OR* = 1.30, 95% CI [1.04, 1.62], $p = .02$). Self-reported exercise volume (*OR* = 1.00, 95% CI [1.00, 1.00], $p = .39$), self-reported positive feelings connected with exercise (*OR* = 0.99, 95% CI [0.90, 1.08], $p = .77$), and automatic valuation of exercise (*OR* = 0.98, 95% CI [0.89, 1.07], $p = .66$) did not contribute significantly to explaining variance in first gaze.

3.2.2 Fixations

Analyses revealed individuals had more fixations on the chosen alternative compared to the non-chosen alternative ($b_{\text{non-ex}} = 1.07$, 95% CI [0.78, 1.36], $p < .001$, $b_{\text{ex}} = -0.79$, 95% CI [-1.05, -0.53], $p < .001$). Figure 2 illustrates this effect, showing participants had more fixations on non-exercise (compared to exercise) when choosing non-exercise (orange line) and more fixations on exercise (compared to non-exercise) when choosing exercise (blue line). In each trial, exercise was fixated on average 3.99 times (95% CI [3.66, 4.31]) and non-exercise 3.90 times (95% CI [3.56, 4.24]) before one of the two alternatives were selected. There was no significant difference in the number of fixations on the exercise vs. the non-exercise alternative accordingly ($b = -0.09$, 95% CI [-0.34, 0.17], $p = .51$).

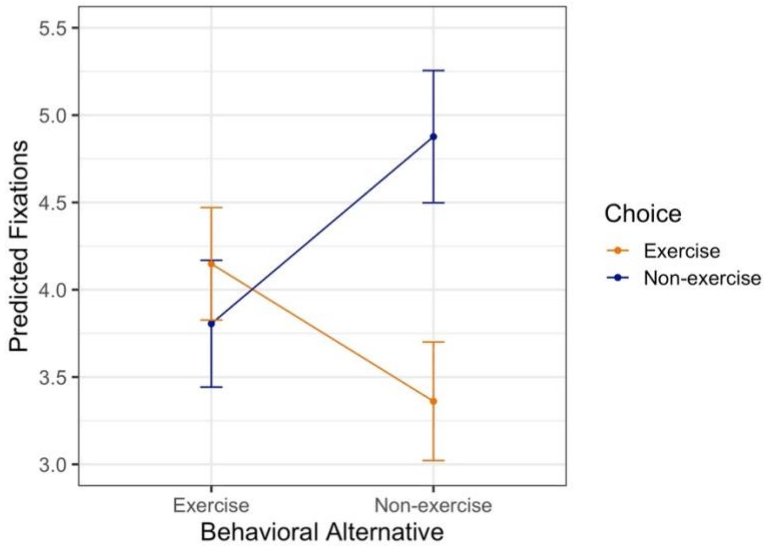

Figure 2 | Predicting fixations on the exercise and the non-exercise behavioral alternative with choice behavior. The orange line shows the model-predicted fixations on the behavioral alternatives exercise and non-exercise when exercise was chosen. The blue line shows the model predicted fixations on the behavioral alternatives exercise and non-exercise when non-exercise was chosen.

Automatic valuation of exercise, self-reported feelings associated with exercise, and self-reported exercise volume were generally unrelated to the number of fixations on the exercise (see Table 2) and on the non-exercise alternative (see Table 3). Only the number of gaze fixations on the non-exercise alternative was slightly associated with self-reported feelings towards exercise (b = -0.27, 95% CI [-0.53, -0.00], p = .05). Figure 3 illustrates that more positive reported feelings associated with exercise were not associated with more exercise fixations (orange line), but more negative reported feelings were associated with more fixations on the non-exercise alternative (blue line). These findings indicate the number of fixations was statistically informative for the behavioral choices in the task, but it was not associated with what participants typically like (automatic valuation and self-reported feelings towards exercise) or their usual behavior (self-reported exercise volume).

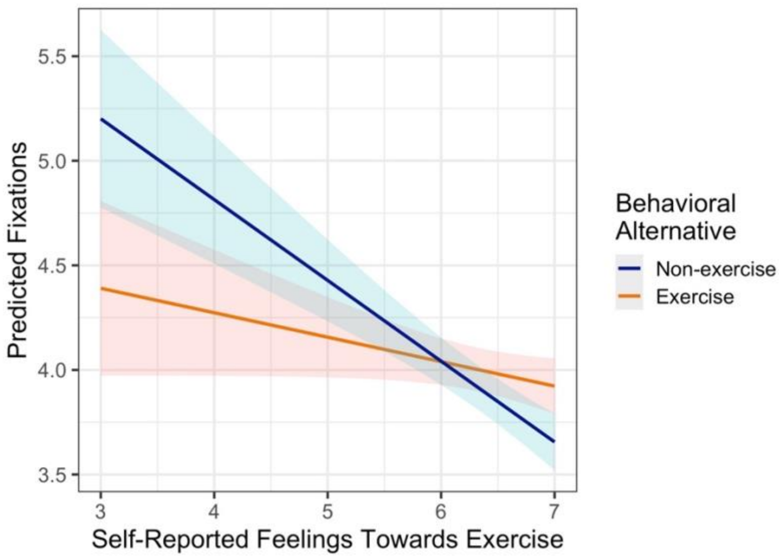

Figure 3 | Predicting fixations on the exercise (orange) and non-exercise alternative (blue) with self-reported feelings associated with exercise.

4 Discussion

This study examined situated processes and interindividual differences in gaze behavior in a sample of healthy individuals when confronted with a choice between two behavioral alternatives: to exercise or not to exercise. We found that individuals' gaze behavior was associated with their in-the-moment choice behavior, but not with their more general automatic affective valuation, their reflective evaluation of exercise, and not even with their self-reported exercise behavior. Findings suggest that individuals are more likely to focus on what they are about to choose in a single situation, but not what they usually like or do. Our results provide evidence that situated processes that arise from very specific stimulus configurations with behavioral alternatives can be independent of individuals' more general preferences.

These findings partially support theoretical perspectives from dual-process models such as the ART (Brand & Ekkekakis, 2018) and the TEMPA (Cheval & Boisgontier, 2021) (or the Automatic Affective Evaluations of Physical Activity model, to name another; Conroy & Berry, 2017) that situated and probably conflicting processes between behavioral alternatives need to become a greater focus of research when analyzing individuals' behavioral choices. After having established the intention, for example, to start an exercise routine, the resulting behavior is often an in-the moment-choice between behavioral alternatives. Individuals may experience conflicts thereby, because choices involve the desired behavior (e.g., exercise) and an alternative behavior that may be a barrier for engaging in the desired behavior (e.g., lying on the couch). Therefore, not only should the processes that drive someone towards the desired behavior (e.g., beliefs, goals) be analyzed, but also the processes that occur in a particular situation (i.e., situated processes) that prevent someone from engaging in that desired behavior.

As expected, individuals who reported to generally like and do exercise were more likely to choose the exercise alternative (65%) than the non-exercise alternative in the behavioral alternatives task. This fits well with self-reported exercise volume per week. We also had a fairly active sample with the middle 50% of participants reporting to have between 180 and 450 minutes of exercise per week (M = 358, SD = 283), on 3 to 6 active days. Thus, the sum of the individual choices in the behavioral alternatives task seems to reflect general exercise preferences.

There was no automatic bias in first gaze to either the exercise or the non-exercise alternative. This neither supported the assumptions of ART nor TEMPA. Based on TEMPA, there would have been a general automatic bias towards the non-exercise alternative due to an inherent universal bias toward effort minimization. Alternatively, ART would suggest automatic responses are learned through experiences and triggered when confronted with an exercise-related stimulus. Based on ART, participants would initially direct their gaze in line with their automatic valuation of exercise. However, those who had a more positive automatic valuation of exercise had no automatic bias towards the exercise alternative. This result could also be biased by the relatively active sample (due to the limited variance in the exercise volume variable).

