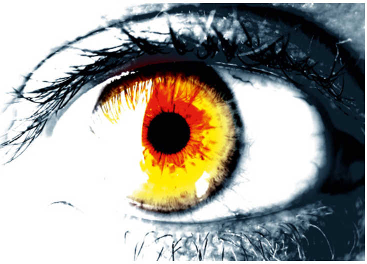
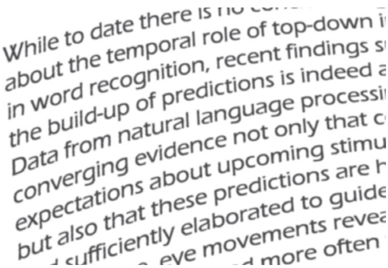
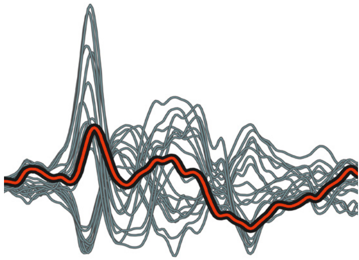
Universität Potsdam







Michael Dambacher

Bottom-up and top-down processes in reading

Influences of frequency and predictability on event-related potentials and eye movements

Potsdam Cognitive Science Series | 1

Potsdam Cognitive Science Series | 1

Potsdam Cognitive Science Series | 1

Michael Dambacher

Bottom-up and top-down processes in reading

Influences of frequency and predictability on event-related potentials and eye movements

Universitätsverlag Potsdam

Bibliografische Information der Deutschen Nationalbibliothek
Die Deutsche Nationalbibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über http://dnb.d-nb.de/ abrufbar.

Universitätsverlag Potsdam 2010
http://info.ub.uni-potsdam.de/verlag.htm

Universitätsverlag Potsdam, Am Neuen Palais 10, 14469 Potsdam
Tel.: +49 (0)331 977 4623 / Fax: 3474
E-Mail: verlag@uni-potsdam.de

Die Schriftenreihe **Potsdam Cognitive Science Series** wird herausgegeben von Johannes Haack, Dr. Christiane Wotschack und Michael Dambacher

Umschlagfotos: Nathalie Bélanger, Liz Schotter, Michael Dambacher

Zugl.: Potsdam, Univ., Diss., 2009
1st reviewer: Prof. Dr. Reinhold Kliegl
2nd reviewer: Prof. Dr. Arthur M. Jacobs
Day of oral defense: December 18, 2009

ISSN (print) 2190-4545
ISSN (online) 2190-4553

Online veröffentlicht auf dem Publikationsserver der Universität Potsdam
URL http://pub.ub.uni-potsdam.de/volltexte/2010/4202/
URN urn:nbn:de:kobv:517-opus-42024
http://nbn-resolving.de/urn:nbn:de:kobv:517-opus-42024

Zugleich gedruckt erschienen im Universitätsverlag Potsdam
ISBN 978-3-86956-059-5

Acknowledgments

I am very grateful to my advisors Reinhold Kliegl and Arthur M. Jacobs who granted me the privilege of being part of two outstanding labs at the University of Potsdam and the FU Berlin. In particular, I thank Arthur M. Jacobs for being such a provident mentor for almost 10 years. Since I was an undergraduate student, he kept on opening doors and provided irreplaceable opportunities to gain ground in the scientific community. Likewise, I thank Reinhold Kliegl for his thrilling creativity and enthusiasm that generates an extremely positive and productive atmosphere, and makes you sure science is one of the most exciting things you can do. I also thank my other colleagues and friends at the University of Potsdam and the FU Berlin; they always gave me the feeling of being a substantial part of both groups. Many thanks to Ralf Engbert, Eike Richter, Jochen Laubrock, and Antje Nuthmann who greatly supported my first (and the following) steps in programming and who shared their immense knowledge about eye movements. They never hesitated to spend time on listening to questions and were more often than not able to give valuable advice. Likewise, I am grateful to Sascha Tamm, Lars Kuchinke, Markus Hofmann, Angela Heine, and Markus Conrad for their helpfulness and for numerous discussions about how to process, analyze, and understand EEG data. I thank Anja Gendt, Katrin Göthe, Sarah Risse, and Daniel Schad for sharing their intellectual skills on multiple occasions and for always being there as a friend. Special thanks go to Mario Braun who spent days and weeks to set up and maintain the lab and who provided me with everything I needed to run experiments. I am very grateful to the former (associated) members of the *Helmholtz Center for the Study of Mind and Brain Dynamics*. Especially, I wish to thank Olaf Dimigen, Konstantin Mergenthaler, Martin Rolfs, Hans Trukenbrod, and Christiane Wotschack for their support and friendship. I learned a lot in our enjoyable, frequent, and sometimes endless scientific exchanges on various fields and disciplines, as well as in our not so scientific conversations about life or non-sense. I also thank the colleagues I got the opportunity to collaborate with. In particular, I thank Werner Sommer for his great EEG expertise as much as for his positive and caring attitude, Kay-Michael Würzner for his irreplacable assistance concerning stimulus materials, as well as Victor Kuperman for giving me a flavor of how "easy" writing can be. Many thanks to Petra Köhler, Elena Schmidt, and Nicole Stietzel who were more than helpful in finding ways out of bureaucratic labyrinths. I am deeply indebted to my parents for their unconditional support in every phase of my life. Finally, and with all my heart, I thank my beloved wife Carina, who did not only bear with great patience my physical and oftentimes mental absence over the last months and years, but who continuously encouraged me, built me up, and kept me grounded.

Abstract

In reading, word frequency is commonly regarded as the major bottom-up determinant for the speed of lexical access. Moreover, language processing depends on top-down information, such as the predictability of a word from a previous context. Yet, however, the exact role of top-down predictions in visual word recognition is poorly understood: They may rapidly affect lexical processes, or alternatively, influence only late post-lexical stages.

To add evidence about the nature of top-down processes and their relation to bottom-up information in the timeline of word recognition, we examined influences of frequency and predictability on event-related potentials (ERPs) in several sentence reading studies. The results were related to eye movements from natural reading as well as to models of word recognition.

As a first and major finding, interactions of frequency and predictability on ERP amplitudes consistently revealed top-down influences on lexical levels of word processing (Chapters 2 and 4). Second, frequency and predictability mediated relations between N400 amplitudes and fixation durations, pointing to their sensitivity to a common stage of word recognition; further, larger N400 amplitudes entailed longer fixation durations on the next word, a result providing evidence for ongoing processing beyond a fixation (Chapter 3). Third, influences of presentation rate on ERP frequency and predictability effects demonstrated that the time available for word processing critically co-determines the course of bottom-up and top-down influences (Chapter 4). Fourth, at a near-normal reading speed, an early predictability effect suggested the rapid comparison of top-down hypotheses with the actual visual input (Chapter 5). The present results are compatible with interactive models of word recognition assuming that early lexical processes depend on the concerted impact of bottom-up and top-down information. We offered a framework that reconciles the findings on a timeline of word recognition taking into account influences of frequency, predictability, and presentation rate (Chapter 4).

Zusammenfassung

Wortfrequenz wird in der Leseforschung als wesentliche Bottom-up Determinante für die Geschwindigkeit des lexikalischen Zugriffs betrachtet. Darüber hinaus spielen Top-down Informationen, wie die kontextbasierte Wortvorhersagbarkeit, in der Sprachverarbeitung eine wichtige Rolle. Bislang ist die exakte Bedeutung von Top-down Vorhersagen in der visuellen Worterkennung jedoch unzureichend verstanden: Es herrscht Uneinigkeit darüber, ob ausschließlich späte post-lexikalische, oder auch frühe lexikalische Verarbeitungsstufen durch Vorhersagbarkeit beeinflusst werden.

Um ein besseres Verständnis von Top-down Prozessen und deren Zusammenhänge mit Bottom-up Informationen in der Worterkennung zu gewährleisten, wurden in der vorliegenden Arbeit Einflüsse von Frequenz und Vorhersagbarkeit auf ereigniskorrelierte Potentiale (EKPs) untersucht. Die Ergebnisse aus mehreren Satzlesestudien wurden mit Blickbewegungen beim natürlichen Lesen sowie mit Modellen der Worterkennung in Beziehung gesetzt.

Als primärer Befund zeigten sich in EKP Amplituden konsistent Interaktionen zwischen Frequenz und Vorhersagbarkeit. Die Ergebnisse deuten auf Top-down Einflüsse während lexikalischer Wortverarbeitungsstufen hin (Kapitel 2 und 4). Zweitens mediierten Frequenz und Vorhersagbarkeit Zusammenhänge zwischen N400 Amplituden und Fixationsdauern; die Modulation beider abhängigen Maße lässt auf eine gemeinsame Wortverarbeitungsstufe schließen. Desweiteren signalisierten längere Fixationsdauern nach erhöhten N400 Amplituden das Andauern der Wortverarbeitung über die Dauer einer Fixation hinaus (Kapitel 3). Drittens zeigten sich Einflüsse der Präsentationsrate auf Frequenz- und Vorhersagbarkeitseffekte in EKPs. Der Verlauf von Bottom-up und Top-down Prozessen wird demnach entscheidend durch die zur Wortverarbeitung verfügbaren Zeit mitbestimmt (Kapitel 4). Viertens deutete ein früher Vorhersagbarkeitseffekt bei einer leseähnlichen Präsentationsgeschwindigkeit auf den schnellen Abgleich von Top-down Vorhersagen mit dem tatsächlichen visuellen Input hin (Kapitel 5).

Die Ergebnisse sind mit interaktiven Modellen der Worterkennung vereinbar, nach welchen Bottom-up und Top-down Informationen gemeinsam frühe lexikalische Verarbeitungsstufen beeinflussen. Unter Berücksichtigung der Effekte von Frequenz, Vorhersagbarkeit und Präsentationsgeschwindigkeit wird ein Modell vorgeschlagen, das die vorliegenden Befunde zusammenführt (Kapitel 4).

Contents

List of Figures

List of Tables

1 Introduction

Reading is an outstanding achievement of the human brain. The ability to read has substantially formed our history and culture and plays an essential role in our everyday lives. Skilled readers can hardly prevent processing a written stimulus and, most often, they grasp a word's meaning in the fraction of a second. The understanding of the underlying mechanisms as well as the time course of this seemingly effortless skill is the goal of psycholinguistic research.

In general, two major sources of information contribute to language comprehension. First, *bottom-up* processes transmit neural codes of sensory input to increasingly complex levels. On success, the appropriate word representation in the long-term memory is activated and semantic information associated with a word becomes available. Second, language-related knowledge and experiences are expressed in *top-down* influences that guide the way words are understood. They permit the integration of word meaning into a wider context and hold the potential to bias expectations about upcoming words.

Despite ample evidence for the relevance of bottom-up and top-down processes, their joint role in the timeline of word recognition is insufficiently understood. Clearly, bottom-up processes account for the elaboration of sensory signals and therefore reflect operations giving rise to the retrieval of a word's mental representation, i.e., *lexical access*. The role of top-down processes, however, is ambiguous. Those may be slow and only play a role for mental operations after lexical access; alternatively, they may rapidly impinge on early lexical processes and co-determine the course of word identification.

The present thesis investigates the relationship of bottom-up and top-down processes in reading and aims at contributing to the picture of their common role in the timeline of word recognition. We will show that top-down information is rapidly available and interacts with early levels of bottom-up processing.

1.1 Tracking the timeline of word recognition

Apparently, our brains do not voluntarily disclose the mechanisms underlying visual word recognition. Introspection alone does not suffice to explicitly describe mental operations, let alone delineating temporal interdependencies. Thus, psycholinguistic research resorts to experimental techniques and measures that shall bring to light processes of word identification.

For several decades, reaction times and error rates served as major tools for the investigation of word recognition. For instance, stimulus properties affecting measures in the lexical decision task (LDT[1]; e.g., Rubenstein, Garfield, & Millikan, 1970) were often considered as (co-)determinants for lexical access. Without doubt, behavioral evidence from this and numerous other paradigms has substantially enriched and formed the current understanding of visual word recognition.

Nevertheless, any inferences from behavioral data remain indirect since they do not exclusively reflect the time necessary for lexical access. For example, the LDT involves stages of decision as well as preparation and execution of motor responses. As a related issue, the exact temporal nature of influences often remains vague since effects can be located on *pre-lexical* (i.e., prior to lexical access) or *post-lexical* (i.e., after lexical access) levels. Thus, questions about relevant processes and the time course of lexical access cannot be fully answered on the basis of these measures.

[1] In the LDT, participants are asked to indicate whether a stimulus is an existing word or a non-sense letter string, i.e., a nonword. The LDT was widely understood as pure measure of lexical access (but see Balota & Chumbley, 1984 for a discussion).

To overcome this shortcoming, psycholinguists make use of several additional sources of information. As one source, theories of word recognition are implemented in computational models. Simulations can be tested against human performance and therefore allow the validation of theoretical assumptions. Importantly, advanced models incorporate hypotheses about dynamics in word recognition, such that the time course can be tracked with high accuracy (e.g., Grainger & Jacobs, 1996; McClelland & Rumelhart, 1981).

Another source of information comes from eye movements in normal reading, reflecting visual word recognition in natural settings. In particular, lexical processing is at least partly expressed in fixation durations, which therefore permit inferences about underlying cognitive processes (e.g., Kliegl, Nuthmann, & Engbert, 2006; Rayner, 1998).

As a third source, electrophysiological data provide insights about cognitive processes with high temporal accuracy. Influences of word properties and their interplay with mental operations can be measured online, without requiring behavioral responses. Thus, ERPs are an important tool to track word processing from the initial uptake of sensory information up to the comprehension and integration of meaning (e.g., Barber & Kutas, 2007; Kutas, Van Petten, & Kluender, 2006).

Considering models, eye movements, and ERPs, the present work takes advantage from all three sources. In accordance with calls for multi-methodological approaches in psycholinguistic research (Barber & Kutas, 2007; Jacobs & Carr, 1995), we aim at gaining insights into mechanisms of word recognition, that go beyond evidence from single approaches. The following sections briefly depict central aspects of eye movements and electroencephalographic measures.

1.1.1 Eye movements

Maybe the most intuitive way to study the processing of written language is to monitor the subjects' gaze while they are reading a text. In reading, the eyes do not smoothly move across the lines but perform sequences of rapid movements, known as *saccades*, and intervals when they stand relatively still, i.e., *fixations*. Causes for this behavior lie in the anatomical structure of the retina. Whereas visual acuity is high in the fovea (i.e., the area of about 2° of visual angle around the center of a fixation), it rapidly drops in parafoveal (i.e., from 2° to 5° around the fixation) and peripheral (i.e., more than 5° around the fixation) regions. Usually, saccades serve the purpose to foveate visual information that is intended for detailed analysis. For word recognition, a viewing location near the word center grants optimal efficiency of stimulus processing (e.g., Jacobs, Nuerk, Graf, Braun, & Nazir, 2008; Nazir, Jacobs, & O'Regan, 1998; Nuthmann, Engbert, & Kliegl, 2007; O'Regan & Jacobs, 1992).

In alphabetic languages, typical reading saccades have durations of 20 to 30 ms and their amplitudes encompass around seven letters; however, a large proportion of saccades deviates from this average score. Since vision is largely suppressed during saccades (Matin, 1974), information must be predominantly extracted in fixation intervals. Skilled readers fixate around four to five words per second, but also here, variability is very high, as fixation durations range from 50 ms to more than 600 ms (Rayner, 1998, 2009).

Importantly, fixation-saccade sequences in reading are sensitive to cognitive influences. For instance, increasing text difficulty entails longer fixation durations as well as shorter saccades; similar patterns are observed for dyslexic readers. Indeed, eye movements permit distinguished inferences about processes of word recognition. There is a long tradition of investigating language-related influences on various measures, such as fixation durations, saccade amplitudes, backward regressions, word skippings, or landing site distributions (for reviews see Rayner, 1998, 2009).

As a major advantage, eye movements disclose dynamics of word processing across the course of sentences. For instance, fixation durations are not only sensitive to properties of a fixated stimulus (i.e., *immediacy effects*), but are also modulated by characteristics of preceding (i.e., *lag effects*) and upcoming (i.e., *successor effects*) words. They therefore unveil important information about the interaction of word recognition and saccade planning (Kliegl et al., 2006). Several sophisticated models deal with these insights about the interplay of oculomotor and cognitive processes and are able to reproduce dynamics of human reading behavior with high accuracy on a quantitative level (e.g. *SWIFT*, Engbert, Nuthmann, Richter, & Kliegl, 2005; *EZ-Reader*, Reichle, Pollatsek, & Rayner, 2006; *Glenmore*, Reilly & Radach, 2006).

Unquestionably, eye tracking is an irreplaceable tool for the investigation of visual word processing. Advantageously, participants move their eyes normally and at their own pace; the data therefore largely reflect natural reading behavior. However, eye movements do not disclose information about processes between the moment when the eyes initially fixate a word and the time when they leave it. In particular, it is not clear, *when* during a fixation a specific word is lexically accessed, or whether it is identified at all. Indeed, words are often inspected longer when the previous stimulus was difficult, a finding that may point to ongoing word processing after the eyes have left a stimulus (Kliegl et al., 2006; see Chapter 3). Thus, despite their sensitivity to lexical processing, fixation durations permit only indirect evidence about word recognition itself. An approach to access this information more directly is the use of event-related potentials.

1.1.2 Event-related potentials (ERPs)

Information processing in the brain relies on the communication between neurons, expressed in the transmission of current flows. When a large number of neighboring neurons fire synchronously, brain-electrical activity is sufficiently strong to be captured by electrodes applied to the surface of the scalp. The resulting electroencephalogram (EEG) is the summation of all signals at an electrode site. Ongoing neural activity manifests as a continuous EEG stream that is characterized by positive- and negative-going voltage changes (Berger, 1929).

Compared to this "spontaneous" EEG, brain-electrical responses to the processing of a specific stimulus are often too small to be detected in the continuous signal. A common way to extract this information is the calculation of event-related potentials (ERPs) by averaging multiple EEG sequences, that are associated with the same experimental class of stimuli. It is assumed that spontaneous EEG activity is not phase-locked to stimulus processing and will cancel out in the averaging procedure. Accordingly, the remaining ERP course is believed to largely reflect brain potentials that are related to the processing of experimentally relevant events (for reviews see Kutas & Van Petten, 1994; Kutas et al., 2006).

A strategy to get insights about stimulus-related processes is the comparison of ERPs from two or more experimental conditions. Differences between the signals indicate that, on average, parts of the brain responded differently to experimental conditions. Such effects manifest in amplitude modulations or in temporal shifts of ERP components. Thereby, the latency of an effect provides an upper temporal bound for distinct processing, since it is possible that variations earlier in the time course were not captured by ERPs.

Over the past 30 years, ERPs have become an important tool for psycholinguistic research. Their most obvious advantage is the high temporal resolution that reflects ongoing neural activity in the range of milliseconds. Unlike measures of reaction times, error rates, or eye movements, ERPs allow the investigation of word recognition *while* stimuli are being processed. As another benefit, ERPs are independent from overt responses or do at least not necessarily focus on them. In contrast, in classical psycholinguistic paradigms (e.g., LDT) speeded motor responses impose additional tasks that may affect mechanisms and strategies of word recognition.

Nevertheless, ERP research has to face some difficulties, that are relevant for the study of reading. First, ERPs are sensitive to ocular artifacts. Because the eyeball acts as a dipole, eye movements and blinks induce changes in scalp voltages that supersede activity related to word processing; further, (eye-)muscular activity can disturb the EEG signal. Consequently, stimuli are usually presented in a way that renders eye movements unnecessary, that is, one at a time in the center of the screen (i.e., Rapid Serial Visual Presentation, RSVP). Second, prominent language-related ERP components (e.g., N400 or P600) have long latencies and range up to one second after stimulus onset. At a natural reading rate of four to five words per second, ERPs to consecutive stimuli would overlap such that signals could hardly be attributed to the processing of a unique word. Therefore, words are often separated by unnaturally long intervals. Given stimulus-wise presentation at rather slow rates, ERP research of word recognition often uses setups that diverge substantially from natural reading. Yet, the importance of ecological validity for reading processes is unknown; parts of the present work will address this issue (see Chapter 4).

Despite these shortcomings, ERPs essentially contribute to the understanding of word recognition. They provide information about the time course of lexical processing with a resolution that is beyond the precision of any behavioral measure. After all, electrophysiology and eye movements appear as complementary approaches, since ERPs hold the potential to uncover mental operations during fixations, while eye movements reveal natural behavior in normal reading.

1.2 Bottom-up and top-down processes in word recognition

Considering empirical evidence from ERPs and eye movements, the present work investigated the role of bottom-up and top-down processes during reading, an issue that is discussed controversially in psycholinguistic research. The following sections describe word frequency and predictability as important representatives of these processes.

1.2.1 Bottom-up information: Word frequency

Reading is determined by bottom-up processing of visual information. As the signal propagates along a hierarchy of increasingly complex neuronal detectors, mental operations become more and more elaborate. In particular, the left occipito-temporal cortex is gradually sensitive to lexical information, ranging from individual letters and bigrams to morphemes and, finally, entire words (e.g., Vinckier et al., 2007). Undoubtedly, word recognition substantially depends on the visual processing of word characteristics; indeed, there are more than 50 stimulus properties affecting performance (cf., Graf, Nagler, & Jacobs, 2005).

Among these, probably the most important characteristic is the frequency with which a word occurs in a language. Starting with the observation that identification requires longer tachistoscopic presentation times for low than for high frequency words (Howes & Solomon, 1951), research over the last decades has consistently yielded robust and sizeable frequency effects across numerous tasks. For instance, in isolated word recognition (e.g., LDT or naming), reaction times are shorter and accuracy is higher for high than for low frequency words (Forster & Chambers, 1973; Frederiksen & Kroll, 1976; Grainger, 1990; Rubenstein et al., 1970). Analogously, during normal left-to-right reading, high frequency words are fixated shorter and are skipped more often (e.g. Inhoff & Rayner, 1986; Kliegl, Grabner, Rolfs, & Engbert, 2004; Kliegl et al., 2006; Rayner & Duffy, 1986; Schilling, Rayner, & Chumbley, 1998). Furthermore, frequency effects in ERPs were reported on the N400 component[2], a negative deflection peaking at around 400 ms post-stimulus over centro-parietal scalp sites. Larger N400 amplitudes for low than for high frequency words pointed to increased processing costs for less familiar stimuli (Rugg, 1990; Van Petten & Kutas, 1990; Young & Rugg, 1992).

[2] The N400 component is one of the best-studied ERP components in psycholinguistic research. The N400 is predominantely modulated by contextual influences (see next section) and is therefore often regarded as an index for the ease of semantic integration into a context (Kutas & Hillyard, 1980, 1984).

Although the exact nature of frequency effects was debated (e.g., Balota & Chumbley, 1984; see Monsell, 1990, for a review), there is general agreement that the variable influences early processes of word recognition (e.g., Hudson & Bergman, 1985; Forster, 1992; Forster & Chambers, 1973). This view is supported by ERPs revealing frequency effects in time intervals well before 200 ms (Braun, Hutzler, Ziegler, Dambacher, & Jacobs, 2009; Hauk, Davis, Ford, Pulvermüller, & Marslen-Wilson, 2006; Hauk & Pulvermüller, 2004; Penolazzi, Hauk, & Pulvermüller, 2007; Sereno, Brewer, & O'Donnell, 2003; Sereno, Rayner, & Posner, 1998). In accordance with influences on fixation durations of around 200 to 250 ms, frequency appears as a relevant factor for rapid bottom-up processing of sensory information.

Given that essentially every task associated with lexical processing is sensitive to word frequency, the variable is understood as a core determinant for lexical access. Therefore, the latency of the first word frequency effect in ERPs is often considered as an estimate that word representations have been identified[3] (e.g., Braun et al., 2009; Hauk & Pulvermüller, 2004; Sereno et al., 2003, 1998; Sereno & Rayner, 2003). After all, the reliability of frequency effects

[3]Certainly, this assumption is an oversimplification as a deterministic relationship between lexical access and ERP frequency effects is rather unlikely. Nevertheless, it is reasonable to assume a link between processes of word identification and detectable influences of frequency in ERPs. For instance, while words of all frequencies consist of a common set of sub-lexical features (e.g., letters), word frequency describes a lexical characteristic of the entire word form. Frequency effects in ERPs are therefore considered as neural responses to the activation of unique word representations. This concept has been strongly inspired by models of word recognition that - given the ubiquitous influence in tasks requiring lexical access - have incorporated frequency as the critical determinant for lexical access (Forster, 1976; McClelland & Rumelhart, 1981; Morton, 1969). As another argument, eye movements in reading are widely believed to be optimized for processes of word identification. Strong frequency effects on fixation durations corroborate the idea of frequency as a valid predictor for the speed of lexical access. On that note, the temporal similarity of fixation durations and early ERP frequency effects provide compatible latencies for word identification (e.g., Sereno et al., 1998; Sereno & Rayner, 2003). Notably, despite these considerations, unequivocal evidence for the moment of lexical access from empirical data is lacking in every domain of psycholinguistic research. Therefore, the first word frequency effect in ERPs must be understood as a proxy rather than as a direct measure of the latency of lexical access.

suggests a fundamental advantage for bottom-up processing of familiar stimuli and a major advantage for the speed of lexical access.

1.2.2 Top-down information: Word predictability

For a long time, the concept of visual perception was dominated by the view that sensory processing relies first and foremost on the hierarchical bottom-up flow of information. Recent findings, however, have radically changed this uni-directional picture. Top-down processes, as for instance attentional control or expectations of upcoming sensory events, affect perception on virtually every level (e.g., Bar, 2007; Carlsson, Petrovic, Skare, Petersson, & Ingvar, 2000; Churchland, Ramachandran, & Sejnowski, 1994; Corbetta & Shulman, 2002; Engel, Fries, & Singer, 2001; Enns & Lleras, 2008; Gilbert & Sigman, 2007; Kastner, Pinsk, De Weerd, Desimone, & Ungerleider, 1999; Kveraga, Ghuman, & Bar, 2007; Mechelli, Price, Friston, & Ishai, 2004; O'Connor, Fukui, Pinsk, & Kastner, 2002; Somers, Dale, Seiffert, & Tootell, 1999; Williams et al., 2008).

Undoubtedly, top-down processes also play a critical role in language comprehension. This becomes intuitively evident considering the processing of ambiguous words: Readers have a different understanding of the word *bank* in a discourse about a *river side* as compared to a *financial institute*. It is assumed that top-down information relying on the interpretation of the context activates the appropriate meaning of an ambiguous word (e.g., Sereno et al., 2003; Simpson, 1994; Van Petten, 1995). As another example, when readers are asked to complete a sentence fragment like *The lumberjack usually used his chainsaw to fell a...*, most of them probably fill in the word *tree*. Apparently, in a constraining context, the interpretation of a sentence message affords specific predictions that activate a mental word representation even in the absence of visual information.

In fact, word predictability[4] from a previous context is an important factor for the efficiency of language processing. Similar to word frequency, robust influences of predictability have been observed across many tasks and in several measures. For instance, in single-word recognition, reaction times as well as naming latencies are shorter for words that are preceded by a supporting compared to a non-supporting context (Kleiman, 1980; Fischler & Bloom, 1979; Schuberth & Eimas, 1977; Stanovich & West, 1983; West & Stanovich, 1982). During normal reading, eye movements reveal shorter fixation durations and higher skipping rates for high than for low predictability words (Ashby, Rayner, & Clifton, 2005; Calvo & Meseguer, 2002; Duffy, Henderson, & Morris, 1989; Ehrlich & Rayner, 1981; Kliegl et al., 2004, 2006; Rayner, Ashby, Pollatsek, & Reichle, 2004; Rayner & Well, 1996). In ERPs, predictability has strong effects on the N400 component; increasing amplitudes point to augmenting processing difficulty as predictability decreases (Kutas & Hillyard, 1980, 1984; for reviews see Kutas & Van Petten, 1994; Kutas et al., 2006; Barber & Kutas, 2007).

Thus, besides the undisputed role of bottom-up flow, word processing appears to be strongly modulated by contextual top-down information. The relation of the two streams, conceptualized as influences of frequency and predictability[5], is described in more detail in the following sections.

[4]Word predictability norms in experimental setups are usually assessed in a paper-pencil cloze task. Analogous to the *lumberjack* example, subjects are presented with a sentence fragment and are asked to guess the next word. Predictability is then computed as the proportion of subjects predicting the correct word from the prior context.

[5]Note that a strict separation of word frequency and predictability into bottom-up and top-down streams presumably is an oversimplification. For instance, it is very likely that bottom-up processes theirselves involve feedback loops reinforcing the signal; in turn, not all top-down processes are independent from feedforward spreading of neural activation (e.g., Di Lollo, Enns, & Rensink, 2000; McClelland & Rumelhart, 1981). Further, during reading acquisition, item-specific codes of a word form may be retained and affect recognition as frequency-based top-down information (cf., Jacobs et al., 2008). After all, there is a positive correlation of frequency and predictability in natural language (Kliegl et al., 2006). Arguably, however, the core influences of frequency and predictability are expressed in bottom-up and top-down processes, respectively (cf., this and the previous section). For the sake of simplicity, the present terminology is confined to these main attributes of the variables.

1.3 Towards a common timeline of bottom-up and top-down processes

1.3.1 Top-down influences in word recognition: Lexical or post-lexical?

In view of the obvious influence of word predictability on various measures of language processing, there is little doubt about the facilitative role of a supporting context. Yet, however, the exact nature of top-down predictions in the course of word recognition is unresolved. There are two controversial views that were both supported by behavioral results. On the one hand, the anticipation of upcoming stimuli from a prior context was considered as too slow to affect early stages of word identification. Contextual top-down influences were therefore expected only on post-lexical levels of semantic integration, while lexical access was regarded as the result of bottom-up processes (e.g., Burgess, Tanenhaus, & Seidenberg, 1989; Lucas, 1987; Onifer & Swinney, 1981; Swinney, 1979). On the other hand, it was assumed that the rapid interpretation of a context affords information that is relevant also on early levels of word recognition. Accordingly, lexical processing should depend on joint influences of bottom-up and top-down information (e.g., Glucksberg, Kreuz, & Rho, 1986; Tabossi, 1988; Schvaneveldt, Meyer, & Becker, 1976; Simpson, 1981; see Simpson, 1994 for a review).

While the debate was not decisively resolved on the basis of behavioral data, the high temporal resolution of ERPs holds the potential to provide evidence about the role of top-down information. In particular, the context-sensitive N400 component was often considered as a pure reflection of post-lexical processes (Brown & Hagoort, 1993; Holcomb, 1993; Misra & Holcomb, 2003), challenging the view of predictability effects on lexical levels. However, the exact nature of the N400 is not yet understood, as several reports pointed to lexical influences on the N400 (Deacon, Dynowska, Ritter, & Grose-Fifer, 2004; Deacon, Hewitt, Yang, & Nagata, 2000; Wang & Yuan, 2008). Thus, the question about the time course of top-down predictions in word recognition is still unresolved.