One possible explanation for these findings is that the AMP is just a proxy for measuring automatic valuations and may not adequately represent the construct of automatic affective valuation of exercise, despite robust findings in other fields (Payne & Lundberg, 2014). Only one study to date has shown a medium size effect (d = 0.59) between the AMP score and exercise behavior (Antoniewicz & Brand, 2014). In particular, these authors showed that frequent fitness center exercisers exhibited more positive affective valuation of fitness center exercising than exercisers who preferred other exercise settings. In the present study, the AMP score was significantly, but only slightly (r = .20, p = .05) correlated with choice behavior and unrelated to self-reported exercise volume (r = .15, p = .12). This does not necessarily mean that the AMP has no validity, but the results obtained with the AMP should be interpreted cautiously and on a more nuanced level. The present findings (a higher, albeit small, correlation between the AMP and choice behavior than with exercise volume) support Antoniewicz and Brand's (2014) conclusion that automatic affective valuations may play a role in qualitative behavioral regulation (e.g., choice of exercise setting) rather than in quantitative behavioral regulation (i.e., exercise volume). Additionally, with the AMP, automatic valuations were not measured on a situational basis (i.e., for each choice situation). According to ART (Brand & Ekkekakis, 2018) automatic valuations of exercise arise and manifest themselves in situated decisions, meaning that automatic processes may vary depending on the situation at hand (e.g., the specific behavioral alternatives an individual faces). In the present study, however, affective valuation was measured only once with the AMP and thus may not be able to predict situated gaze behavior. This would require a tool that measures automatic valuations for each individual situation, which to our best knowledge does not yet exist.

As expected, we found that the first gaze was associated with whichever alternative was chosen in that situation. This pattern of results is even more evident for fixations where participants directed their gaze on a specific location in the picture. These findings are in line with a large body of evidence on the gaze cascade effect, the tendency to look longer at items that are eventually chosen (e.g., Onuma et al., 2017). Interestingly, similar to the first gaze, the number of fixations were not associated with the assessed interindividual differences. For example, active individuals did not look longer at the exercise stimuli than inactive participants. These results seem to contradict previous findings from exercise psychology which have demonstrated an attentional bias towards exercise for active individuals (e.g., Berry et al., 2011; Cheval et al., 2020). However, in comparison to the study here, participants in previous studies were not forced to make a choice. There is research showing that attentional processes are more strongly influenced by the task itself (i.e., the goal of the decision: to choose what you want vs. what you do not want) than individual preferences (van der Laan et al., 2015). Our findings support this by showing that the task (to make a choice) and the specific alternatives presented in each situation (i.e., the presented behavioral alternatives) were associated with gaze behavior but not with individual preferences or behaviors. Hence, this lends support for the importance of situated processes emphasized in theoretical perspectives from dual-process framework (Brand & Cheval, 2019; Rhodes et al., 2019).

Although an individual may report liking exercise, certain features of an alternative behavior may drive the individual to choose the alternative over exercise. This is well in line with the idea of an inner conflict. Even if someone generally likes to exercise, but the couch seems more attractive in that very situation, an internal conflict arises. More attention may be on the non-exercise alternative and it increases the likelihood the alternative behavior will be chosen. This suggests that in the moment individuals are confronted with the decision to exercise, additional processes in the moment may influence the decision. Thus, our results support the assumption that attentional processes may play an active role in constructing choice behavior above and beyond general preferences (Orquin & Mueller Loose, 2013).

Assuming that the present findings are robust and replicable, this could imply that neither an inherent nor a learned automatic bias toward exercise or a sedentary alternative can sufficiently explain behavioral choices. This challenges assumptions of TEMPA regarding a negative automatic bias towards exercise and some predictions of ART regarding a learned automatic association of exercise. On the other hand, a more fundamental assumption of dual process models can be supported. We found that processes that take place in-the-moment of choice play an active role in constructing a choice. This is consistent with the assumption of a continuous interaction between situated automatic-affective and reflective processes until a choice is reached (Brand & Ekkekakis, 2021). Further refinement would be needed with respect to assumptions about the interplay between psychological states and traits. The present study suggests that individuals bring some inherent general trait-like preferences (e.g., liking exercise) into a situation, but these general preferences may operate independently of state-like situated processes (e.g., the affective state).

In line with current perspectives of exercise behavior change (Rhodes et al., 2019), exercise interventions largely focused on interindividual preferences or differences may fail at long-term behavior change because they neglect the role of situated processes and competing behavioral tendencies (e.g., the appeal of a non-exercise behavioral alternative). Empirical studies focused on interindividual difference – such as perceived autonomy, competence, or relatedness – may explain behavior change, but intervention focused on these variables fail to result in sustained behavior change (Chevance et al., 2019; Compernolle et al., 2019; Ntoumanis et al., 2021). In order to improve exercise interventions, situational features such as attention to specific behavioral alternatives should be considered in addition to interindividual differences, e.g., in expectations and goals.

4.1 Limitations and Future Directions

While the study had several strengths (e.g., capturing processes in-the-moment of choice, using generalized mixed models), some limitations need to be considered. In the present study, hypothetical scenarios were used as a proxy for situated decision-making, and future studies should examine how the present results unfold in real life. One way to investigate situated processes in real life decisions could be the use of ecological momentary assessment (EMA) which can capture time-varying factors and intraindividual fluctuations (e.g., Dunton, 2017). EMA has been shown to be a feasible way to measure exercise behavior and motivation in real-time and naturalistic settings (Maher et al., 2018; Reichert et al., 2022). Studies using this technique already yielded reliable associations between momentary affective states and physical activity behavior (Liao et al., 2015). However, a randomized-controlled trial that investigated the effects of an intervention on controlled processes (goal setting) on daily physical activity levels failed to demonstrate a significant effect. Instead, these results revealed substantial individual variability, suggesting that other processes may play a role in promoting or hindering physical activity (Utesch et al., 2022). Automatic processes could be one of those variables. However, there is yet to be a tool that can capture automatic processes - such as those measured with the AMP - on a momentary basis. As an alternative, quick implicit measures such as the brief implicit association test (Sriram & Greenwald, 2009) or eye-tracking (Peng et al., 2021) could be modified for mobile devices. Despite the use of a within-subject design, the present study is unable to conclude causal relationships. Future work is needed to understand whether exercise-related choice preferences can be influenced by experimentally manipulating attentional processes. Moreover, as the study sample consisted mostly of university students, generalizability is limited. It is possible that because many participants were enrolled in a physical activity focused program, this may have caused the bias toward the exercise alternative. The behavioral alternatives task appears to successfully assess a tendency of individuals to choose exercise, but it is important to note that the odds found in this study (preference for the exercise alternative) may not reflect the general population. This calls for replication studies with more heterogenous and larger sample sizes.

In addition, this task had relatively few trials compared to other eye-tracking or experimental studies (van der Laan et al., 2015). However, the focus of the present task was to examine processes within trials (choices) and not on an overall general score across all trials. Modeling both, participants and stimuli as random effects helped to increase the robustness of statistical analytics beyond the specific stimuli used (Westfall et al., 2014). However, if the focus of a

study would be to examine a general preference across trials, more trials would certainly be needed.
The unique features of the computerized decision task – such as modeling single situated choices on different levels and the use of eye-tracking as a process-tracing method – open up possibilities to test hypotheses derived from exercise psychology theories. For example, whether limited self-control alters the interplay of automatic and controlled processes or whether changing the affective experience during the behavior (e.g., Jones et al., 2020; Timme & Brand, 2020) influences exercise-related information processing could be studied. Furthermore, it would be interesting to investigate how stable these processes are and whether situational influences (such as exercising before the task) would render, for example, sedentary activities more attractive.
In terms of practical implications, our findings suggest that, for example, personal trainers should consider that situational factors (e.g., the specific behavioral alternatives) influence whether or not individuals follow an exercise program, probably quite independently of their more general beliefs and preferences.

5 Conclusion

Previous studies and interventions for exercise behavior change have largely focused on interindividual differences in automatic and controlled processes. This study provided partial support for dual-process theories in exercise psychology. We found that interindividual differences in general exercise preferences (i.e., automatic-affective valuation, controlled evaluation and exercise behavior) are related to the choice behavior among concrete behavioral alternatives (exercise vs. non-exercise). However, situated gaze behavior in these choice situations does not follow these interindividual preferences, but rather depends on the concrete available behavioral alternatives. This implies that situated processes may augment interindividual differences in automatic and controlled (e)valuations when it comes to exercise-related choices. The importance of situated processes in behavior change has been neglected by most exercise psychology theories so far, and thus may be an important missing piece in understanding the processes underlying exercise motivation.

6 Declarations

6.1 Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

6.2 Author Contributions

M.R. R.B. and S.T. developed the experimental design and carried out the data collection. Data analysis was performed by S.T. A first draft of the manuscript was written by S.T. and edited by M.R. and R.B. All authors read and approved the final manuscript.