1.3.2 Models of word recognition

Given the central role of bottom-up and top-down information in language processing, the opposing views concerning their relationship were also expressed in different models of visual word recognition. The following paragraphs describe the most influential representatives reflecting this controversy.

1.3.2.1 Serial approaches

According to serial search models, lexical access is exclusively driven by bottom-up processing of visual input. In particular, word frequency is considered as the primary agent for the speed of lexical access (cf., Rubenstein et al., 1970). The most prominent approach of this kind is the *Bin Theory* (Forster, 1976, 1992; Murray & Forster, 2004). In this account, word representations in the mental lexicon are organized in sublists, called *bins*. Within each bin, lexical entries are sorted in descending order according to their frequency. The identification of a given letter string is performed in a sequential comparison of the visual input with each entry, from top to bottom. Due to the serial nature of the search, positive matches are found faster for high than for low frequency words. Information of a successful match is then used to activate semantic and syntactic information of the word for later processing.

In contrast to word frequency, contextual top-down influences are considered as slow factors in this framework. In line with a modular view of word recognition, postulating the absence of top-down effects on lexical phases of word processing (Fodor, 1983; Kintsch & Mross, 1985), word predictability is assumed to act only on a post-lexical stage. Thus, high expectancy of words facilitates the combination of linguistic information with contextual and background knowledge and eases semantic integration into a broader context, but has no role for lexical access (Murray & Forster, 2004).

1.3.2.2 Parallel approaches

Also parallel models have incorporated word frequency as the major determinant for the speed of lexical access. In Morton's (1969) *Logogen Model*, the mental lexicon is described as a set of detectors (i.e., *logogens*), each representing a word. Sensory input sharing features with a logogen increases its activation level, until a virtual threshold of lexical access is reached and a word is identified. The threshold is lower and therefore accessed faster for high than for low frequency words. Importantly, the *Logogen Model* assumes top-down influences on early stages of word recognition. A supporting context increases the activation level of an expected logogen, such that less sensory information is necessary for lexical access of high predictability words.

Another milestone in theories of visual word recognition is the computational *Interactive Activation Model* (IAM; McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982), providing quantitative estimates of dynamics in the mental lexicon. Similar to Morton's approach, words are represented as *nodes* that increase their activation level with matching visual input. To account for frequency effects, a higher resting level grants an activation advantage for high over low frequency words. A core assumption of the IAM is the interactive nature of perception. Top-down and bottom-up processes work simultaneously, such that knowledge about words interacts with the lower processing levels and co-determines lexical access. In particular, the model comprises three hierarchical levels for letter string processing: Feature detectors activate letter units, which in turn project to whole word representations. Letter and word levels are connected bi-directionally and send inhibitory and excitatory signals; units within one level are subject to lateral inhibition. Although the IAM primarily accounts for single word recognition, a supporting sentence context was assumed to increase the activation level of high predictability words, while low predictability nodes are inhibited (Rumelhart & McClelland, 1982).

1.3.2.3 Other approaches

Of course, the landscape of theories on word recognition is much richer than the approaches outlined above, as there are highly sophisticated models accounting for a variety of effects (for reviews see e.g., Barber & Kutas, 2007; Jacobs & Grainger, 1994; Monsell, 1990; Seidenberg, 2007). For instance, several localist models build on the core principles of the IAM and successfully simulate phenomena of orthographic and phonological processing (e.g., *DRC*, Coltheart, Rastle, Perry, Langdon, & Ziegler, 2001; *MROM*, Grainger & Jacobs, 1996; *MROM-p*, Jacobs, Rey, Ziegler, & Grainger, 1998). Further, *Activation-Verification* models incorporate serial as well as parallel aspects, proposing an initial phase of parallel activation of a set of candidates, which are subsequently compared with the input in a serial manner (e.g., Becker, 1980; Schvaneveldt & McDonald, 1981; Paap, Newsome, McDonald, & Schvaneveldt, 1982). As another case, the family of *Connectionist Models* expresses lexical information as activation patterns that are distributed across neuron-like units in a network, rather than as local representations in a mental lexicon (e.g., Plaut, McClelland, Seidenberg, & Patterson, 1996; Seidenberg & McClelland, 1989; Zorzi, Houghton, & Butterworth, 1998). Especially interesting examples are *Simple Recurrent Networks* implementing context-derived predictions as a core mechanism in word processing (e.g., Elman, 1990, 2004).

Importantly, while some psycholinguistic models are rather detached from neuroscience, recent approaches increasingly take into account biological constraints and therefore follow calls for physiological plausibility (e.g., Barber & Kutas, 2007; Dehaene, Cohen, Sigman, & Vinckier, 2005; Grainger, 2008; Jacobs & Carr, 1995). As one case, some theories have incorporated the transmission of visual information from the left and right hemifields to contralateral hemispheres (e.g., *SERIOL*, Whitney, 2001; *Split Model*, Shillcock, Ellison, & Monaghan, 2000). For instance, in the *SERIOL* model, location gradients within the hemispheres encode the ordinal position of letters, which are serially processed in oscillatory cycles (Whitney, 2008; Whitney & Cornelissen, 2008).

As another case, models of word recognition take into account temporal constraints of the availability of different information types for stimulus processing. As a remarkable example, evidence from various ERP studies yielded a timeline of orthographic and phonological processing in the *Bi-Modal Interactive Activation Model* (Grainger & Holcomb, 2009, 2008). Finally, patterns of neural activation can serve as a touchstone for model assumptions. For instance, *MROM*-based estimates of different levels of lexical activity in the mental lexicon compatibly entailed graded neural responses in ERPs (Braun et al., 2006).

In general, models of word recognition essentially contribute to the understanding of language processing, since explicit assumptions about mechanisms and determinants allow testable predictions. In particular, the joint consideration of models and neurophysiological data holds the potential to provide important insights about language-related mental operations. Thereby, models will prospectively also be judged in terms of their anatomical and functional plausibility.

Despite the large variety of models, the present work primarily focused on the comparison of the serial *Bin Theory* (Forster, 1976, 1992; Murray & Forster, 2004) and the parallel *IAM* (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982) for two reasons. First, the opposing implementations of bottom-up and top-down processes permit strong and unambiguous predictions about the time course of word recognition. Second, the core assumptions of the two frameworks represent prototypes that have influenced several other approaches (see above). Therefore, evidence about the role of bottom-up and top-down information serves not only as a validation of these two models, but generalizes as a proof of concept to numerous other accounts.

1.3.3 Predictability and the anticipation of upcoming events

While to date there is no conclusive agreement about the temporal role of top-down influences in word recognition, recent findings suggest that the build-up of predictions is indeed a rapid process. Several data from natural language processing provide converging evidence not only that context directs expectations about upcoming stimuli "on the fly", but also that these predictions are highly specific and sufficiently elaborated to guide behavior.

For instance, concerning eye movements, words in sentences are skipped more often when they are of high than of low predictability. Notably, fixation durations prior to high predictability words are prolonged. It was proposed that these words are processed and retrieved from memory while the eyes are still on the preceding stimulus (Kliegl et al., 2006). Accordingly, word identity in natural reading can sometimes be accessed without foveal information of the stimulus.

Compatible evidence for real-time predictions in eye movements was demonstrated in *visual world paradigms*. In these experiments, participants are viewing pictures containing several objects while listening to narratives relating to the scene. Critically, objects reflecting likely continuations of the story are often inspected shortly *before* they are actually mentioned (Altmann & Kamide, 2007; see also Altmann & Kamide, 1999; Altmann & Mirkovic, 2009; Kamide, Altmann, & Haywood, 2003; Kamide, Scheepers, & Altmann, 2003). These results demonstrate that context-based expectations of upcoming stimuli are fast and strong enough to trigger anticipatory saccades.

Anticipatory activity to highly expected words was also found in electrophysiological measures. For instance, subjects listened to Dutch stories (e.g., *The burglar had no trouble locating the secret family safe. Of course, it was situated behind a ...*) that biased predictability of a specific target noun (e.g., $painting_{neu}$). The target was preceded by a gender-marked adjective, whose suffix either matched (e.g., big_{neu}, neuter gender with no suffix) or mismatched (e.g., $big[e]_{com}$, common gender with e-suffix) the syntactic gender of the high predictability noun. ERPs to prediction-consistent and -inconsistent adjectives revealed amplitude differences prior to the onset of the target noun. Since all adjectives were fully grammatical in the sentence structure, the effect points to specific expectations of upcoming nouns at target position (Van Berkum, Brown, Zwitserlood, Kooijman, & Hagoort, 2005)[6]. Importantly, it was shown that the effect is indeed related to active top-down predictions derived from the message-level rather than to automatic spreading activation due to prime words in the preceding context. In an analogous experiment, ERPs revealed anticipatory effects to gender-marked adjectives only, when the context triggered high target predictability. The effect disappeared when the discourse was less predictive but preserved potential primes (Otten, Nieuwland, & Berkum, 2007; Otten & Van Berkum, 2008).

Together, these results indicate that readers and listeners generate online predictions about upcoming stimuli as sentences unfold. The anticipatory patterns cannot be fully explained in terms of bottom-up priming, but point to top-down pre-activation of phonological, syntactic, and semantic characteristics of specific word forms. Thus, elaborate predictions *prior* to the appearance of an expected stimulus suggest high efficiency of anticipatory processes.

1.3.4 The interplay of bottom-up and top-down information

Arguably, the amenability of specific predictions at the moment of sensory input concedes rapid and simultaneous influences of top-down and bottom-up information in word recognition. As outlined before, however, the common role of the two streams for lexical processing is debated. We have proposed word frequency and context-based predictability as suitable variables to investigate this issue. In fact, their joint influence on the time course was addressed in several previous ERP studies.

First electrophysiological evidence for the interplay of frequency and contextual information on a common stage of word recognition was observed by Van Petten and Kutas (1990; see also Van Petten

[6]Comparable results have been obtained for the visual modality in English (DeLong, Urbach, & Kutas, 2005) and Spanish (Wicha, Moreno, & Kutas, 2003, 2004).

& Kutas, 1991; Van Petten, 1993). In a sentence reading study, they took advantage from the fact that, on average, contextual constraint increases with word position in a sentence. Thus, serial word position was considered as a proxy for predictability. An interaction of word position and frequency on the N400 component revealed larger amplitudes for low than for high frequency words at early positions, whereas the effect disappeared as sentences unfolded. The authors proposed that frequency plays a subordinate role in word recognition when contextual constraint is high.

While influences on the N400 are often regarded as too late for lexical processing, early interactions of bottom-up and top-down information were reported by Sereno et al. (2003). In a reading study, they investigated the influence of context on the processing of ambiguous words. The rational was that in a biasing context the low frequency meaning of the ambiguous word should be activated, while in a neutral context its high frequency meaning should be dominant. Indeed, from 132 to 192 ms post-stimulus ambiguous words in a biasing context evoked ERP amplitudes similar to those of low frequency control words, whereas in a neutral context amplitudes corresponded to those of high frequency words. It was proposed that the meaning of ambiguous words was selectively activated due to the rapid interpretation of the preceding context, suggesting top-down influences on early levels of word recognition.

Rapid bottom-up and top-down effects were also observed by Penolazzi et al. (2007) who reported influences of frequency and predictability on ERP amplitudes from 110 to 130 ms as well as in an N400 interval. Notably however, the two variables did not interact throughout the entire ERP course, which is at odds with the interactive patterns observed by Van Petten and Kutas (1990) and Sereno et al. (2003). It was proposed that frequency-driven lexical access and context-based semantic integration are rapid and parallel processes that operate on functionally dissociable systems.

In summary, these results corroborate the view that frequency and predictability act in a common time range and point to contextual influences in early intervals. Nevertheless, the question about the common role of bottom-up and top-down processes remains vague since early and late intervals revealed interactions as well as additive effects of frequency and context.

1.4 Overview of the present studies

In the present work, we aimed at providing further insights about the impact of bottom-up and top-down processes in the timeline of word recognition. In several sentence reading experiments, we examined word frequency and predictability effects on ERPs and related the data to eye movements from natural reading and to models of word recognition. The following sections provide an overview of the present studies.

1.4.1 Frequency and predictability effects on event-related potentials during reading (Chapter 2)

In Chapter 2, we examined the time course of word recognition employing natural and continuous variations of frequency and predictability in German sentences. The *Potsdam Sentence Corpus 1* (PSC1; see Appendix A), comprising frequency and predictability norms for each of 1138 words, served as stimulus materials. ERPs were assessed from 48 subjects reading 144 sentences, which were presented word by word (RSVP) with a stimulus-onset asynchrony (SOA) of 700 ms; each word was presented for 250 ms and was followed by a 450 ms blank screen. Repeated-measures multiple regression analyses on single-trial EEG amplitudes were used to examine influences of content word frequency and predictability in a P200 interval from 140 to 200 ms as well as in an N400 time window from 300 to 500 ms. We also included serial word position as predictor, since position served as an estimate for predictability in a previous study (Van Petten & Kutas, 1990).

As a major finding in the P200 epoch, we observed a reliable influence of word frequency on ERP amplitudes. The result is compatible with other reports of frequency effects before 200 ms post-stimulus (Braun et al., 2009; Hauk & Pulvermüller, 2004; Hauk et al., 2006; Penolazzi et al., 2007; Sereno et al., 2003, 1998). Notably, our result goes beyond previous findings since the observed effect followed a quadratic trend: Amplitude differences increased with word frequency; that is, frequency effects were more prominent within the high than within the low frequency range. Considering word frequency effects as a proxy for lexical access, we proposed that word recognition was presumably completed for high frequency words while low frequency words were still being processed. The absence of predictability effects on P200 amplitudes suggested that identification of high frequency words relies on rapid bottom-up processes, independent from contextual information. However, it is also possible that the natural variation of predictability was not strong enough to reveal early top-down effects.

In the N400 interval, amplitudes linearly decreased with word predictability, a finding that lines up with numerous reports of an inverse correlation between N400 amplitudes and predictability (e.g., Kutas & Hillyard, 1984; Kutas & Van Petten, 1994). Predictability accounted for the influence of word position, corroborating the notion that position effects on the N400 relate to increasing contextual constraint (Van Petten & Kutas, 1990). Importantly, the N400 revealed a strong interaction of frequency and predictability. Predictability effects were larger for low than for high frequency words. Moreover, and contrary to the P200 interval, the pattern of frequency influences suggested greater differences within the low than within the high frequency range. We proposed that N400 modulations largely reflected the late access of low frequency words, a process that was strongly modulated by contextual information.

In summary, while there was no evidence for context effects on P200 amplitudes, the interactive pattern on the N400 pointed to influences of frequency and predictability on a common stage of word recognition. Compatible with assumptions from parallel models incorporating simultaneous influences of bottom-up and top-down information (e.g., McClelland & Rumelhart, 1981; Morton, 1969; Rumelhart & McClelland, 1982), the data suggested that contextual information is involved in lexical processing.

1.4.2 Synchronizing timelines: Relations between fixation durations and N400 amplitudes during sentence reading (Chapter 3)

Besides the joint influence of frequency and predictability on N400 amplitudes (Chapter 2), it is well-known that fixation durations during normal reading are strongly modulated by the two determinants (e.g., Inhoff & Rayner, 1986; Kliegl et al., 2004, 2006; Rayner, Binder, Ashby, & Pollatsek, 2001; Rayner & Well, 1996; Schilling et al., 1998). Thus, we considered the possibility that ERPs and eye movements are similarly influenced by a common stage of word recognition, that acts as a connecting link between the two measures.

In Chapter 3, we investigated nature and strength of relations between fixation durations and N400 amplitudes. Eye movements were recorded from 125 participants[7] while they were silently reading sentences of the PSC1. ERPs were taken from the experiment described in Chapter 2, i.e., 48 subjects were reading the PSC1 in an RSVP setting (see previous section). Because the two data sets were assessed in independent experiments with different subjects, relations between single fixation durations and N400 amplitudes were examined in item-based path analyses. Critically, the analyses were not restricted to single words, but captured reading dynamics across word triplets.

Significant correlations confirmed the strong visual impression of increasing fixation durations with larger N400 amplitudes. The relation was accounted for by frequency and predictability, indicating that word difficulty was similarly reflected in fixation durations and N400 amplitudes. Moreover, predictability of the next word

[7] These data have been collected in previous experiments and are described elsewhere in detail (Kliegl et al., 2004, 2006).

accounted for covariance, suggesting that the anticipation of upcoming stimuli comparably influenced eye movements (cf., Kliegl et al., 2006) and ERPs (cf., DeLong et al., 2005; Van Berkum et al., 2005).

In addition, N400 activity predicted subsequent fixation durations: Larger amplitudes entailed longer fixations on the next word, a relation accounted for by word frequency. The finding offers a neurophysiological explanation for *lag effects* in eye movements, which are characterized by increased fixation durations when the previous word was of low frequency (e.g., Kliegl et al., 2006). Considering that the N400 emerges at a latency (e.g., from 300 to 500 ms) when the eyes during normal reading have already proceeded to the next word, the temporal overlap of the two measures suggests that word processing is not over at the end of a fixation. Instead, ongoing neural activity, as indicated by enhanced N400 amplitudes to more difficult words, may interfere with processing on subsequent fixations.

In summary, relations between fixation durations and N400 amplitudes pointed to common underlying word recognition processes that are mediated by both bottom-up and top-down influences. Further, evidence for ongoing processing beyond the duration of a fixation provides a critical finding for the understanding of oculomotor control in the timeline of word recognition.

1.4.3 The interplay of word frequency, predictability, and SOA in sentence reading: Evidence from event-related potentials (Chapter 4)

In Chapters 2 and 3, we investigated bottom-up and top-down influences considering ERPs and eye movements from PSC1 reading. The availability of frequency and predictability norms for each word in the PSC1 granted high statistical power. Moreover, normal variations of word characteristics ensured generalizability of the data. As a natural consequence, however, word properties in such corpora are confounded[8]. Although the analyses statistically accounted for covariations, the examination of unique contributions of frequency and predictability in highly controlled materials can provide additional insights. Moreover, since the PSC1 does not comprise very strong variations of predictability, top-down influences may have been too weak to manifest in early ERP intervals.

We therefore created a new corpus, the *Potsdam Sentence Corpus 3* (PSC3; see Appendix B), that realized an orthogonal and strong manipulation of frequency and predictability, while potentially confounding variables (e.g., word length, position, word class) were held constant across conditions. The PSC3 consists of 144 sentence units, each comprising two context sentences and one neutral sentence. The latter is identical across conditions except for target words setting up a two-by-two factorial design of frequency and predictability. Pairs of high and low frequency target words are embedded at the same positions in the neutral sentence frames. Predictability of targets is manipulated by a context sentence preceding the neutral sentence. High frequency targets are of high predictability in context 1 and of low predictability in context 2. In turn, low frequency targets are of low predictability in context 1 and of high predictability in context 2. Norms for target predictability were assessed in a cloze study performed by a total of 151 participants.

The sentences of the PSC3 were used in two ERP reading studies. Data were recorded from 32 participants in Experiment 1. In every trial, a context sentence was presented entirely on the screen. Thereafter, words of the neutral sentence were presented one at a time at monitor center. Analogous to the procedure described in Chapter 2, each word was displayed for 250 ms and was followed by a 450 ms blank screen (i.e., SOA of 700 ms). As a main result of Experiment 1, ERPs revealed an interaction of frequency and predictability from 90 to 140 ms, demonstrating the interplay of bottom-up and top-down processes at a considerably early latency.

[8]For instance, in the PSC1, predictability of open-class words significantly correlates with word frequency ($r = .41$) and position ($r = .41$), while frequency correlates with word length ($r = -.53$).

Critically, the interaction translated into a frequency effect for high, but not for low predictability words. The latter revealed an influence of frequency from 240 to 290 ms. Thus, in accordance with assumption about processing advantages for words in a supporting context (e.g., McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982), the timeline suggests rapid access for words of high predictability, whereas lexical processing appears to be delayed for unpredictable stimuli.

The procedures in Experiment 1 as well as in the PSC1 study in Chapter 2 are well in line with traditional ERP reading research. In most experiments, sentences are presented word by word with an SOA of 500 to 1000 ms. Compared to normal reading rates of four to five words per second, however, this timing is unnaturally slow. To date, it is unclear whether the timeline of word recognition is sensitive to the presentation rate of words. Yet, it is possible that the time available to process a current and to predict an upcoming word substantially affects word recognition.

To investigate the interplay of bottom-up and top-down processes under a near-normal reading speed, we recorded ERPs from another 32 subjects in Experiment 2. Compatible with fixation durations during normal reading, words of the neutral sentences were presented for 250 ms. The blank screen interval between words was set to 30 ms, corresponding to the duration of an inter-word saccade (i.e., SOA of 280 ms). Importantly, the problem of overlapping ERP components at this fast presentation rate is minimized in the PSC3 because target words are preceded and followed by stimuli that are physically identical across conditions.

ERPs in Experiment 2 yielded an interaction of frequency and predictability from 140 to 190 ms. Hence, consistent with Experiment 1 as well as with predictions of parallel models (McClelland & Rumelhart, 1981), the result revealed joint influences of bottom-up and top-down processes on early lexical levels. Notably, frequency effects within both predictability conditions pointed to lexical access for high and low predictability words in the same epoch. This finding contrasts to temporally distinct frequency effects for high and low predictability words at the slow reading rate of Experiment 1. We therefore concluded that presentation rate is a critical factor for the timeline of word recognition.

We offered an interactive activation framework incorporating bottom-up and top-down influences as well as effects of reading rate on lexical access. In accordance with recent electrophysiological findings (e.g., DeLong et al., 2005; Van Berkum et al., 2005) and assumptions of parallel models (e.g., McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982), the approach took into account the pre-activation of expected stimuli prior to their occurrence and reconciled the data patterns from Experiment 1 and 2.

Interestingly, the PSC3 experiments yielded differences to the PSC1 data (Chapter 2). First, both PSC3 studies revealed interactions of frequency and predictability within 200 ms post-stimulus, whereas the frequency effect from 140 to 200 ms in the PSC1 experiment was independent of predictability. Second, in both PSC3 experiments predictability strongly modulated N400 amplitudes, but there was no influence of frequency, neither as a main effect nor as an interaction with predictability. In contrast, ERPs from PSC1 reading yielded a strong interaction of frequency and predictability on the N400. Possible reasons for these discrepancies are discussed in Chapter 6.

In summary, two PSC3 studies provided novel findings about the interplay of word frequency, predictability, and SOA in sentence reading. First, early interactions of frequency and predictability pointed to the joint influence of bottom-up and top-down information on lexical levels. Second, reading rate affected the timeline of word recognition, a finding challenging the generalizability of data from artificial setups. In line with conclusions from Chapter 2, the data demonstrate that lexical access is not a passive accumulation of bottom-up information. Instead, interactions of top-down and bottom-up operations suggest the integration of information from multiple levels.

1.4.4 Event-related potentials reveal rapid verification of predicted visual input (Chapter 5)

Two experiments in Chapter 4 converged on the notion that top-down predictions about upcoming words are generated rapidly and affect lexical stages of word recognition. Together with evidence about anticipatory responses to expected stimuli (e.g., Altmann & Kamide, 2007; DeLong et al., 2005; Van Berkum et al., 2005), it appears likely that mental representations of predicted visual input are activated prior to stimulus onset. Given the availability of top-down information at earliest moments of sensory processing, it was proposed that pre-activated representations may be compared to incoming signals prior to object identification (Gilbert & Sigman, 2007). Such forms of hypothesis testing are implemented in several models incorporating bottom-up and top-down processes (Di Lollo et al., 2000; Grossberg, 1999; McClelland & Rumelhart, 1981; Mumford, 1992; Rao & Ballard, 1999; Rumelhart & McClelland, 1982; Ullman, 1995). Accordingly, the congruence of prediction and input facilitates stimulus processing potentially at early perceptual levels. Yet, however, temporal characteristics of such comparisons between top-down prediction and bottom-up information are unclear.

In Chapter 5, we provided evidence for rapid verification of predicted input. We scrutinized a small but highly reliable effect in data from PSC3 reading (Experiment 2 in Chapter 4; see also previous section). In this experiment, ERPs were recorded from 32 participants while words were presented at a near-normal reading rate (i.e., SOA of 280 ms). In an interval from 50 to 90 ms, ERP amplitudes to high predictability targets diverged from those to low predictability words. Importantly, the predictability effect was observed within low and high frequency categories, pointing to its robustness and to the independence from word familiarity. The absence of amplitude modulations on preceding words corroborated the view that differences were related to the experimental manipulation of target predictability. In accordance with the idea that active top-down processes impinge on early perceptual levels, we proposed, that the effect emerged from a rapid match of form-specific predictions with incoming visual patterns.

The latency of the effect is remarkable since, to the best of our knowledge, influences of word predictability in a comparably early interval have been only reported for the auditory modality (Van Berkum et al., 2005). Notably, there was no evidence for rapid verification in the first of the PSC3 studies, employing a slow SOA of 700 ms. We suggested that the near-normal reading rate approximated optimal temporal conditions for word recognition and encouraged rapid integration of both top-down and bottom-up information (cf., Gilbert & Sigman, 2007; Lavie, 1995; Lavie & Tsal, 1994; Luck, Woodman, & Vogel, 2000).

In summary, the results suggest that, under near-normal reading speed, strong predictions are compared with visual input very early in the time course. In accordance with evidence about pre-activation of expected word forms, the finding points to the rapid availability of stimulus-specific top-down information. Moreover, the interaction with bottom-up input at earliest perceptual levels suggests high efficiency of stimulus encoding.

2 Frequency and predictability effects on event-related potentials during reading

Michael Dambacher[1,2], Reinhold Kliegl[1], Markus Hofmann[2], and Arthur M. Jacobs[2]

[1] Universität Potsdam, Germany
[2] Freie Universität Berlin, Germany

Running Head: Frequency and predictability in ERPs

---

published 2006 in *Brain Research, 1084*, 89-103.

Abstract

Effects of frequency, predictability, and position of words on event-related potentials were assessed during word-by-word sentence reading in 48 subjects in an early and in a late time window corresponding to P200 and N400. Repeated-measures multiple regression analyses revealed a P200 effect in the high frequency range; also the P200 was larger on words at the beginning and end of sentences than on words in the middle of sentences (i.e., a quadratic effect of word position). Predictability strongly affected the N400 component; the effect was stronger for low than for high frequency words. The P200 frequency effect indicates that high frequency words are lexically accessed very fast, independent of context information. Effects on the N400 suggest that predictability strongly moderates the late access especially of low frequency words. Thus, contextual facilitation on the N400 appears to reflect both lexical and post-lexical stages of word recognition, questioning a strict classification into lexical and post-lexical processes.

2.1 Introduction

The frequency of words and their predictability in the context of a given sentence are two of the strongest determinants influencing reading. Despite much research, the role of word frequency as an indicator of ease of lexical access and of word predictability as an indicator of ease of semantic processing or of post-lexical integration, as well as the interaction of these two variables are not yet well understood. Here we report timelines of these effects as revealed in early (P200) and late (N400) event-related potentials (ERPs) which were measured on open-class words in a sentence-reading experiment.

Word frequency (i.e., the printed frequency of a word in a text corpus) is well known to affect the speed of word identification. Readers take longer to recognize low than high frequency words (e.g., Forster & Chambers, 1973; Rubenstein et al., 1970). Eye movement research corroborated this finding, revealing longer fixations on low than on high frequency words (e.g., Inhoff & Rayner, 1986; Kliegl et al., 2004, 2006; Rayner & Duffy, 1986; Schilling et al., 1998).

Also, word predictability or cloze probability (i.e., the proportion of subjects that fill in a particular word as the most probable next word in a sentence) influences word recognition. Reaction times (e.g., Fischler & Bloom, 1979; Kleiman, 1980) as well as fixation or gaze durations during natural reading (e.g., Kliegl et al., 2004, 2006; Rayner & Well, 1996; Rayner et al., 2001) are shorter for high than for low predictability words.

Despite an agreement on independent contributions of frequency and predictability to word recognition, there are conflicting theoretical perspectives on the exact time course and interaction of the two variables. In general, lexical access (i.e., the moment, when an orthographic word form uniquely activates the corresponding representation in the mental lexicon and therefore is identified) is assumed to be fast and automatic, whereas post-lexical integration is presumably a much slower process. Word frequency has served as one of the prime indicators of difficulty in lexical access (e.g., Hudson & Bergman, 1985; Monsell, Doyle, & Haggard, 1989) and is one of the key factors constraining models of word recognition (Grainger & Jacobs, 1996; Jacobs & Grainger, 1994). In contrast, there is some controversy about whether predictability affects word recognition at an early stage, at the moment of lexical access, or whether it only influences post-lexical levels, like semantic integration. These perspectives are reflected in different implementations of lexical and contextual information in models of language comprehension:

In modular approaches (e.g., Fodor, 1983; Forster, 1979), functionally independent lexical subsystems are assumed to activate word representations by bottom-up processing, whereas context merely affects post-lexical integration processes. Consequently, these approaches do not predict interactions between frequency and context. In contrast, interactive activation models (e.g., McClelland, 1987; Morton, 1969) allow interactions between these two variables: Both frequency and context may affect early stages in word recognition.

Experimental evidence relating to this theoretical distinction has not been consistent. Context was shown to facilitate recognition of low frequency words stronger than recognition of high frequency words (e.g., Becker, 1979) but purely additive effects have been reported as well (e.g., Schuberth, Spoehr, & Lane, 1981). In eye movement measures, frequency and predictability generally did not interact reliably although there were some deviations from additivity (for review see Rayner et al., 2004). In summary, while there is strong evidence for the relevance of frequency and predictability on language comprehension it has not been resolved whether they link specifically to temporally distinct processes of lexical access and post-lexical integration.

2.1.1 Frequency and predictability in ERPs

ERPs can be used to delineate the time course of word recognition because they provide an online measure of neural activity with a high temporal resolution (Kutas & Van Petten, 1994). The first occurrence of a frequency effect in ERPs serves as an upper time limit for lexical access (Hauk & Pulvermüller, 2004). ERP differences after this point are often interpreted as post-lexical. Several researchers reported frequency effects in the time range of approximately 400 ms after stimulus onset (N400, see below; e.g., Rugg, 1990; Van Petten & Kutas, 1990). However, the eyes of a skilled reader usually rest for less than 250 ms on a word before they move on to the next word; therefore, some part of lexical access is likely to occur during this typical fixation duration (Sereno et al., 1998). Indeed, Sereno et al. obtained a word frequency effect as early as 132 ms post-stimulus in an ERP study. Similarly, results of a single-case MEG study revealed a frequency effect for short words in a window from 120 to 160 ms and for all word lengths between 240 and 290 ms (Assadollahi & Pulvermüller, 2001). Hauk and Pulvermüller (2004) reported smaller amplitudes for high frequency than for low frequency words in an epoch from 150 to 190 ms. In summary, lexical access as indicated by word frequency effects appears to occur within the first 200 ms after stimulus presentation, but there is also evidence for temporally later influence of word frequency.