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6.4 Ethics

All participants gave their full informed consent prior to the study and formally accepted the data sharing regulations and privacy policies. Data were stored anonymously according to the EU General Data Protection Regulation (GDPR). All procedures were conducted in compliance with the Declaration of Helsinki and ethical guidelines of the American Psychological Association (APA).

6.5 Data Availability Statement

The datasets analyzed and R code used during the current study will be made available publicly in the OSF repository after publication https://osf.io/ubrj7/.

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Tables

Table 1

Means, Standard Deviations, and Correlations with Confidence Intervals

Variable	*M*	*SD*	1	2	3	4	5	6
(1) Exercise volume	358.36	283.39						
(2) Reflective evaluation	6.33	0.86	.43**					
			[.26, .58]					
(3) Automatic-affective valuation	0.02	0.17	.15	.17				
			[-.04, .34]	[-.03, .35]				
(4) First gaze (exercise)	13.68	2.06	.14	.01	-.06			
			[-.05, .33]	[-.19, .21]	[-.25, .14]			
(5) Exercise fixations	4.00	2.67	-.02	-.07	-.10	.16		
			[-.22, .18]	[-.26, .13]	[-.29, .09]	[-.03, .35]		
(6) Nonexercise fixations	3.92	2.73	-.04	-.23*	-.13	.04	.82**	
			[-.23, .15]	[-.41,-.04]	[-.32, .07]	[-.16, .23]	[.74, .88]	
(7) General decision tendency	0.62	0.20	.43**	.58**	.20*	.09	-.13*	-.34**
			[.25, .58]	[.43, .70]	[.00, .38]	[-.11, .28]	[-.31,-.07]	[-.50, -15]

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation.

* indicates $p < .05$. ** indicates $p < .01$

Table 2 | Predicting exercise fixations with automatic valuation of exercise (Model A), self-reported feelings towards exercise (Model B) and self-reported exercise behavior (Model C) when making exercise-related choices

	Model A			Model B			Model C		
	b	95% CI	*p*	*b*	95% CI	*p*	*b*	95% CI	*p*
(IC)	3.80	3.43, 4.16	<.001	3.79	3.43, 4.16	<.001	3.78	3.27, 4.29	<.001
Choice [Ex]	0.37	0.11, 0.63	.01	0.38	0.12, 0.64	<.01	0.33	0.09, 0.57	.01
Aut. Ex Valuation	-0.16	-0.46, 0.13	.27						
SR Ex Feelings				-0.17	-0.46, 0.12	.25			
SR Ex Volume								-0.00, 0.00	.55

Note. CI = Confidence Interval; *b* = unstandardized regression estimate; IC = intercept; Ex = exercise; Aut. = automatic; SR = self-reported

Table 3 | Predicting non-exercise fixations with automatic valuation of exercise (Model D), self-reported feelings towards exercise (Model E) and self-reported exercise behavior (Model F) when making exercise-related choices

	Model D			Model E			Model F		
	b	95% CI	*p*	*b*	95% CI	*p*	*b*	95% CI	*p*
(IC)	4.88	4.49, 5.26	<.001	4.87	4.48, 5.26	<.001	4.75	4.24, 5.25	<.001
Choice [Ex]	-1.54	-1.78, -1.31	<.001	-1.53	-1.77, -1.29	<.001	-1.56	-1.80, -1.32	<.001
Aut. Ex Valuation	-0.16	-0.42, 0.10	.27						
SR Ex Feelings				-0.27	-0.53, -0.00	.05			
SR Ex Volume							0.00	-0.00, 0.00	.79

Note. CI = Confidence Interval; *b* = unstandardized regression estimate; IC = intercept; Ex = exercise; Aut. = automatic; SR = self-reported

Exercise as the sum of our choices between behavioral alternatives: The Decisional Preference in Exercising Test (DPEX)

Abstract

Exercising can be theorized as the result of choosing one behavior over alternative behaviors. The Decisional Preferences in Exercising Test (DPEX) is a computerized, easy-to-use, publicly available (*insert link after review*) and highly adaptive research tool based on this rationale. In the DPEX, participants are asked to choose between two images by pressing a key on the computer keyboard, one showing a physical exercise and the other showing a non-exercise behavioral alternative. Combinations are randomly assembled from two definable pools of stimuli trial-per-trial. The test can be scored with either a random effects model (which allows the use of variable stimulus material in different studies while maintaining comparability of test scores) or with a simple proportion score. Data from various studies ($N = 451$) showed strong correlations of DPEX scores with past and prospective exercise behavior ($r = .42$ to $.47$) as well as with affective experiences with exercise ($r = .64$). The test was able to sufficiently discriminate between exercisers and non-exercisers according to receiver operating curve (ROC) analysis. The DPEX helps avoid common method bias with self-reports of exercise behavior. It may be used to examine research questions derived from dual process theories, such as testing the effects of psychological states on behavioral choices, or to evaluate the effects of behavior change interventions.

Key words: exercise behavior, decisional preferences, motivation, dual processing,

1. Introduction

It is well-known that exercise behavior is of great importance to our health. Numerous studies show the benefits of exercise on cardiovascular disease mortality, type-2 diabetes, cancer and mental health (Baumeister et al., 2019; Blond et al., 2020; Schuch et al., 2019). In particular, engaging in regular exercise is associated with improved mental well-being and lower prevalence of depressive symptoms and anxiety (Ekeland et al., 2005; Stubbs et al., 2018). In addition to the health benefits, exercise as a form of transportation, such as walking or biking, can also have a substantial environmental impact (Woodward & Wild, 2020). Despite evidence that these benefits are widely recognized (Martin et al., 2000), 28% of adults and 81% of adolescents do not meet the WHO recommendations of participating in a minimum of 150 minutes of moderate-to vigorous physical activity (MVPA) per week (WHO, 2020).

The high prevalence of physical inactivity has led to the development of various theories that aim to explain motivation and adherence in exercise behavior, dominated mainly by work in the social-cognitive and the humanistic framework (Rhodes et al., 2019b). The Theory of Planned Behavior (Ajzen, 1991) and Self-Determination Theory (Deci & Ryan, 2012) are well-established protagonists of this paradigm. Commonalities of these approaches lie in the assumption that mental projections about a desired target state (e.g., goals and intentions) are fundamental for motivated behavior change to occur, and that trait-like constructs (e.g., beliefs) must be addressed and changed to generate behavior change (Brand & Cheval, 2019; Ekkekakis & Brand, 2021b). Recently, there has been growing interest in the dual systems / process approach (Rhodes et al., 2019). In contrast to the social-cognitive framework, dual process approaches hold the shared theoretical assumptions that aside from controlled rational type-2 processes (e.g., goal setting, self-efficacy beliefs), automatic type-1 processes are considered to play an important role in behavior change (e.g., Evans & Stanovich, 2013; Strack & Deutsch, 2004). Some of these theories focus especially on momentary processes and decisions that occur in specific situations (i.e., situated processes) that generate a subsequent, resulting behavioral state. For example, affective-reflective theory of physical inactivity and exercise (ART; Brand & Ekkekakis, 2018) proposes that when confronted with the choice between exercise and a behavioral alternative, a continuous interplay between learnt automatic-affective and reflective processes takes place. A resulting affective valuation and (if self-control resources are available) a controlled evaluation inform an individual's situated decision to maintain or change his or her current state of physical inactivity.

Based on the idea that exercise behavior is often guided not only by goals and intentions but also by situated processes linked to the specific behavioral options, the aim of the present article is to develop an adaptive research tool to measure an individuals' preference to choose an exercise activity over a non-exercise behavioral alternative across different situations.

1.1. Exercise behavior as the sum of repeated choices between exercise vs non-exercise alternatives

For exercise behavior to be health-promoting, it needs to be repeated continuously over an extended period of time across the lifespan (Rhodes & Nigg, 2011). At least in the early stages of behavior change (i.e., exercise initiation; Nigg et al., 2008), this requires behavioral decisions based on deliberation. However, the more frequent the decision to become physically active is made, especially in repeated choice situations, the greater the contribution of situational contextual processes (stimulus-response associations; Gardner & Tang, 2014). Eventually, the overall exercise behavior will be constituted by repeated situated choices between exercise and a behavioral alternative in different situations. In this context, researchers have recently reiterated that exercise maintenance should be conceptualized as a shift in the underlying psychological mechanisms rather than just a change in overt behavior (Dunton et al., 2022; Rhodes & Sui, 2021).