Context effects in ERPs were predominantly found on the N400 component, a negative deflection occurring in a time range between 200 and 500 ms after stimulus presentation. It is largest over centro-parietal sites, although it can be observed across the whole scalp (Coulson & Federmeier, in press; for reviews see Kutas & Federmeier, 2000; Kutas & Van Petten, 1994). The N400 was described first by (Kutas & Hillyard, 1980). They presented sentences with final words that were semantically congruent or incongruent with the preceding context. Semantically incongruent words elicited a large N400. The sensitivity of the N400, however, is not constrained to anomalous words within a context; its amplitude correlates negatively with predictability (Kutas & Hillyard, 1984; Kutas & Van Petten, 1994). Moreover, Kutas and Hillyard (1983) reported N400s for positions other than final ones with larger amplitudes for earlier than later word positions.

Sereno et al. (2003) investigated effects of word frequency and context effects on an early ERP component. Ambiguous words with a low and a high frequency meaning were used as final words in sentences. The context of the preceding sentence fragment was either neutral or biased the low frequency meaning. The neutral context should activate the dominant high frequency meaning of the final word. In contrast, the subordinate low frequency meaning should only play a role in the biasing context. In a time window from 132 to 192 ms post-stimulus, ambiguous words in a biasing context elicited amplitudes similar to those of low frequency words, whereas in a neutral context amplitudes resembled those of high frequency words. Thus, a biasing context selectively activated the subordinate meaning of an ambiguous word and marginally facilitated low frequency but not high frequency words. The authors concluded that this pattern of results provides evidence for an early influence of context on lexical stages in word recognition.

The relation between word frequency and context was also addressed by Van Petten and Kutas (1990; see also Van Petten & Kutas, 1991; Van Petten, 1993). They categorized open-class words (nouns, verbs, adjectives, and "ly" adverbs) according to their frequency. Cloze-probability values were available for the terminal words in each sentence. For the remaining words the position in a sentence was taken as a proxy of contextual support. The authors reported three main results on the N400. First, amplitudes were larger for low frequency than for high frequency words. Second, N400 amplitudes decreased with increasing position, presumably reflecting the build-up of context "online". Third, low frequency words elicited a larger N400 than high frequency words only if they occurred early in the sentence, not at later positions. The authors considered this finding as "evidence that frequency does not play a mandatory role in word recognition, but can be superseded by the contextual constraint provided by a sentence" (Van Petten & Kutas, 1990, p. 380). Premise for this argument is that the N400 reflects lexical processes. However, there is disagreement concerning the temporal nature of N400 effects: Some experimental results indicated that the amplitude is modulated by lexical processes (e.g., Besson, Boaz, Fischler, & Raney, 1992; Deacon et al., 2000); other studies argued that the N400 is sensitive to post-lexical integration (e.g., Brown & Hagoort, 1993; Holcomb, 1993).

In summary, the question of timelines associated with lexical access and post-lexical integration during reading still requires further investigation. Frequency plays an important role in lexical access, but apparently also modulates temporally later ERP components like the N400. Predictability (or, alternatively, position of word in sentence) correlates with the N400 amplitude, but also with word recognition processes on early components. Interactions of these variables have also been described early and late in the ERP time course. However, these effects have been assembled across several experiments. To our knowledge, there is no study yet which examined lexical access and post-lexical integration during reading with independent measures of frequency, predictability, and word position in early and late ERP components.

2.1.2 Present study

In the present study, a corpus of 144 sentences (1138 words) was used as stimulus set. Values for frequency and predictability were available for all corpus words, along with other independent variables such as word length and ordinal position of the word in the sentence. To our knowledge, there exist only two sets of sentences with predictability norms for all words (i.e., Kliegl et al., 2004; Schilling et al., 1998, augmented by Reichle, Pollatsek, Fisher, & Rayner, 1998).

We tested effects of word frequency, predictability, and position in sentence, as well as the interactions between these variables, in early and late stages of word recognition using single-trial EEG amplitudes as dependent variables. This design allows us to go beyond previous research in at least two respects. First, we assume that predictability is a more direct measure of the contribution of sentence context than word position. Therefore, we hypothesized that, irrespective of the position of the word in the sentence, frequency and predictability would interact on the N400 as previously was shown for frequency and position. Second, we expected that the decrease of N400 amplitudes across word position would be attributable to the build-up of contextual information as proposed by Van Petten and Kutas (1990, 1991). If predictability completely accounts for context-related variance in ERPs, there should be no unique variance associated with word position after statistical control for the effects of predictability. In other words, predictability should absorb all N400 effects associated with word position, but not vice versa.

We examined the data using repeated-measures multiple regression analyses (rmMRAs; Lorch & Myers, 1990, method 3; see Kliegl et al., 2006, for a recent application to the analyses of eye movements in reading) in an early (P200) and a late (N400) time window. Mean EEG amplitudes were computed within these time windows (collapsed across sampling points and selected electrodes for the components) for each word within each subject. These single-trial EEG amplitudes served as criterion in the rmMRAs. An advantage of this procedure is that rmMRAs statistically control for differences between participants. Then, after between-subject variance has been removed, effects of variables such as frequency, predictability, and word position as well as their interactions can be estimated within one single model statistically controlling for correlations between the predictors. Since predictors need not be divided into discrete categories but can be submitted to the models as continuous values, the whole variability of word properties mapping on the dependent variable is used. Using EEG amplitudes on a single-trial level instead of values collapsed across many items provides information of electrophysiological correlates as a function of different properties of single words. Furthermore, the large amount of data points yields high statistical power. However, waiving data averaging results in a loss of noise reduction. Thus, necessarily the variance accounted for by rmMRA models on single-trial EEG amplitudes is very small.

We limited our analyses to open-class words, i.e., nouns, verbs, adjectives, and most of the adverbs. Closed-class words, like auxiliary verbs, pronouns, conjunctions, and determiners, were excluded. This restriction was motivated by findings suggesting that words of different classes are processed by distinct neural systems, because open-class and closed-class words evoke different ERP components. For instance, an N280 component was elicited only by closed-class words, whereas open-class words evoked an N400 (Neville, Mills, & Lawson, 1992). However, this issue is discussed controversially. Results of other studies revealed that differences between word classes do not reflect qualitatively separate processing mechanisms, but rather are a function of word frequency or of frequency and length (e.g., King & Kutas, 1998; Münte et al., 2001; Osterhout, Bersick, & McKinnon, 1997).

Another restriction was the exclusion of sentence-final words. Previous studies revealed that ERPs for sentence-final words differ from those of words occurring earlier in a sentence. They often appear to evoke more positive-going ERPs than sentence-intermediate words (e.g., Friedman, Simson, Ritter, & Rapin, 1975; Osterhout & Holcomb, 1995; Osterhout, 1997; see also Kutas, Van Petten, & Besson, 1988; Van Petten, 1993). This effect can most probably be attributed to sentence wrap-up, decision, and/or response and reduces the comparability of ERPs of sentence-intermediate and sentence-final words (Hagoort, 2003; Osterhout & Nicol, 1999).

2.2 Methods

2.2.1 Participants

Fifty students (19 to 35 years; 19 males) of the Catholic University of Eichstätt-Ingolstadt were paid for their participation. All were native German speakers and had normal or corrected-to-normal vision. Forty-three subjects were right-handed.

2.2.2 Stimuli

The Potsdam Sentence Corpus 1 (PSC1; see Appendix A) comprises 144 German sentences (1138 words) with a large variety of grammatical structures. The mean sentence length is 7.9 words with a range from 5 to 11 words. Words were divided into three categories with respect to the variables frequency and predictability. These categories were used for repeated-measures analyses of variance (rmANOVAs) and for the visualization of effects; repeated-measures multiple regression analyses (rmMRAs) were based on the continuous values of these predictors.

Word frequencies of the corpus words are based on DWDS norms (Das Digitale Wörterbuch der deutschen Sprache des 20. Jahrhunderts), which are computed on a total of 100 million words (http://www.dwds.de, 2006; Geyken, 2007; Kliegl, Geyken, Hanneforth, & Würzner, manuscript in preparation). Each of three logarithmic frequency classes contains at least 254 words [class 1 (log frequency: 0 to 1): 254 words, $mean$: .46, SD : .29; class 2 (log frequency: 1 to 2.5): 406 words, $mean$: 1.82, SD : .42; class 3 (log frequency: 2.5 to max.): 478 words, $mean$: 3.57, SD : .55].

Predictability of words was collected in an independent norming study from 282 native speakers of German ranging in age from 17 to 80 years. Participants guessed the first word of the unknown sentence and entered it via the keyboard. In return, the computer presented the first word of the original sentence. Thereafter, subjects entered their guess for the second word followed by presentation of the second word of the original sentence. This procedure continued until a period indicated the end of a sentence. Correct words stayed on the screen. The order of sentences was randomized. Twenty subjects generated predictions for all of the 144 sentences. The other participants worked through a quarter of the corpus. Collapsing the complete and partial protocols across participants yielded 83 complete protocols. The obtained predictability values were logit-transformed [$logit = .5 * ln(pred/(1 - pred))$]. Predictabilities of zero were replaced with $1/(2 * 83)$ and those of perfectly predicted words with $(2 * 83 - 1)/(2 * 83)$, where 83 represents the number of complete predictability protocols (J. Cohen & Cohen, 1975). That means that for a word with predictability .5 the odds of guessing are $.5/.5 = 1$, and consequently the log odds of guessing are $ln(1) = 0$. Thus, words with predictabilities larger than .5 yield positive logits, and predictabilities smaller than .5 negative logits. The logit transformation corrects for the dependency of mean probabilities (p) and associated standard deviations (SD) [i.e., $SD = p(1 - p)$] by stretching the tail of the distribution (see also Kliegl et al., 2004). The corpus contains at least 254 words in each of three logit-based predictability classes [class 1 (-2.553 to -2.0): 464 words, $mean : -2.47$, $SD : .14$; class 2 (-2.0 to -1.0): 254 words, $mean : -1.46$, $SD : .29$; class 3 (-1.0 to 2.553): 420 words, $mean : -.04$, $SD : .77$].

2.2.3 Procedure

Subjects were seated at a distance of 60 cm from the monitor and were instructed to read the sentences for comprehension. After ten practice trials, the 144 sentences were presented word by word (Font: Courier New, Size: 12) in randomized order. The first word of each sentence was preceded by a fixation cross presented for 500 ms in the middle of the monitor and followed by a blank screen for another 500 ms. Stimuli together with the adjacent punctuation were displayed for 250 ms in black on a white screen in the center of the monitor. The stimulus onset asynchrony (SOA) was 700 ms. A multiple-choice question was presented after 27% of the sentences; subjects pressed one of three buttons to indicate their answer. After the remaining sentences an array of asterisks appeared for 2000 ms (preceded and followed by a 1000 ms blank screen) in the center of the screen. During the presentation of a question or asterisks subjects were allowed to blink. They took a break of 10 minutes after the first half of the experiment. Sessions lasted about 1.5 hours.

2.2.4 Electrophysiological recording

An electrode cap (ElectroCap International) was used to record EEG data on 26 scalp locations (FP1, FP2, AFZ, FZ, F3, F4, F7, F8, FC3, FC4, FC5, FC6, CZ, C3, C4, T7, T8, CP5, CP6, PZ, P3, P4, P7, P8, O1, O2) corresponding to the revised 10/20 International System. All scalp electrodes and one electrode on the right mastoid were originally referenced to one electrode on the left mastoid. Data were converted offline to average reference. In addition, two horizontal (situated at the outer left and outer right canthus) and two vertical EOG electrodes (above and below the right eye) recorded bipolarly eye movements and blinks. Impedances of scalp electrodes were kept below $5k\Omega$. Data were recorded continuously with a sampling rate of 256 Hz. The recordings were high- and low-pass filtered by amplifier adjustment of .1 and 100 Hz, respectively.

2.2.5 Analyses

EEG data contaminated by artifacts were rejected offline via an automatic algorithm and visual inspection. Data of two subjects had to be completely removed, one because of loss of data due to technical problems and one because of a former neurological disease. From the remaining 48 subjects a total of 11.43% of trials was eliminated. The continuous EEG recording was divided into 800 ms epochs beginning 100 ms before stimulus onset. Data were analyzed relative to a baseline of 100 ms preceding each stimulus.

In order to reduce effects due to the large variability of sentence lengths those with less than 7 and more than 9 words were excluded. Only open-class words were included in the analyses; closed-class words were eliminated. Additionally, sentence-final words were removed from the data set. This left us with a total of 105 sentences comprising 497 open-class words for statistical analyses. Number of words, mean values, and standard deviations of three categories of frequency and predictability are listed in Table 2.1.

Correlations between frequency and predictability ($r = .41$), predictability and word position ($r = .41$), and frequency and position ($r = .12$) were significant ($p \leq .01$). Descriptive statistics for the distribution of words across the positions in sentences are presented in Table 2.2.

Table 2.1: Number of words, mean values, and standard deviations (SD) in three categories of logarithmic frequency and logit-transformed predictability for open-class words in sentences containing seven to nine words in the Potsdam Sentence Corpus 1. Sentence-final words are excluded.

	Frequency			Predictability		
Class	No. of Words	Mean	SD	No. of Words	Mean	SD
1	153	.47	.29	278	−2.49	.13
2	218	1.82	.42	108	−1.50	.27
3	126	3.36	.48	111	−.24	.58

Two time windows were chosen for analyses. The selection of the first window was based on the hypothesis that an early frequency effect would occur well within the first 200 ms after the presentation of a stimulus. Visual inspection of the data in an epoch between 100 and 200 ms post-stimulus revealed differences between frequency classes on a fronto-central positivity peaking at 170 ms[1]. This component was identified as P200. We defined the first time window in an interval between 140 to 200 ms (peak amplitude at 170 ms $\pm$ 30 ms) on fronto-central electrodes (AFZ, FZ, F3, F4, FC3, FC4, FC5, FC6, CZ, C3, C4). The second epoch ranged from 300 to 500 ms over centro-occipital electrodes (CZ, C3, C4, CP5, CP6, PZ, P3, P4, P7, P8, O1, O2), a time window often used in N400 research.

Effects of frequency, predictability, and position on P200 and N400 amplitudes were analyzed in rmANOVAs. According to the classification in Table 2.1, words were divided into three categories of frequency and three categories of predictability. Also, three classes of word position were generated (positions 1-2: $N = 128$; positions 3-5: $N = 234$; positions 6-8: $N = 135$). On the basis of these categories, ERP single-averages were computed for each subject and were submitted to two separate 3 x 3 rmANOVAs for each of the components: One with frequency (1, 2, 3) and predictability (1, 2, 3), and one with frequency (1, 2, 3) and position (1-2, 3-5, 6-8)

[1]We also tested for amplitude differences in the epoch from 100 to 140 ms post-stimulus, however effects in this time window appeared to be unstable.

Table 2.2: Number of words, mean values, and standard deviations (SD) of logarithmic frequency and logit-transformed predictability for open-class words on eight word positions in the Potsdam Sentence Corpus 1.

Word	Number	Frequency		Predictability	
Position	of Words	Mean	SD	Mean	SD
1	38	1.58	.90	−2.42	.30
2	90	1.54	.98	−2.29	.59
3	90	1.76	1.18	−1.95	.79
4	72	1.97	1.28	−1.74	.89
5	72	1.73	1.11	−1.54	1.08
6	76	2.08	1.32	−1.24	1.08
7	37	1.76	1.12	−1.41	1.07
8	22	2.02	.94	−1.06	1.02

as within-subject factors. The high correlation between predictability and position did not permit an ANOVA including both factors at the same time (i.e., the lack of high predictability words on early positions would have caused empty cells). Where appropriate, the Huynh-Feldt correction for the violation of sphericity (Huynh & Feldt, 1976) was used to adjust degrees of freedom.

The results of the rmANOVAs for each of the components were scrutinized in separate rmMRAs (Lorch & Myers, 1990, method 3). In these analyses the influence of frequency, predictability, and position together with their interactions could be tested within one model. Mean single-trial EEG amplitudes, collapsed across the selected electrodes of the P200 and the N400 as well as across the sampling points corresponding to each of the time intervals of the two components, were computed for each open-class word within each subject. This resulted in a total of 21,176 amplitude values per epoch serving as dependent variables. The rmMRAs were used to examine P200 and N400 effects of the following six predictors: Frequency, frequency x frequency, predictability, position, predictability x frequency, and position x frequency. Additionally, position x position was included in the rmMRA on P200 amplitudes since visual inspection suggested a quadratic trend. All analyses are based on continuous predictor values instead of the categories utilized in the rmANOVAs. The redundancy of the predictors was checked by removing one predictor at a time and by computing the decrease of explained variance for the reduced model.

2.2.6 Plots

Figures 2.1 and 2.2 present grand average plots for three frequency and predictability classes corresponding to the categories defined in Table 2.1, respectively. The grand averages were computed for open-class words collapsed across all word positions except for final ones in sentences comprising 7 to 9 words.

The effects of the predictors on ERP amplitudes in rmMRAs for open-class words are visualized in Figures 2.3 and 2.4. For purposes of illustration, the predictor frequency (panels 1) was divided into six quantiles, each containing roughly the same number of data points ($N \geq 3506$). The same procedure was applied to predictability (panels 2): Six quantiles were computed, but since the proportion of words not predictable at all was very high, the lowest quantile contained more data ($N = 9405$) than the rest of the quantiles ($N \geq 1859$). Consequently, the second quantile did not capture any data at all. Thus, only five points are plotted for predictability. No quantiles were computed for word position (panels 3), since each word was uniquely attributable to one value. For the purpose of noise reduction, the number of bins was reduced in the interaction plots (panels 4 and 5): Frequency and predictability were categorized according to three classes defined in Table 2.1; word position (panels 5) was divided into three classes (positions 1-2, 3-5, and 6-8).

Open symbols in each panel of Figures 2.3 and 2.4 reflect the mean of empirical single-trial EEG amplitudes collapsed across the selected electrodes and across sampling points for each time window, across words of corresponding categories, and across subjects. Errorbars reflect the 99% within-subject confidence intervals (Loftus & Masson, 1994).

2.3 Results

Grand average plots for open-class words are presented in Figures 2.1 and 2.2 illustrating the effects for three frequency classes and three predictability classes, respectively. A small negativity, peaking at 100 ms, was followed by a large positive deflection reaching its maximum amplitude 170 ms after stimulus onset (P200). At this latency, differences in ERPs for word frequency are visible on fronto-central electrodes predominantly on the left hemisphere. After about 260 ms a negative deflection occurred mainly over centro-occipital electrode sites peaking at a latency of approximately 400 ms (N400). During this epoch, grand average curves of predictability classes are gradually arranged with larger amplitudes for words of low than of high predictability classes.

2.3.1 P200

Effects of frequency, predictability, and position on P200 amplitudes were examined in two separate 3 x 3 repeated-measures analyses of variance (rmANOVAs). The first rmANOVA with frequency and predictability as within-subject factors revealed significant results for frequency [$F(2,94) = 6.52$, $p < .01$, $\eta_p^2 = .12$] and predictability [$F(1,92) = 4.33$, $p = .02$, $\eta_p^2 = .08$]. The interaction between predictability and frequency was not reliable [$F(3,177) = .63$, $p = .63$, $\eta_p^2 = .01$].

The second rmANOVA comprised frequency and position as factors. Again, the main effects were significant [Frequency: $F(1,79) = 11.79$, $p < .01$, $\eta_p^2 = .20$; Position: $F(1,75) = 13.03$, $p < .01$, $\eta_p^2 = .22$], whereas the interaction was not [Frequency x Position: $F(3,166) = .94$, $p = .43$, $\eta_p^2 = .02$].

The effects of frequency, predictability, and position were scrutinized within a single rmMRA model. The regression coefficients of the rmMRA for open-class words on the P200 are listed in Table 2.3. They are the mean of the unstandardized regression coefficients calculated separately for each subject (Lorch & Myers, 1990, method 3, individual regression equations). Moreover, Ta-

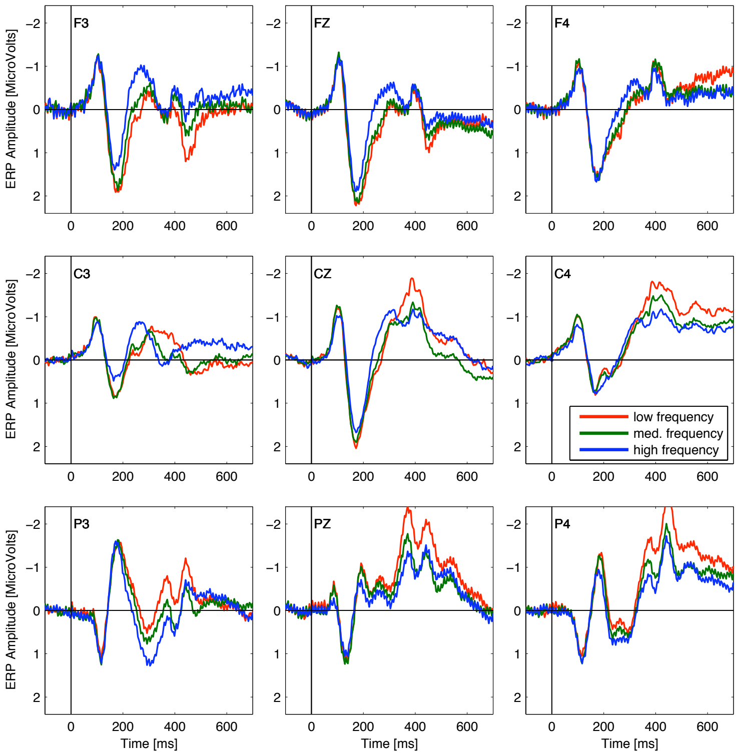


Figure 2.1: Frequency grand averages. Grand average plots of effects of three frequency classes for open-class words in sentences comprising seven to nine words; sentence final words are exluded. The three classes are based on categories of Table 2.1. Amplitude differences are visible on the P200 predominantly over fronto-central electrodes on the left hemisphere.

ble 2.3 lists standard errors of regression coefficients, the drop of R^2 for removing the predictor from the complete model, as well as probabilities of significance tests for the regression coefficients and the R^2 decrement.

The effects of predictors are visualized in Figure 2.3. Open symbols reflect the mean of empirical ERP amplitudes in the time range

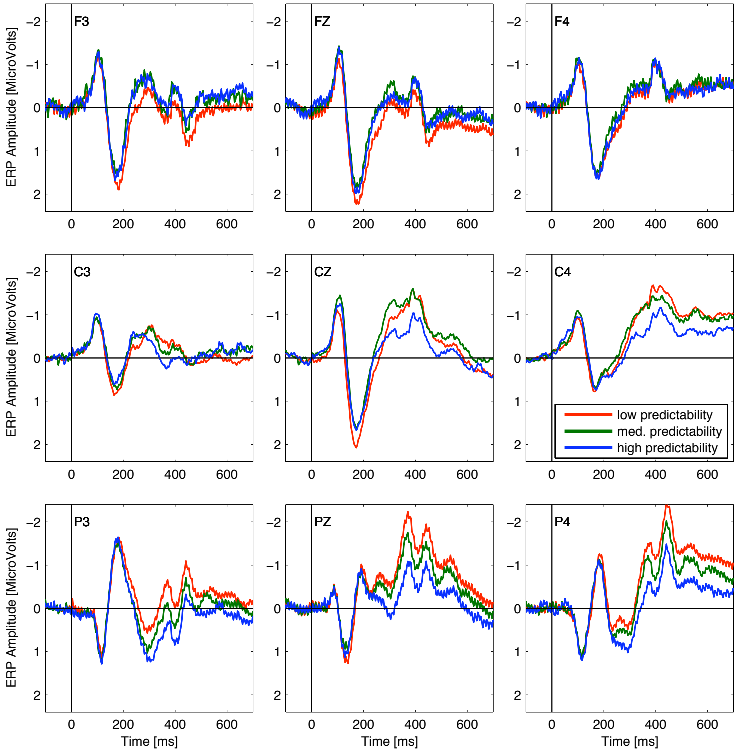


Figure 2.2: Predictability grand averages. Grand average plots of effects of three predictability classes for open-class words in sentences comprising seven to nine words; sentence final words are exluded. The three classes are based on categories of Table 2.1. Amplitudes are graded on the N400 over centro-occipital electrodes.

from 140 to 200 ms post-stimulus. Bins in the plots for frequency and predictability (panels 1 and 2) were computed on the basis of predictor quantiles ensuring a similar number of data points for each category. Categories for frequency and predictability in the interaction plots (panels 4 and 5) correspond to classes in Table 2.1. Error bars reflect 99%-within-subject confidence intervals (Loftus & Masson, 1994). Raw correlations between predictor and the crite-

Table 2.3: Mean and standard errors (SE) of regression coefficients of the rmMRA for ERP amplitudes of open-class words in the time window 140 - 200 ms at fronto-central electrode sites.

P200 (7 predictors)	Mean	SE	t	p_t	$-\Delta R^2$	$p_{-\Delta R^2}$
Constant	1.134	.128	8.83	<.01		
Frequency	.074	.090	.82	.21	<.0001	.46
Frequency^2	−.030	.015	−1.96	.03	.0002	.05
Predictability	.004	.051	.09	.47	<.0001	.92
Position	−.293	.058	−5.08	<.01	.0018	<.01
Position^2	.029	.006	4.74	<.01	.0014	<.01
Pred. x Freq.	.003	.021	.16	.44	<.0001	.84
Position x Freq.	−.007	.009	−.84	.20	<.0001	.47
[$R^2_{Predictors} = .005$; $R^2_{Subjects} = .110$; $R^2_{Model} = .115$]						

Note. Means, SE, t-values, and associated p-values for predictors. $-\Delta R^2$ is the drop of variance of the full model due to removal of the predictor; $p_{-\Delta R^2}$ gives p-values for the significance of the variance decrement. $R^2_{Predictors}$, $R^2_{Subjects}$, and R^2_{Model} show variance accounted for by predictors alone, by subjects alone, and by the full model, respectively. Statistics are based on 48 subjects, i.e. 47 degrees of freedom for t-statistics.

rion are given in parentheses as supplementary information along with the description of the results.

P200 amplitudes were smaller for high than for low frequency words (panel 1). The quadratic frequency term ($r = -.045$) was significant, whereas the linear ($r = -.040$) was not. Amplitude differences were larger among three high frequency bins than among those of low frequency words. That means the size of the frequency effect increased with augmenting frequency. Consequently, the quadratic trend accounted for a larger amount of unique variance than the linear trend.

The predictors accounting for most of the unique variance in P200 amplitudes were linear and quadratic terms of word position ($r = -.044$ and $r = -.034$, respectively). Amplitudes decreased during early positions in a sentence, reached a minimum around the middle position (5th word), and started to increase again towards the end of the sentence (panel 3). This is an unexpected and, as far as we know, novel result.

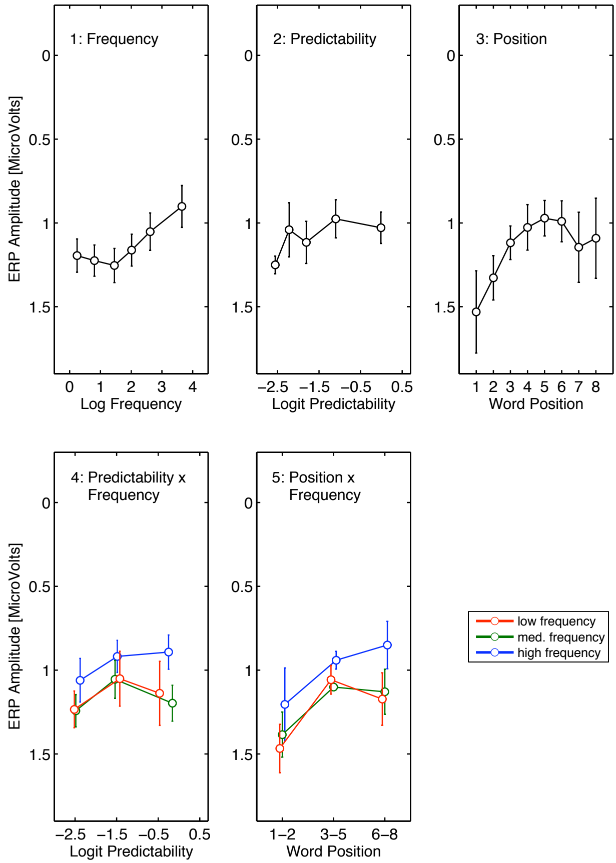


Figure 2.3: rmMRA on P200 amplitudes. Illustrations of the predictor effects of the rmMRA in the interval from 140 to 200 ms over fronto-central electrodes. Bins of frequency and predictability in panels 1 and 2 are based on quantiles of the predictors. Categories of frequency and predictability in panels 4 and 5 reflect predictor classes of Table 2.1. Open symbols show empirical mean amplitude values. Error bars represent 99% within-subject confidence intervals.

Neither predictability (panel 2; $r = -.029$), nor the interaction of predictability and frequency (panel 4; $r = .007$), nor the interaction of position and frequency (panel 5; $r = -.053$) were significant in the rmMRA model for the P200.

2.3.2 N400

Like on the P200, two rmANOVAs were carried out to examine effects on N400 amplitudes. In the first rmANOVA with frequency and predictability as within-subject factors, predictability [$F(1, 89) = 24.21$, $p < .01$, $\eta_p^2 = .34$] and the interaction between predictability and frequency [$F(2, 125) = 2.94$, $p = .04$, $\eta_p^2 = .06$] were reliable. Frequency was marginally significant [$F(1, 71) = 3.39$, $p = .05$, $\eta_p^2 = .07$]. The second rmANOVA with the factors frequency and position revealed significant effects for frequency [$F(1, 68) = 24.86$, $p < .01$, $\eta_p^2 = .35$] and the interaction between position and frequency [$F(3, 168) = 2.60$, $p = .04$, $\eta_p^2 = .05$]. Word position yielded a trend [$F(1, 78) = 2.89$, $p = .07$, $\eta_p^2 = .06$]. The effects in the rmANOVAs on the N400 were scrutinized in rmMRAs. The results are listed in Table 2.4 showing unstandardized regression coefficients, along with associated standard errors, the drop of R^2 for removing the predictor from the model, and probabilities of significance tests for the regression coefficients and the R^2 decrement. Figure 2.4 presents a visualization of the effects; error bars reflect 99%-within-subject confidence intervals (Loftus & Masson, 1994).

In the first rmMRA [Tab. 2.4; *1: N400 (6 predictors)*], the strongest predictor for the N400 was predictability ($r = .077$). Panel 2 shows that amplitudes decreased substantially with increasing predictability. The interaction of predictability and frequency ($r = -.006$) was also reliable. Panel 4 reveals a larger predictability effect for words of low than of high frequency. The interaction of position and frequency (panel 5; $r = .057$) was not significant in the rmMRA. However, the pattern of means corresponded to previous reports: The frequency effect was strong at early positions and became weaker across the sentence. Neither the linear ($r = .066$) nor the quadratic terms ($r = .056$) of frequency (panel 1), nor word position (panel 3; $r = .027$) reached significance.