The idea that exercise behavior can be conceptualized as a decisional preference between physically active vs sedentary behaviors can be traced back to the early 1990s, with Epstein's (1992) application of behavioral choice theory (Allison, 1983; Rachlin, 1989) to exercise behavior. Epstein et al. (1991) examined the influence of reinforcement learning and proximity on the choice to be physically active or sedentary. Yet, Epstein was more concerned with the paradigmatic position that exercise is often the result of a behavioral choice (rather than how repeated choices or decisions might form preferences or habits).

Later, this idea was utilized in exercise psychology and further developed by Brand and Schweizer (2015) into the "Situated Decisions to Exercise Questionnaire (SDEQ)" to assess participants' tendency to decide between competing behavioral alternatives (exercise vs non-exercise) in specific exercise-related decision situations. The SDEQ includes descriptions of eight prototypical situations (e. g., coming home tired from work but planned to go work out that night) and asks participants to indicate whether they would choose to exercise or rather choose the behavioral alternative in such a situation. Results showed that self-reported reflective evaluations and automatic processes (as assessed via evaluative priming) independently explained the decision tendency in the SDEQ, which in turn explained participants' self-reported time spent for exercising (Brand & Schweizer, 2015). However, by using a self-report questionnaire with no time constraints, the test focused on controlled and reflective decisions to exercise. Timme et al. (2023) expanded on this approach and examined the interplay of interindividual differences in automatic-affective valuations (measured with an affective misattribution procedure) and controlled evaluations (measured with self-report) with momentary situated processes (measured with eye-tracking) in-the-moment of choice when individuals are confronted with an exercise and a behavioral alternative. That study showed that in addition to interindividual differences in affective and controlled (e)valuations of exercise, situated processes that are specific to the defined behavioral alternatives may independently influence exercise-related choice behavior. The authors concluded that having either a positive affective or reflective (e)valuations of exercise would not always lead the individual to select exercise as a pending behavior. For example, despite positive automatic affective evaluation of exercise and positive reflexive evaluation of such behavior, individuals may disregard the behavioral option of exercise in the face of a more attractive behavioral alternative (e.g., going out with friends).

1.2. The present work

In light of these considerations, we followed recent theoretical claims that the investigation of psychological mechanisms of exercise maintenance should include a decision-making perspective (e.g., Maltagliati et al., 2022). Therefore, the aim of this study was to develop an easy-to-use research tool that measures decisional preferences in exercising. This test should reflect exercise behavior as the sum of situated decisions between behavioral alternatives across different situations.

The work presented here on the development of the (computerized) Decisional Preferences in Exercising test (DPEX) is based on the concept that individuals shall make a series of choices between exercise and a non-exercise behavioral alternative. To evaluate convergent and predictive validity, correlations with variables that have been shown to be useful in exercise psychology, especially in recent studies on exercise behavior, were analyzed (e.g., with self-reported remembered and future exercise volume, and prior affective experiences with exercise). In addition, a receiver operating characteristic curve analysis was conducted to demonstrate the accuracy of the DPEX in classifying individuals with regard to their activity status. Further, we provided an exemplary analysis of how the DPEX can be used to test hypothesis derived from theoretical assumptions (such as dual process models) by examining reaction times.

In the following article, we first summarize how the DPEX can generally be constructed and applied as a research tool (i.e., test characteristics). We then explain how we specified the DPEX in the present paper with different subsamples to empirically test central properties and exemplary research questions.

2. Decisional Preferences in Exercising Test: The DPEX

2.1. Test characteristics

The DPEX is designed as a flexible, computer-based research tool that allows researchers to select specific behavioral alternatives depending on the research question. Open-source software (PsychoPy v2022.2.4; Peirce et al., 2019) with publicly available Python code (*insert link after review*) was used to implement the test. This allows every researcher and practitioner to use the tool and adapt it for their specific purposes.

In the DPEX, participants indicate their preference between two behavioral alternatives (exercise vs non-exercise; e.g., playing soccer or running vs watching TV or meeting with friends) in a series of choices. The two alternatives are presented randomly interchanged from trial to trial, on the left and right sides of the screen. Alternatives are randomly selected from stimulus pools and represent prototypes of the intended category (e.g., a picture displaying a player shooting a goal as representative for soccer). The stimulus material can be varied within the intended category, but it is important that the configuration of the test (exercise vs non-exercise) is adhered to.

Overall, the test design is highly flexible and can be adapted according to the researcher's needs. For example, the stimulus material, the number of trials and the presentation times are modifiable. The respective selection (e.g., stimulus material) may depend on the specific research question (e.g., group exercise vs individual sports). The same applies to the number of trials, which can be flexibly adjusted to produce a robust test score. To achieve significant inter-item variability, we suggest using at least 20 stimuli per category, according to a simulation analysis with our data. Clearly, reliability and generalizability improve the more trials are run. Once inferential statistics, such as correlations, are performed, the minimum number of trials and study participants to obtain a certain effect should be calculated using a power analysis. Participants should choose quickly, but not rush through the test. Presentation times can also be adjusted, depending on sample characteristic (e.g., older participants).

2.2. Test procedure

After opening the test script in PsychoPy, participants are guided through the instructions. They are informed that they will see two images depicting an exercise activity (e.g., running) and a non-exercise activity (e.g., watching TV). The task is to choose one of the behavioral alternatives according to their preferences by pressing the "E" key for the alternative on the left side of the screen and "I" for the alternative on the right side of the screen. The choice for exercise is logged as '1' and '0' for non-exercise. For each choice, the reaction time (i.e., the time it takes the participant to make a choice) is recorded. After the choice is made, a white fixation cross is displayed, signaling a new trial. The participants first complete practice trials, followed by the test trials.

2.3. Test configuration and stimulus material in the present work

In the present work, we assessed different configurations of the DPEX in four subsamples to test its properties. All subsamples completed 4 practice trials, followed by 64 test trials in subsample 1, which was reduced to 39 trials in subsample 2-4. Different stimulus pools of 32-34 pictures (equally distributed between exercise and non-exercise) were used in the respective subsamples. Pictures were randomly selected from the stimulus pools, with no fixed combinations of exercise vs non-exercise. A sample selection of the images used can be found at (*insert link after review*).

The images represented a wide range of exercise and non-exercise activities. They were either taken by the authors or from freely available databases (e.g., Pixabay). Exercise pictures included sports such as soccer, basketball, swimming, or activities such as hiking and fitness. Non-exercise pictures included leisure time activities such as going out with friends, reading, watching TV or playing board games. Pictures were black and white with similar brightness and without obvious affective content (e.g., emotional expressions) displayed on a black background screen. The chosen exercise activities represented the most common types of sport and exercise activities (Ham et al., 2009) and were selected according to recommendations for exercise images (Cope et al., 2018). In all samples, the images were shown for one second, following by a black screen. When a choice was made, a white fixation cross appeared on the screen for two seconds, signaling the next trial. This enabled the participants to get a sense of the behavioral alternatives presented without having the opportunity to delve into details on the scenarios presented.

2.4. Test scoring: DPEX - Random Effects Model (REM) score

To account for both systematic between-stimuli and between-participant variation, we applied a random-effects model in which participants and stimuli are modeled as crossed random effects to calculate the DPEX test scores (Baayen et al., 2008). It would also be possible to compute a simple proportions score (i.e., percentage of exercise choices), but this entails the problem that the results would only apply to the specific stimuli used. A simple proportions score would imply that only participants are treated as a random factor (i.e., as a sample of all possible participants who could be included to the study), whereas stimuli are treated as a fixed factor (i.e., they are not treated as a sample from all possible stimuli that could represent the target of the measurement). These scores are problematic because they ignore systematic variation between the stimuli and can only be generalized to other samples of participants if the exact same stimuli are used. This would make comparison with the results of other studies using different stimuli difficult. Findings based on these types of scores (stimuli as fixed factor) have been shown to result in seriously inflated type 1 statistical errors, leading researchers to claim statistically significant effects that may be unlikely to replicate with different samples of pictures (Judd et al., 2012).

To reach conclusions that generalize to both subjects and stimuli, a more general analytic approach is necessary. By applying a crossed random effects model, variance estimation is done on several levels (simultaneous between-, within-participants and stimuli variance estimation) and thus offers more information about the variance and covariance components associated with the random effects of the design. Thus, this test is not limited to a specific set of stimuli and obviates the need to pre-test image material (as long as appropriate stimuli were selected according to rational criteria). Instead, if an REM score is calculated, the stimulus material can be selected based on theory and adapted according to the specific research question.