To test whether the interaction of predictability and frequency absorbed variance of other predictors, we carried out a second rmMRA without this interaction term. The results of this five-

Table 2.4: Mean and standard errors (SE) of regression coefficients of the rmMRA for ERP amplitudes of open-class words in the time window 300 - 500 ms at centro-occipital electrode sites.

1: N400 (6 predictors)	Mean	SE	t	p_t	$-\Delta R^2$	$p_{-\Delta R^2}$
Constant	−.283	.122	−2.31	.01		
Frequency	.093	.131	.70	.24	<.0001	.39
Frequency^2	−.022	.018	−1.26	.10	.0001	.20
Predictability	.396	.068	5.84	<.01	.0019	<.01
Position	.011	.027	.40	.34	<.0001	.76
Pred. x Freq.	−.090	.028	−3.22	<.01	.0005	<.01
Position x Freq.	−.010	.012	−.77	.22	<.0001	.37
[$R^2_{Predictors} = .009$; $R^2_{Subjects} = .065$; $R^2_{Model} = .073$]						

2: N400 (5 predictors)	Mean	SE	t	p_t	$-\Delta R^2$	$p_{-\Delta R^2}$
Constant	−.283	.122	−2.31	.01		
Frequency	.439	.097	4.54	<.01	.0015	<.01
Frequency^2	−.057	.017	−3.44	<.01	.0006	<.01
Predictability	.203	.036	5.56	<.01	.0026	<.01
Position	.042	.028	1.47	.07	.0001	.10
Position x Freq.	−.022	.012	−1.84	.03	.0002	.03
[$R^2_{Predictors} = .008$; $R^2_{Subjects} = .065$; $R^2_{Model} = .073$]						

Note. Means, SE, t-values, and associated p-values for predictors. $-\Delta R^2$ is the drop of variance of the full model due to removal of the predictor; $p_{-\Delta R^2}$ gives p-values for the significance of the variance decrement. $R^2_{Predictors}$, $R^2_{Subjects}$, and R^2_{Model} show variance accounted for by predictors alone, by subjects alone, and by the full model, respectively. Statistics are based on 48 subjects, i.e. 47 degrees of freedom for t-statistics.

predictor model are listed in Table 2.4 [*2: N400 (5 predictors)*]. In this model, predictability still accounted for the largest amount of variance and was highly reliable.

Different from the first rmMRA, linear and the quadratic frequency terms, as well as the interaction of position and frequency were significant. This indicates that variance related to frequency and word position was absorbed by the interaction of predictability and frequency in the rmMRA with six predictors. The visualization of the frequency effect on the N400 (Figure 2.4, panel 1) reveals

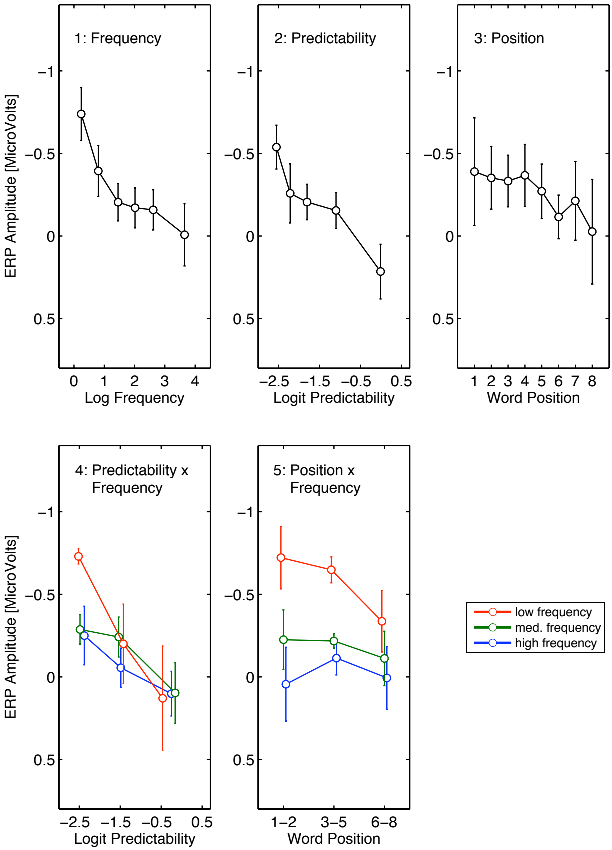


Figure 2.4: rmMRA on N400 amplitudes. Illustrations of the predictor effects of the rmMRA in the interval from 300 to 500 ms over centro-occipital electrodes. Bins of frequency and predictability in panels 1 and 2 are based on quantiles of the predictors. Categories of frequency and predictability in panels 4 and 5 reflect predictor classes of Table 2.1. Open symbols show empirical mean amplitude values. Error bars represent 99% within-subject confidence intervals.

a striking contrast to the one on the P200 (Figure 2.3, panel 1): Amplitude differences are now largest between the three low frequency bins. Modulations among the bins of high frequency words are much smaller. Word position was not significant in the second model.

Finally, in order to examine whether the effect of position was superseded by predictability, the latter was also excluded. We carried out an rmMRA on the four remaining predictors of linear frequency, quadratic frequency, position, and the interaction of position and frequency. In this model, the coefficient for position was significant ($t = 2.99$, $p < .01$) indicating that N400 amplitudes decreased with increasing word position (panel 3). The result provides evidence that predictability had absorbed variance of word position. Concerning significance, the other predictors did not change when compared to the rmMRA on five predictors. All coefficients revealed significant results (Frequency: $t = 5.26$, $p < .01$; Frequency^2: $t = -3.35$, $p < .01$; Position x Frequency: $t = -2.07$, $p = .02$).

2.3.3 Supplementary analyses

For a further validation of the above results, we carried out additional analyses. First, the predictor of word length was added to the rmMRA models. In previous studies, length was found to affect ERP amplitudes particularly around the P200 time window (e.g., Hauk & Pulvermüller, 2004; Van Petten & Kutas, 1990). Furthermore, frequency and length are not independent of each other but are negatively correlated ($r = -.56$). Thus, we tested whether the pattern of results would change by including both predictors at the same time. When added to the primary rmMRA models, word length was neither reliable on the P200 ($t = -.46$, $p = .32$) nor on the N400 ($t = -.29$, $p = .39$). The basic patterns of significance concerning the other predictors did not change. Additionally, we included the interaction between word length and frequency. This predictor also failed to reach significance for P200 ($t = 1.13$, $p = .13$) and N400 ($t = .28$, $p = .39$) amplitudes. However, on the P200 it absorbed variance accounted for by the quadratic term of frequency, which was no longer significant ($t = -.63$, $p = .26$).

The other predictors on the N400 did not change with respect to significance.

2.3.4 Goodness of fit

The total variance accounted for by each of the rmMRA models described above was small. For example, from the 11.5% in the model for the P200, 11.0% can be attributed to between-subjects variance whereas the predictors explained .5%. The model for the N400 accounted for a total of 7.3% of variance; 6.5% were due to differences between subjects and .9% could be traced to the influence of the predictors. At first glance this seems to be a very poor fit in all cases. Remember, however, that we predicted single-trial EEG amplitudes. As mentioned earlier, this results in substantial loss of noise reduction in the data. The power of variance reduction due to data aggregation can be seen in the values of η_p^2 in the rmANOVAs. This measure of effect-size has roughly the same dimension as in analyses on averaged data from studies using experimental designs. In contrast to that, a small R^2 in analyses on unaveraged data is the rule rather than the exception. Consequently, the amount of variance accounted for should not be unconditionally considered as an adequate measure for the evaluation of model fit, at least not for analyses on unaggregated data.

2.4 Discussion

The present ERP study addressed four issues. The first issue related to the timeline of word recognition during reading. The first appearance of a word frequency effect was considered as an upper limit for lexical access. The second issue addressed the role of context in word recognition. Unlike any previous study, we used predictability norms for each word in the sentences as an independent measure of prior sentence context. Third, with this information we could also test the interaction of predictability and frequency and study the question of whether they map onto temporally distinct stages of word recognition. Finally, we could assess the contribution of word position, independent of context effects reflected in predictability. In the following two sections we discuss results on the P200 and on the N400. Thereafter, we attempt to present an integrative account of our results.

2.4.1 P200

In both rmANOVAs in the latency range from 140 to 200 ms post-stimulus, we found a strong frequency effect over fronto-central electrodes. Amplitudes were smaller for high frequency than for low frequency words. With respect to frequency as an index for lexical access, this provides evidence that words are identified within the first 200 ms after stimulus presentation during sentence reading. This result is in line with previous studies. Early frequency effects were reported by Sereno et al. (1998) at 132 ms, by Sereno et al. (2003) between 132 and 192 ms, by Assadollahi and Pulvermüller (2001) between 120 and 170 ms, and by Hauk and Pulvermüller (2004) between 150 and 190 ms. The rmMRA on single-trial EEG amplitudes confirmed this finding. The quadratic trend of frequency illustrated in Figure 2.3 (panel 1) revealed larger amplitude differences among high frequency than among low frequency words. Thus, lexical access was presumably completed for high frequency words while low frequency words were still being processed. Results from behavioral and eye movement studies corroborate this hypothesis revealing longer reaction times (e.g., Forster & Chambers, 1973; Rubenstein et al., 1970) and fixation durations on low frequency words (e.g., Inhoff & Rayner, 1986; Kliegl et al., 2004, 2006; Rayner & Duffy, 1986; Schilling et al., 1998). In supplementary analyses we tested whether the result was caused by words of different lengths rather than by frequency. This was necessary because frequency and length are negatively correlated, i.e., on average, high frequency words are shorter than low frequency words. Previous studies also revealed effects of word length on ERP amplitudes in early time windows (e.g., Hauk

& Pulvermüller, 2004; Van Petten & Kutas, 1990). However, word length did not affect P200 amplitudes. Also the interaction between length and frequency was not reliable, but it should be noted that, as a consequence of the additional predictor, word frequency lost significance in the P200 time window. This can be attributed to the fact that both variables account for variance of the very same effect: The interaction plot of length and frequency (not illustrated in this paper) revealed that especially short words (i.e., high frequency words) show a frequency effect in the P200 time window. The quadratic frequency effect demonstrated that predominantly high frequency words (i.e., short words) are lexically accessed. Although the correlation between the variables complicates an ascription of the amplitude modulations to either length or frequency, we attribute the effect on the P200 primarily to the contribution of frequency rather than of length, because the latter predictor did not significantly account for unique variance in the rmMRAs.

Word predictability revealed a significant effect in the rmANOVA on P200 amplitudes suggesting an early influence of context information on word recognition. However, it is important to note that word position strongly modulating the P200 was not included as factor in this analysis. Since predictability and position are highly correlated ($r = .41$), it is conceivable that the effect was related to position rather than to predictability. This possibility was examined in the rmMRA where effects of predictability and position were estimated within one model. Neither word predictability nor the interaction of predictability and frequency affected P200 amplitudes in the rmMRA. The variance was absorbed by word position better accounting for this effect. Thus, on the basis of the present results we cannot conclude that predictability influenced word recognition at this latency. This is at odds with the results of Sereno et al. (2003) reporting that context affected lexical access of ambiguous words and marginally facilitated processing of low frequency words. The conflicting results can be attributed to differences between the studies. Sereno et al. experimentally manipulated the context, in which selected ambiguous words appeared. In the present study neither predictability nor sentences realized extreme conditions for context effects and, consequently, were not significant.

Surprisingly, the strongest influence on the P200 was provided by word position. The rmMRA made clear that amplitude modulations were not linear but a quadratic function of position. Words occurring early or late in sentences elicited larger amplitudes than words in middle positions. This effect was independent of word length. One might wonder whether the frequency effect on the P200 was an artifact of the influence of position. However, this is very unlikely because both position and frequency were included as predictors in the regression models at the same time. If the frequency effect was an artifact of word position, the latter would have absorbed the variance accounted for by frequency, which was not the case. Furthermore, the correlation between position and frequency is small ($r = .12$). A systematic effect of position would have caused a rather unsystematic effect of frequency.

Reasons for the decreasing P200 towards the center of a sentence and for subsequent increasing amplitudes remain unclear on the basis of the present data. There were no a priori theoretical considerations predicting a quadratic word position effect. We included the quadratic term in the rmMRA only after visual inspection of the data, so suggestions for a solution are speculative. One possibility is that increasing working memory load in the middle of a sentence caused a negative shift, tantamount to decreasing P200 amplitudes. At the beginning of a sentence, only very few words must be kept in mind; towards the end of a sentence, high predictability facilitates recognition and semantic integration of new words and contextual information eases remembering the content of the sentence. Compared to this, the effort of recognizing and integrating upcoming words while keeping the previous sentence fragment in mind might be largest in the middle of a sentence. Another possibility is that different parts of a sentence vary in importance of semantic content. In the German language, it is very likely that the words carrying the most important meaning for a fast and correct understanding occur in the middle of a sentence (e.g., a verb). Expectancy or "alertness" could have caused a long-term negative variation whenever a sentence proceeded towards its major contents. Finally, it is also possible that the position effect was specific for the stimulus material of the present study. In any case, further investigation is necessary to clarify the nature of the word position effect.

2.4.2 N400

Both the rmANOVA and the rmMRA showed a strong effect of predictability on the N400. This is in line with findings of previous experiments (e.g., Kutas & Hillyard, 1984; Kutas & Van Petten, 1994). N400 amplitudes are inversely correlated with predictability. Obviously, this measure is an appropriate predictor for modulations of N400 amplitudes. Considering that none of the sentences contained any semantic violation and that no artificially strong variation of predictability was intended during the construction of the stimulus material, this result corroborates once more the robustness of the N400 effect.

In the rmANOVA with the factors of frequency and position we found a strong main effect of frequency; N400 amplitudes decreased with augmenting frequency, which corresponds to previous reports (Rugg, 1990; Van Petten & Kutas, 1990). The size of this effect was attenuated in the rmANOVA with the factors frequency and predictability indicating that either predictability or the interaction term absorbed variance of frequency. The rmMRAs supported this hypothesis: Linear and quadratic frequency terms were strongly reliable only when the interaction of predictability and frequency was excluded from the model. Obviously, the interaction term was enough to explain frequency-related variance.

The interactions of predictability and frequency as well as of position and frequency were significant in the rmANOVAs, pointing to an interplay of frequency and context information on the N400. Given the argument that predictability and position capture similar concepts, the two interactions may account for the same effect: The frequency effect degraded as context information increased. The results of the rmMRA confirmed this view showing a strong interaction of predictability and frequency while the interaction of position and frequency was not significant. Although the interaction plot clearly reveals that the frequency effect was decreasing with increasing word position (Figure 2.4, panel 5), this pattern could be completely due to the interaction of predictability and frequency (Figure 2.4, panel 4). Thus, the joint effect of predictability and frequency is sufficient to account for the decrease of the frequency effect across words; there may be no independent contribution of word position. The finding is in line with our hypothesis that predictability as a more direct measure of context information accounts better for N400 effects than word position.

Further support is provided regarding the main effect of position. Amplitudes were smaller for words occurring late in a sentence as reported in previous studies (Van Petten & Kutas, 1990, 1991; Van Petten, 1993). While the rmANOVA showed a statistical trend, the rmMRAs made clear that the effect of word position was absorbed by predictability. The position effect was significant only when predictability as well as the interaction of predictability and frequency were removed from the rmMRA model.

The results can be compared directly with Van Petten and Kutas' (1990, 1991) reports of a word position effect and a significant interaction of position and frequency. Except for the final words, they used word position as a metric for the strength of contextual information. They proposed that the decline of N400 amplitudes and the decrease of the frequency effect across the sentence reflect the influence of contextual constraint rather than word position. Given that predictability better accounted for the N400 effects than position and therefore absorbed the variance of position and frequency, our data strengthen Van Petten and Kutas' (1990) view that position "can serve as metric of the semantic and structural links that differentiate a sentence from a string of unconnected words" (p. 388).