To calculate individual test scores, the random effect is extracted from the REM for each subject (i.e., the individual deviation from the 'grand mean' overall intercept). These values are estimated using information from the entire dataset and are corrected for the unreliability of extreme scores due to shrinkage (Kliegl et al., 2011). The subject random effects are added to the overall intercept and the resulting log-odds values are transformed into probabilities. In this way, we obtain a model-based probability score (ranging from 0 to 1) for each participant that reflects each individual's probability of choosing the exercise alternative. These individual random effect scores are used for further analysis. The R code for calculating the DPEX-REM score can be found on OSF (*insert link after review*).

3. Verification of the test properties

In the following, we present the variables tested to validate the theoretical assumptions underlying the DPEX with exercise-related variables. We tested the associations of the DPEX with usual and prospective weekly exercise volume as well as with affective exercise experience. We expected medium to high correlations of the DPEX with all variables. In addition, a receiver operating curve analysis was used to test the property of the DPEX to discriminate exercisers from non-exercisers. In a last step, we applied the derived DPEX-REM model to test whether exercisers and non-exercisers differ in their time to make a choice.

3.1. Measures

3.1.1 Usual weekly exercise volume: IPAQ

Weekly exercise behavior was assessed with questions from the International Physical Activity Questionnaire – Short Form (IPAQ-SF; Craig et al., 2003). Participants were asked to report the frequency and average duration of moderate (e.g., walking or biking) and vigorous (e.g., running, playing soccer or aerobic) exercise sessions of a usual week. This information was used to calculate weekly moderate and vigorous exercise behavior (MVPA; sessions per week x min per session). We did not assess light activity and sedentary behavior because the DPEX is designed to capture moderate to vigorous activities. All subsamples provided responses on the IPAQ after completing the DPEX. Additionally, demographic information, concentration level, and medical reasons that might affect participants' usual exercise behavior were assessed.

The IPAQ is currently one of the most widely used international survey instruments for exercise behavior (Nigg et al., 2020) and has been applied, for example, by the WHO to calculate estimates of inactivity prevalence in 146 countries (Guthold et al., 2018). To test the relationship of the DPEX with usual weekly exercise volume, the DPEX – REM scores were correlated with usual weekly exercise volume as measured with the IPAQ.

However, validations studies of the IPAQ have shown mixed results. Criterion measures (e.g., direct measurement of physical activity), which should be highly associated with the IPAQ, show only low-to-moderate correlations and differ substantially between studies 11/17/2023 8:37:00 AMTherefore, we assessed an exercise e-diary in addition to the IPAQ in subsample 3 and 4. Unlike retrospective assessment with the IPAQ, an e-diary is a more direct measure of exercise behavior and can be used to predict future exercise behavior prospectively from the DPEX. E-diaries are more time consuming but reduce the potential for participant recall error (Eisenberg et al., 2017) and show a higher correlation with objectively-measured physical activity compared to the IPAQ (Knell et al., 2017).

3.1.2. Exercise e-diary: PIEL

In subsample 3 and 4, participants first completed the DPEX followed by a daily exercise e-diary for 14 days. For this purpose, the open-source 'Participation in Everyday Life' (PIEL) survey app for smartphones was used (Jessup et al., 2012). Each evening, participants received a push notification on their mobile phone at 7.30 pm. They were asked to report their exercise behavior for that day with questions from the IPAQ-SF (Craig et al., 2003). Questions were adapted to same-day activities. Specifically, participants were asked about the duration, intensity and type of activity they performed on the same day. From this, weekly moderate and vigorous active minutes were calculated as the exercise behavior score. Only participants with 10 or more valid days were included in the analysis. To evaluate the predictive power of the DPEX, DPEX – REM scores were used to predict exercise behavior over the following 14 days (measured with the PIEL app) by linear regression analysis.

3.1.3 Affective exercise experiences: AFFEXX

The AFFEXX is a self-report questionnaire developed to measure affective experiences with exercise. Ekkekakis et al. (2021) define affective experiences as the sum of unpleasant and pleasant feelings an individual experiences over the life course reflecting their association towards exercise. The AFFEXX consists of 36 items in 10 subscales. Participants respond on a 7-point bipolar scale which of two statements (e.g., “Exercise is stimulating” vs “Exercise is boring”) is closer to their view. Three subscales assess core affective feelings related with exercising (pleasure-displeasure, energy-tiredness, calmness-tension). According to the conceptual model of the questionnaire, these core affective feelings mediate the correlation between six classes of antecedent cognitive appraisals (e.g., ‘showing off-shying away’, ‘competence – incompetence’; full list in Table 3) and the motivational tendency to approach or avoid exercise (‘attraction-antipathy’).

Ekkekakis et al. (2021) demonstrated that all subscales of the AFFEXX were correlated with MVPA (as measured with the IPAQ) (r = .16 - .48). In support of their conceptual model, the ‘attraction-antipathy’ subscale (i.e., the motivational outcome variable theorized to stem from affective experiences) showed the highest correlation with MVPA (r = .48). In addition, the original version of the AFFEXX showed good reliability with a test-retest reliability of r_{xx} = .78 - .88 and all indices of internal consistency (Cronbachs α and McDonald ω) over .80, which is supported by the present study, with Cronbachs α between .85 and .93.

Conceptually, the AFFEXX is related to the notion of “affective valuation” in the ART, that gives rise to an action impulse for the in-the-moment choice to exercise or not to exercise (Brand & Ekkekakis, 2018). The present work focuses on the correlation of the DPEX – REM score with the subscales ‘attraction-antipathy’ and the core affective exercise experiences (pleasure- displeasure, energy-tiredness, tension-calmness), as these subscales are conceptually closest to the relevant behavior (exercise). The questionnaire was implemented in subsample 4 with SoSci Survey (Version 3.3.0.0) after participants completed the DPEX and the IPAQ.

3.1.4 Receiver Operating Characteristic (ROC) curve analysis

ROC curve analysis (Metz, 1978) was used to evaluate the specificity and sensitivity of the DPEX – REM scores for classifying individuals as exercisers or non-exercisers. For this, participants were classified as exercisers based on the IPAQ data if they reported that they participate in more than 150 min of MVPA per week. This classification (exercisers vs non-exercisers) was predicted by the DPEX-REM score in a binomial generalized linear model. The fitted values of these model were used to determine how accurately the DPEX can classify someone as an exerciser or a non-exerciser by creating true positive and false positive rates for all possible values of the DPEX. These rates were plotted against each other and created the ROC curve and the area under the curve (AUC). AUC provides an aggregate measure (from 0-100%) of performance across all possible classification thresholds.

3.1.5 Reaction (choice) time

The DPEX random effects model was applied to explore the role of reaction times in the DPEX. In particular, the probability of choosing exercise (vs the non-exercise alternative) was predicted by reaction times (per choice trial) and exercise behavior (per subject) in a random effects model with participants and stimuli as random effects. Reaction times were log-transformed to achieve normally distributed values. Weekly exercise behavior was transformed to hours per week for better interpretation of parameter estimates. Using this model, we were able to investigate whether active and inactive individuals differ in their reaction time when choosing between exercise and non-exercise.

Reaction times can be interpreted in several ways. On the one hand, research showed that faster reaction times indicate preferences (approach tendency) while longer reaction times indicate avoiding tendencies (Kühne et al., 2022). On the other hand, other studies showed an opposite pattern of responses, namely faster reaction times as an indication for an avoidance tendency (Ledoux & Armony, 1999). Taking these mixed results into account, examining reaction times was considered an exploratory analysis. If faster reaction times indicate a preference, active individuals should have faster reaction times when they choose exercise (vs non-exercise). Inactive individuals, on the other hand, should have slower reaction times when they choose the exercise alternative (vs non-exercise).

3.2. Study participants

A total of 480 participants took part in a series of four data collections (M_{age} = 28.76, SD_{age} = 15.03). Table 1 shows the four subsamples and the assessed measures. For data analysis, the samples of the respective measures were aggregated.

Table 1

Subsample information for each assessed measure

Sample	Measures			
	DPEX	**IPAQ**	**E-diary**	**AFFEXX**
N_{S1} = 97	X	X		
N_{S2} = 93	X	X		
N_{S3} = 119	X	X	X	
N_{S4} = 142	X	X	X	X
Total	N_{DPEX}= 451	N_{IPAQ} = 451	N_{PIEL} = 212[a]	N_{AFFEXX} = 142
M_{age}	28.9 ± 15.2	28.9 ± 15.2	29.1 ± 11.4	30.9 ± 13.8

a) Not all participants in sample 3 and 4 completed the 14-day PIEL exercise e-diary. Therefore, the N_{PIEL}=212 is smaller than the sum of N_{S3} and N_{S4}

217 participants identified themselves as male, 262 as female and 1 as diverse. Participants were recruited by written invitation in digital form. Prior to participating, all participants gave informed consent. The study was conducted following the ethical standards laid out in the Declaration of Helsinki and the local institution's ethical guidelines. 19 participants were excluded due to medical reasons that prevented them from currently exercising as usual, 4 due to low concentration level, 1 for not following task instructions and 5 for implausible data (e.g., exercise duration > 180 min per session or > 12 sessions per week). Additionally, we excluded 39 trials from data analysis in which the reaction time was longer than 10 seconds, indicating that the participant was likely distracted. The data subjected to data analysis therefore included data from 451 participants (M_{age} = 28.88, SD_{age} = 15.21, 204 men and 247 women) with 97 participants from subsample 1, 93 from subsample 2, 119 from subsample 3 and 142 from subsample 4.

According to the WHO recommendations on minutes spent exercising, individuals accumulating at least 150 min of combined MVPA per week are considered as sufficiently active (WHO, 2020). Following these guidelines, 66% of our participants are classified as sufficiently active and 34% as inactive. On average, participants reported exercising 3.7 (SD = 2.26) times per week with moderate intensity and 2.5 (SD = 1.85) times with vigorous intensity, for a total of 142.4 (*SD* = 151.4) and 147.7 (*SD* = 150.2) minutes per week, respectively.

3.3. Statistical analyses

All analyses were performed with the statistic software R Studio (4.0.5) (R Core Team, 2021). We used the lmer program of the lme4 package (Bates et al., 2015) for random effects modeling and the pROC package (Robin et al., 2011) for conducting the ROC analysis. Since there is no evidence on the DPEX yet, a power / sample size estimation would have been without empirical and theoretical basis and might have led to biased effect sizes (Scheel et al., 2021). To obtain robust correlation estimates, the aim was to sample as many participants as possible (at least 250, Schönbrodt & Perugini, 2013). Scripts and data are available as a supplement and at (*insert link after review*).

4. Results

4.1. The DPEX – REM score

The DPEX-REM score is based on a random effects model predicting the probability of choosing the exercise over the non-exercise alternative. Random intercepts for exercise stimuli (Model B), non-exercise stimuli (Model C) and their combination (Model D) were iteratively added to a model with only subjects as a random intercept (Model A) and tested against the model without the respective component. Model iteration revealed significant variance for exercise stimuli (χ^2 (1) = 639.71, p < .001), non-exercise stimuli (χ^2 (1) = 477.93, p < .001), but not the exercise vs non-exercise combination (χ^2 (1) = 0, p = 1). This means that Model C with random intercepts for subject, exercise and non-exercise stimuli provided the best model fit (AIC = 23440). The random effects of this model indicate substantial interindividual variance (σ_s^2 = 1.59) and less but still significant variance between exercise stimuli (σ_{ex}^2 = 0.26) and non-exercise stimuli ($\sigma_{non\text{-}ex}^2$ = 0.19). Model parameters and model fit information can be found in Table 2. The R syntax for fitting the recommended crossed random-effects models can be found on OSF (*insert link after review*).

Table 2

Model parameters and information fit of the model selection process

	Model A		**Model B**		**Model C**		**Model D**	
	OR	*p*	*OR*	*p*	*OR*	*p*	*OR*	*p*
Intercept	1.07 [0.96-1.20]	.20	1.17 [0.96-1.43]	.12	1.17 [0.91-1.51]	.22	1.17 [0.96-1.51]	.22
Random Effects								
σ^2_{s}	1.33		1.50		1.59		1.59	
σ^2_{ex}			0.25		0.26		0.26	
$\sigma^2_{non\text{-}ex}$					0.19		0.19	
$\sigma^2_{ex:non\text{-}ex}$							0.00	
Model fit								
AIC	24554		23916		23440		23442	
BIC	24570		23940		23472		23482	

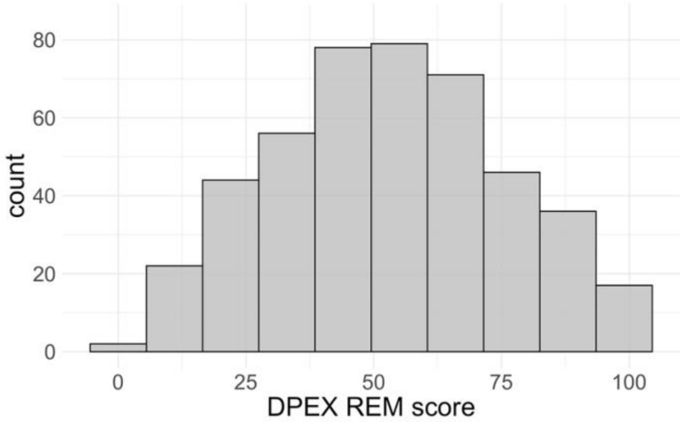
Note. Model A = random effect for subjects; Model B = random effects for subjects and exercise stimuli, Model C = random effects for subjects, exercise stimuli and non-exercise stimuli, Model D = random effects for subjects, exercise stimuli, non-exercise stimuli and exercise:non-exercise stimuli combination; OR = Odds Ratio with 95% confidence interval, Random effects: σ^2_{s} = subject variance, σ^2_{ex} = exercise item variance, $\sigma^2_{non\text{-}ex}$ = non-exercise item variance, $\sigma^2_{ex:non\text{-}ex}$ = item combination variance; AIC = Akaike information criterion, BIC = Bayesian information criterion.

The intercept of the final Model C reveals that participants were 1.17 more likely to choose the exercise alternative (95% CI [0.91; 1.51], p = .22) compared to the non-exercise alternative. This means that there was no significant difference in the average probability to choose the exercise alternative (53.9%) vs the non-exercise alternative (46.1%) across all participants and stimuli.

The model-based individual DPEX - REM scores (extracted random effects, indicating individual probabilities to choose the exercise alternative) were normally distributed with a mean of 52.7% (SD = 22.48) ranging from 4% to 96% (see Figure 1). Split half reliability suggested a satisfactory level of reliability for the DPEX (r = .82).

Figure 1

Distribution of the DPEX – REM score



4.2. Correlation with self-reported weekly exercise volume (IPAQ)

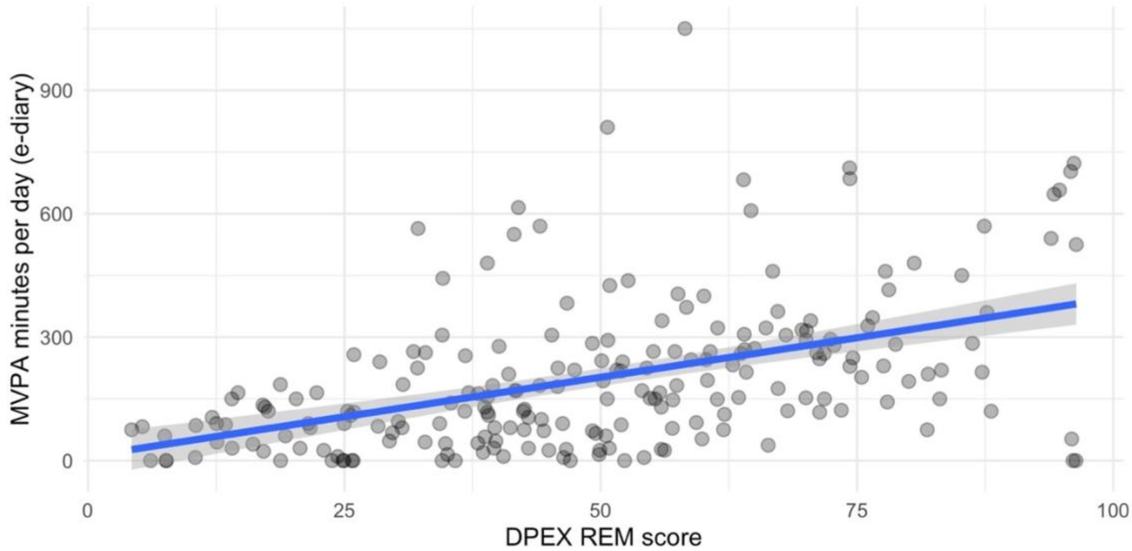
The DPEX – REM score was strongly correlated with weekly moderate to vigorous exercise volume (MVPA) based on the IPAQ, $r = 0.42$, 95% CI [0.35, 0.50], $p < .001$. A higher DPEX - REM score was associated with higher self-reported usual exercise volume, indicating a strong relationship between the DPEX and exercise behavior. There was no significant variation in the relationship of the DPEX and the IPAQ between data collections ($ICC_{sample} = 0.01$).

4.3. Prediction of future exercise behavior (e-diary PIEL app)

The DPEX – REM score predicted weekly moderate-vigorous exercise volume over the following 14 days, as measured by an exercise e-diary, $b = 3.84$, 95% CI [2.87; 4.81], $p < .001$, $R^2 = 22.0$ %. Parameter estimates reveal that for each percentage increase in the DPEX - REM score, weekly exercise volume rises by nearly 4 minutes, indicating that participants who had a 50% probability to choose exercise, averaged 203 minutes of exercise per week (see Fig. 2).

Figure 2.

Graphical display of the correlation between the DPEX-REM score and weekly exercise volume measured with the app-based exercise e-diary



4.4. Correlation with prior affective experiences with exercise (AFFEXX)

The DPEX - REM score showed significant correlations with all subscales of the AFFEXX (*r* = .25 to .64; see Table 3). The highest correlation was found, as expected, for the attraction-antipathy subscale (*r* = .64, 95% CI [.53, .73], *p* <.001). Correlation with core affective exercise experiences (pleasure-displeasure, energy-tiredness, calmness-tension) were moderate to high (*r* = .42 to .47, *p* <.001). Correlation of all AFFEXX scales with the DPEX can be found in Table 3.

Table 3

Bivariate product-moment correlations with 95% confidence intervals between the scales of the AFFEXX and the DPEX - REM score

	DPEX – REM score		
	r	***95% CI***	***p***
Antecedent Appraisals			
liking vs disliking groups	.25	[.09, .40]	<.001
showing off vs shying away	.36	[.21, .50]	<.001
empowerment vs damage	.40	[.25, .53]	<.001
pride/honor vs shame/guilt	.56	[.43, .66]	<.001
competence vs incompetence	.39	[.24, .52]	<.001
interest vs boredom	.51	[.38, .62]	<.001

Core Affective Exercise Experiences			
pleasure vs displeasure	.47	[.33, .59]	<.001
energy vs tiredness	.42	[.28, .55]	<.001
calmness vs tension	.43	[.29, .56]	<.001
Attraction-Antipathy			
attraction vs antipathy	.64	[.53, .72]	<.001

All other correlations (between IPAQ, PIEL and AFFEXX) can be found in the Supplementary.

4.5. Using the DPEX to discriminate exercisers from non-exercisers (ROC curve analysis)

ROC curve analysis was used to evaluate the accuracy of the DPEX as a diagnostic tool to discriminate between sufficient exercisers vs non-exercisers. True positive rates (sensitivity; correctly classifying exercisers as exercisers) and false positive rates (1-specificity; falsely classifying exercisers as non-exercisers) were obtained for all possible DPEX scores (for a selection see Table 4). For example, with a DPEX score of 50 or less, participants who chose exercise in less than half of the trials would be considered as having a high risk of not exercising enough (i.e., classified as “non-exerciser”). According to ROC, this cut-off score would result into 71% true positives and 35% false positives. This means that if 200 participants (100 ‘true’ exercisers and 100 ‘true’ non-exercisers) would complete the DPEX, 70 of the 100 non-exercisers would be correctly classified as non-exercisers (and 30 as falsely exercisers) and 34 of the 100 exercisers would be falsely classified as non-exercisers (and 66 as correctly exercisers).

Figure 3 displays the true positive and false positive rates for the range of possible DPEX scores. From this, the area under the curve (AUC) is derived, a measure of the ability of the test to discriminate between exercisers and non-exercisers. For our data, the AUC is 0.74. This suggests a 74% chance that a non-exerciser (according to the IPAQ) will be identified as a non-exerciser based on his or her DPEX – REM score. According to convention, an AUC between 0.7 to 0.8 is considered acceptable (Mandrekar, 2010).

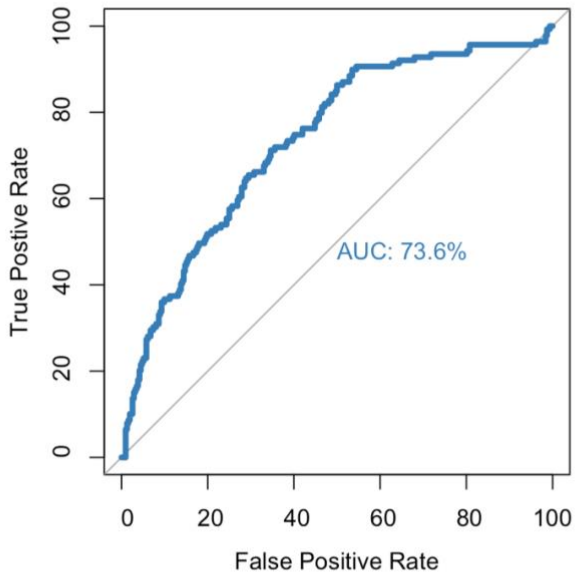
Table 4

ROC curve analysis

DPEX score	True Positive Rate	False Positive Rate
0.10	5	1
0.20	18	4
0.30	36	10
0.40	53	21
0.50	71	35
0.60	86	51
0.70	93	68
0.80	96	84
0.90	96	93

Figure 3

ROC Curve Analysis of the DPEX



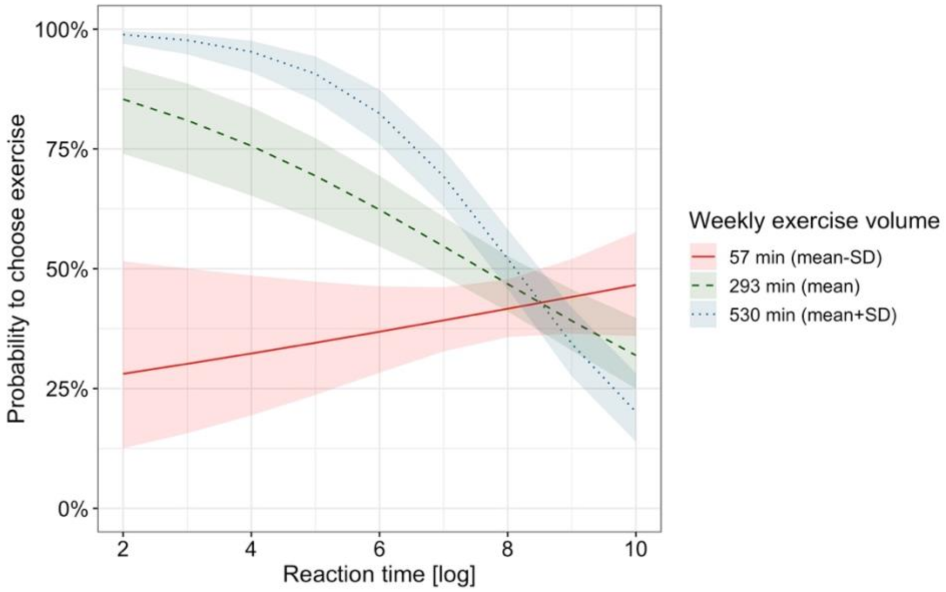
Note. AUC = area under the curve

4.6. Exploring DPEX reaction (choice) times

To examine reaction times in the DPEX, choice behavior (0 = non-exercise vs 1 = exercise) was predicted by reaction times and weekly exercise behavior (as measured with the IPAQ) in a generalized random effects model. There was a significant interaction of reaction time and exercise behavior (*OR* = 0.90, 95% CI [0.87, 0.93], $p < .001$). This indicates that the relationship between choice behavior and reaction time differed depending on the activity level of the participants. Specifically, the faster active participants made their choice, the more likely they were to choose exercise. Inactive individuals, on the other hand, were more likely to choose exercise the longer it took them to make a choice (see Figure 4).

Figure 4

Predicted probabilities to choose exercise depending on decision times and IPAQ exercise volume



Note. Weekly exercise volume (as measured with the IPAQ) was categorized into the mean as well as well as one standard deviation below and above for graphical purposes only. Analyses were still performed with exercise volume as a continuous predictor

5. Discussion

In this article, we introduced a new research tool to assess decisional preferences in exercising, the DPEX. The DPEX is based on the rationale that in order to establish an exercise routine, individuals repeatedly choose exercise over a behavioral alternative across situations. Until now, there has been a lack of a measure that conceptualizes and operationalizes exercise behavior against this background. Whereas previous measures in exercise psychology typically assess exercise volume using self-reported questionnaires, the DPEX measures underlying preferences in making exercise behavioral choices. The idea that health behaviors, especially exercise, are choices that individuals make among alternatives has been around for some time but has not yet been put into practice (Antoniewicz & Brand, 2014; Epstein, 1992).

As hypothesized, we demonstrated in a large sample that the DPEX score is highly correlated with self-reported exercise behavior. In line with these findings, the DPEX score also predicted prospective exercise behavior as measured with an app-based exercise e-diary. This supports the theoretical considerations underlying the conceptual framework of the DPEX that decisional preferences in exercising are highly related to exercise behavior.

Moreover, we found strong correlations between the DPEX score and both core affective exercise experiences (e.g., pleasure vs displeasure) and the motivational tendency to be attracted towards exercise as measured with the AFFEXX (Ekkekakis et al., 2021). According to ART (Brand & Ekkekakis, 2018), type-1 and type-2 processes influence exercise-related choices in the moment they are made. Repeating this process over and over, exercise maintenance emerges when exercise is continuously chosen over a behavioral alternative. In line with the conceptualization of exercise maintenance as changes in underlying psychological mechanisms (rather than just overt behavior; Dunton et al., 2022; Rhodes & Sui, 2021), the results suggest that the DPEX may be a measure to capture changes in psychological processes necessary for behavior change and exercise maintenance.

These results corroborate the findings by Brand and Schweizer (2015), who introduced the concept of situated decisions as a functional link between type-1 and type-2 processes and exercise behavior. However, by using a self-report questionnaire (the SDEQ) without any time constraints, Brand and Schweizer (2015) were limited in the variety of situations and on reflective and deliberate decisions. The DPEX extends this work, providing an image-based computerized tool that allows researchers to implement different stimulus material and test configurations. In addition, by using a random effects model score, participants and stimulus material are modelled as a random selection from the intended category (e.g., exercise). This allows more possibilities for statistical analysis (e.g., variance distributions) and higher comparability between studies using different stimulus material.

Timme et al. (2023) also developed the SDEQ into an image-based computerized test. In contrast to the present work, they used eye-tracking technology to demonstrate that situated processes (which are specific to the different behavioral alternatives) are associated with individuals' choice behavior, over and above more general trait-like measured processes (e.g., general exercise preference).

This knowledge is transferred to the DPEX and provides first evidence that the concept of situated decisions can be implemented and investigated with a computerized behavioral alternatives test. The DPEX integrates the theoretical considerations and underlying properties of that test (juxtaposed behavioral alternatives in a series of choices), but modifies the test configurations to make it easier and more flexible for a broader, more general use. The DPEX is written using open source software (PsychoPy) with freely available code (*insert link after review*), providing a versatile alternative to other measures of exercise behavior, such as self-report questionnaires. It avoids common-methods bias and can be easily adapted to test a wide range of research questions, such as hypotheses derived from dual process models. By using random effects modelling, researchers can examine both momentary processes that change intra-individually from choice to choice (e.g. ease of choosing) and more stable dispositions that change inter-individually (e.g., general preference for / against exercise).

In the present study, for example, we examined how (intra-individually varying) choice times and (inter-individually varying) exercise behavior were related to individuals' choice behavior. Our findings revealed that more active individuals had faster reaction times when choosing exercise, while inactive individuals had faster reaction times when choosing non-exercise. This supports the assumption that reaction times are indicative of an approach tendency (Kühne et al., 2022) and gives additional insights into the mechanisms underlying exercise-related choices. Previous research showed that the easier one can access the mental representation of behavior in memory, the less likely the behavior is guided by conscious intent (Danner et al., 2008). Therefore, assessing the mental accessibility of goal-directed behavior may provide additional information about the extent to which the behavior has become habitual (Fazio & Olson, 2003). Individuals who exercise regularly do not deliberately think about whether or not to exercise, they choose exercise rather automatically (Galla & Duckworth, 2015). Non-habitual exercisers instead have to rely on goals and intention, meaning cognitive constructs that require cognitive control to implement their intentions (Neal et al., 2012). This is in line with the present finding that inactive participants had higher chances of choosing exercise when reaction times were longer because relying on reflective processes is more time consuming. This carries important practical implications, such as non-habitual exercisers should take their time to make exercise decisions.

5.1 Implications for research and practice

The theoretical conceptualization takes into account that the option to exercise is always contrasted with at least one non-exercise behavioral alternative (e.g., staying on the couch). Research that focuses primarily on the motivating force of why someone exercises neglects the impact of possible restraining situated processes in the moment of choice (e.g., the alternative of lying on the couch feels more appealing) (Brand & Cheval, 2019). To facilitate exercise behavior, the focus should not only be on imagined end states (e.g., behaviors or goals), but also on momentary forces that may be restraining someone from the desired behavior (e.g., the current affective state). The decision to exercise depends not only on how we feel and how we think about exercise, but also on what we would do instead (i.e., the behavioral alternative). An individual may generally like to exercise, but in a particular situation prefers the more attractive sedentary alternatives. The goal of an intervention may therefore not only be to provide a program for enhancing activity but also to decrease the reinforcing value of being sedentary (Epstein, 1992).

The conceptualization of the DPEX illustrates and provides empirical evidence that exercise behavior is not just a one-time decision to begin an exercise routine. Instead, exercise behavior is constituted of the sum of choices in which situated driving and restraining forces play a role. Future studies should investigate which underlying processes have to change (e.g., habit, identity, automatic associations of exercise) to achieve sustained exercise maintenance. The DPEX can serve as a simple and easy-to-use tool to examine whether a change in any of these variables has resulted in a change in an individual's decisional preferences towards exercise.

The DPEX could also be applied in a clinical context to easily classify exercisers and non-exercisers. With the help of an ROC curve analysis, we were able to identify a cut-off value (DPEX score of 0.50) at which the majority of individuals who are actually inactive would be correctly identified (while keeping the false positives to a minimum). This equips clinical practitioners with a simple diagnostic tool without the need to rely on self-reported behavior or to objectively monitor behavior over a long period of time (e.g., with an accelerometer).

In addition, the DPEX provides the opportunity to gain more insight into individual choice patterns (e.g., someone repeatedly chooses group exercises but not individual exercises). This data can be used to create an individualized profile that characterizes when an individual is more likely to choose exercise and when he or she is more likely to choose an alternative behavior. For example, a person might prefer exercise when compared to reading alone, but not when compared to meeting with friends. This provides practical insights (e.g., for personal trainers) when it comes to establishing an exercise routine. On the one hand, the DPEX can help to find a suitable activity and, on the other hand, it can identify possible barriers why and in which situations it might be difficult for an individual to realize their intentions to be active.

5.2 Limitations and Future directions

One limitation of the present study is that we used cross-sectional designs for data collection. Future research should consider measuring the DPEX more frequently and examine its stability and relationship to exercise behavior over time. One example would be to investigate whether a change in decisional preferences in exercising leads to a change in exercise behavior.

As the DPEX uses hypothetical scenarios, it is unclear whether participants will indeed make the choices they report. Future studies should investigate how the DPEX relates to everyday exercise choices using ecological momentary assessment methods (Reichert et al., 2020). For further theoretical insight, future studies should investigate the relationship with type-1 processes, such as automatic associations with exercise (Antoniewicz & Brand, 2014) or exercise-related habits (Rebar et al., 2016b).

6. Conclusion

With the development of the DPEX, we have not only introduced a new research tool, but our results also have the potential to improve the theoretical understanding of what constitutes exercise behavior. The present study provides empirical evidence that exercise behavior can be conceptualized as the sum of situated decisions between an exercise activity and a behavioral alternative. By providing a versatile, publicly-available open source tool, we hope to stimulate further research assessing decisional preferences in exercising as a situation-sensitive proxy of future exercise behavior. Not in the least, the concept of situated decisions can be integrated into intervention strategies to promote a more active lifestyle. The DPEX can be used to identify individual preferences and barriers to exercise and, more generally, to classify individuals as exercisers vs non-exercisers. Thus, the DPEX can serve as an important additional tool to previous measures to improve future investigations of exercise behavior

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