2.4.3 Frequency and predictability: Lexical and post-lexical processes?

The decreasing N400 amplitude with increasing predictability demonstrates that context facilitates word processing and language comprehension, independent of the position of the word in the sentence. Additionally, we showed that the interaction of predictability and frequency absorbed the variance accounted for by the interaction of word position and frequency. Thus, word position in a sentence reflects primarily the build-up of contextual constraint (Van Petten & Kutas, 1990, 1991; see also Van Petten, 1993). Do the results also confirm the proposal that context supersedes the role of word frequency concerning lexical access while we read through a sentence? It was concluded that "word frequency plays a role in these processes only when meaningful semantic context is weak, as at the beginning of a congruent sentence [...]" (Van Petten, 1993, p. 498). This interpretation implies a uni-directional influence of contextual constraint on the impact of word frequency in a sense that context can affect the relevance of frequency but not the other way round. On the basis of the present results, we propose that word frequency and context interact in a bi-directional way.

Concerning the N400 amplitudes, there are two crucial illustrations in Figure 2.4. First, panel 5 reveals that the frequency effect decreases with increasing word position. In principle, this replicates Van Petten and Kutas' (1990, 1991) results. One might conclude that, on the N400, frequency does not play a role as context increases. Remember, however, that the term was only significant when the interaction between predictability and frequency was left out of the rmMRA.

The second relevant illustration relates to the interaction of predictability and frequency (panel 4). This plot allows an alternative interpretation: The effect of contextual information (indicated by predictability) is larger for low frequency than for high frequency words. In other words, frequency modulates the strength of the predictability effect on the N400.

This conclusion is also in line with the frequency effects in the rmMRAs. Our results suggest that high frequency words are lexically accessed before 200 ms indicated by the quadratic trend of frequency in the P200 epoch (Figure 2.3, panel 1). Predictability did not influence this fast process. As was shown in the analysis using a reduced rmMRA model, frequency affected the N400 amplitude following a quadratic trend: Amplitudes of low frequency words differed from high frequency words, whereas differences were smaller among the latter. This indicates that, at this later time, especially low frequency words were accessed. The variance accounted for by frequency on the N400 was absorbed by the interaction of predictability and frequency. Thus, both lexical access of low frequency words and the effect of predictability affected ERPs at the same latency. The interaction suggests that both variables act on the same stage of word recognition. Lexical access of low frequency words benefits from contextual information and this benefit is strongly reduced in the case of high frequency words having been recognized earlier (see also Becker, 1979; Sereno et al., 2003).

Interactive models of word recognition (e.g., Grainger & Jacobs, 1996; McClelland, 1987; Morton, 1969) can explain the present results, because they allow feedback from higher to lower levels of processing. However, the findings present a problem for modular approaches (e.g., Fodor, 1983; Forster, 1979) assuming distinct and sequential lexical and post-lexical stages, at least using word frequency and predictability as primary indicators. Alternatively, one would need to establish post-lexical sources in word frequency and lexical sources in word predictability norms. After all, there is a substantial correlation ($r = .41$) between them.

In sum, word recognition seems to be a gradual process rather than a strict sequence of distinct stages (see also Coulson & Federmeier, in press). Also, Van Petten (1995) pointed out that "although word frequency is a lexical variable, the human language-processing system does not always respect the boundary between lexical and sentential processing" (p. 520). The brain seems to use all sources of information as soon as they become available in order to provide a fast and correct understanding.

2.4.4 Conclusions

The purpose of this study was to investigate joint effects of frequency and predictability on early and late ERP components, taking into account also effects of word position. In the present experiment we reconciled several isolated findings of previous studies and contributed a few novel results: High frequency words triggered a differential ERP response in the first 200 ms after stimulus onset; there was no evidence for an effect of predictability on this early P200 component. In contrast, predictability correlated strongly and linearly with the N400 amplitude. In addition, the N400 amplitude exhibited a larger predictability effect for low frequency than for high frequency words, compatible with a late-access interpretation of low frequency words. Finally, P200 amplitudes decreased across sentence-initial words and increased towards the end of a sentence. Apparently, this effect does not relate to the recognition of the currently presented word, at least not exclusively. In general, the results suggest different time constraints but also overlapping processes for frequency-related lexical access and predictability-related post-lexical integration during reading.

Acknowledgments

We thank Mario Braun for research assistance as well as Olaf Dimigen and two anonymous reviewers for helpful and constructive comments. This research was supported by grant KL 955/6 from Deutsche Forschungsgemeinschaft.

Copyright

3 Synchronizing timelines: Relations between fixation durations and N400 amplitudes during sentence reading

Michael Dambacher[1,2] and Reinhold Kliegl[1]

[1] Universität Potsdam, Germany
[2] Freie Universität Berlin, Germany

Running Head: Synchronizing timelines

published 2007 in *Brain Research, 1155*, 147-162.

Abstract

We examined relations between eye movements (single-fixation durations) and RSVP-based event-related potentials (ERPs; N400's) recorded during reading the same sentences in two independent experiments. Longer fixation durations correlated with larger N400 amplitudes. Word frequency and predictability of the fixated word as well as the predictability of the upcoming word accounted for this covariance in a path-analytic model. Moreover, larger N400 amplitudes entailed longer fixation durations on the next word, a relation accounted for by word frequency. This pattern offers a neurophysiological correlate for the lag-word frequency effect on fixation durations: Word processing is reliably expressed not only in fixation durations on currently fixated words, but also in those on subsequently fixated words.

3.1 Introduction

Eye tracking and EEG hold the potential to deliver precise timelines of word recognition during reading. Here we show how their joint consideration takes advantage of their respective strengths and yields novel insights into this process.

Tracking eye movements provides accurate information about where the eyes look at a given moment. When an individual reads a text, a word is fixated for approximately 200 to 250 ms before a saccade is made and the next word is fixated. The time spent on a given word strongly depends on the ease with which the stimulus can be processed (see Rayner, 1998 for a review). For instance, words rarely occurring in a language (i.e., low frequency words) are fixated longer than common (high frequency) words. Also contextual information affects reading speed. Words are fixated longer when they are not or hardly predictable compared to high predictability words[1] (e.g., Inhoff & Rayner, 1986; Kliegl et al., 2004, 2006; Rayner et al., 2001; Rayner & Well, 1996; Schilling et al., 1998). The instantaneous influence of properties of a fixated word n on inspection durations on word n is known as *immediacy effect*.

Moreover, spillover or *lag effects* during reading characterize word properties affecting fixation durations on the next word. For instance, fixation durations on word n are longer when the preceding stimulus (i.e., word n-1) was of low frequency (Kliegl et al., 2006; Schroyens, Vitu, Brysbaert, & d'Ydewalle, 1999). Kliegl et al. reported that low predictability lengthens fixation durations on a subsequent word as well, but this effect was smaller than the lag-frequency effect. One explanation for lag effects is that word recognition might not be finished during fixation time. Kolers (1976; see also Bouma & de Voogd, 1974) proposed that fixation durations between 150 to 300 ms are too short to grant full language comprehension. Instead, the mind lags behind the eyes. Accord-

[1] Predictability usually measured in a cloze task is the proportion of people correctly predicting a word from a given context.

ing to this *cognitive-lag hypothesis* (Rayner, 1977, 1978), linguistic processing continues while the eyes have already moved on to the next word[2]. Processing incompleteness of word n-1 spills over and causes longer fixation durations on word n. As incomplete processing is more likely for difficult stimuli, longer fixation durations occur predominantly after low frequency words. This interaction between frequency of word n-1 and word n has been obtained in nine eye tracking experiments after statistical control of a large number of alternative sources of variance (Kliegl, 2007).

In addition to immediacy and lag effects, properties of upcoming words within the perceptual span (e.g., word n+1) exert reliable influences on fixation durations on word n, so-called *successor effects*. Despite much controversy whether inspection time on word n is modulated by sublexical or lexico-semantic features of a not yet fixated, parafoveal word n+1 (e.g., Kennedy & Pynte, 2005; Rayner, White, Kambe, Miller, & Liversedge, 2003; Vitu, Brysbaert, & Lancelin, 2004), a novel successor effect has been reported recently: Fixation durations on word n are longer when word n+1 is highly predictable (Kliegl et al., 2006). Since predictability is generated before a word is fixated[1], information about a highly predictable word n+1 may be extracted from memory while the eyes are resting on word n. Memory retrieval then may make unnecessary a saccade to word n+1 and prolong inspection duration on word n. Consequently, no or only minimal visual information may be necessary to access a highly predictable word n+1 during the fixation of word n. In a subsequent analysis of this data, the positive correlation of single-fixation duration on word n and

[2]Several other theories account for lag effects from an eye movement perspective [e.g., reduced parafoveal preview (Balota, Pollatsek, & Rayner, 1985) or dynamical perceptual span due to foveal load (Henderson & Ferreira, 1990)]. However, these assumptions do not suit the present ERP paradigm of word-wise sentence presentation. Hence, they cannot serve as explanation for lag effects in our linked eye movement and ERP data, and are not further discussed here (see Kliegl et al., 2006 for a review).

predictability of word n+1 was linked primarily to constellations where word n or word n+1 was a function word (Kliegl, 2007).

Besides eye tracking, the measurement of event-related potentials (ERPs) is a valuable instrument for the investigation of reading processes. ERPs provide an online measure of neural activity with excellent temporal resolution (for reviews see Kutas & Federmeier, 2000; Kutas & Van Petten, 1994; Kutas et al., 2006). One of the best documented ERP components is the N400, a negative deflection most prominent over centro-parietal sites in an epoch from approximately 300 to 500 ms (e.g., Kutas & Hillyard, 1980, 1983). The N400 is sensitive to the ease, with which words are processed. Low frequency as well as low predictability words evoke larger N400 amplitudes than high frequency or high predictability words (e.g., Dambacher, Kliegl, Hofmann, & Jacobs, 2006; Rugg, 1990; Van Petten, 1993; Van Petten & Kutas, 1990). Figure 3.1 illustrates these effects for data of the present study (i.e., a subset of data from Dambacher et al., 2006; see *3.2 Methods*).

In an ongoing debate on its functional nature, several authors argued that the N400 peak-latency occurs too late to reflect lexical processes like word recognition. On the assumption that a word is usually lexically accessed before the eyes leave it, and given an average fixation duration of about 200 to 250 ms during normal reading, the N400 must be associated with post-lexical integration (e.g., Brown & Hagoort, 1993; Holcomb, 1993; Sereno & Rayner, 2003; Sereno et al., 1998). However, N400 amplitude effects often start at around 200 ms post-stimulus, a time, when difficult words even during normal reading are still fixated. Moreover, empirical evidence for sensitivity to lexico-semantic processes in priming studies suggests that the N400 does not purely reflect post-lexical integration (e.g., Deacon et al., 2000, 2004). Also, reports of larger N400 predictability effects for low than for high frequency words indicate that frequency as lexical (bottom-up) and predictability as post-lexical (top-down) variable affect the same stage of word

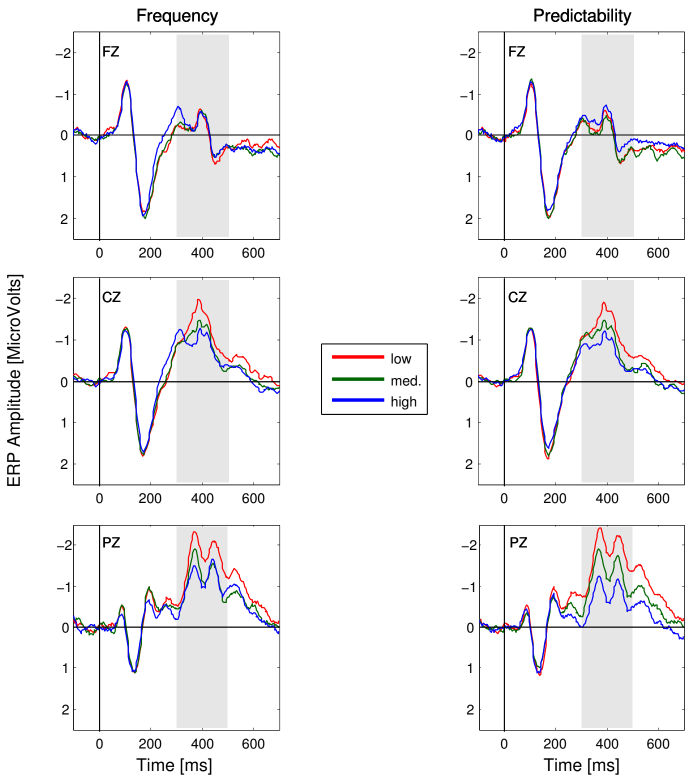


Figure 3.1: Grand average ERPs. ERPs for three categories of frequency (left panels) and predictability (right panels). N400 amplitudes in the epoch from 300 to 500 ms over centro-parietal electrodes are larger for words of low than of high frequency and predictability. Averages are computed on the basis of 48 subjects and 343 open-class words varying between third and antepenultimate position in sentences (see *3.2 Methods*). Categories (low, medium, high) each comprising approximately one third of the stimuli are computed on the basis of quantiles. Data are from Dambacher et al. (2006).

recognition (Dambacher et al., 2006; Van Petten, 1993, 1995; Van Petten & Kutas, 1990). Dambacher et al. proposed that lexical access of difficult words extends into the N400 epoch. In this time range, processing of low frequency words is strongly supported by predictability.

Both eye movement measures and ERPs separately contribute to the understanding of word recognition. Of course, combining the two measures, namely recording eye movements and ERPs simultaneously from the same subjects within one experiment, would achieve even better insights into the timeline of reading processes (Sereno & Rayner, 2003). Unfortunately, several problems render a co-registration very complex. First, EEG signals are contaminated by eye movements during normal reading. The eyes can be thought of as dipoles, which are positive towards the cornea. When an eyeball alters orientation, voltage changes due to the movement are gradually propagated back over the scalp. Also blinks cause substantial artifacts, because closing eyelids connects frontal scalp sites to the positively charged cornea (Lins, Picton, Berg, & Scherg, 1993). Therefore, in EEG studies, stimuli are often presented at a fixed position making eye movements unnecessary. Furthermore, participants are asked not to blink, which disadvantageously imposes an additional task. Although by now various valuable techniques have been developed to handle eye artifacts in the EEG signal [e.g., Multiple Source Eye Correction (Berg & Scherg, 1994); Independent Component Analysis (Jung et al., 1998)], the second problem of component overlap is severe. Language-related ERP components, like the N400, occur at latencies, when the eyes during normal reading already fixate a subsequent word. If ERPs were recorded at normal reading speed of 200 to 250 ms per word, neural responses evoked by different words would temporally coincide, so effects could not be uniquely attributed to processing of a certain word. Consequently, sentences in ERP experiments are usually presented word by word with unnaturally long intervals between stimuli.

Present study

One possibility to circumvent these difficulties at least in part is to compare eye movements and ERPs from separate experiments using similar stimuli (e.g., Raney & Rayner, 1993; Sereno & Rayner, 2003; Sereno et al., 1998). We followed this approach in the present paper. In one experiment, eye movements were recorded during reading of 144 sentences of the Potsdam Corpus 1 (PSC1; see Appendix A). In another experiment with different subjects, ERPs were assessed while the PSC1 was displayed word by word, during rapid serial visual presentation (RSVP). We examined relations between fixation durations and N400 amplitudes and determined whether both measures are comparably sensitive to the same mechanisms of word recognition. On the one hand, assuming a tight coupling between the two measures is not trivial because they originate from different sources and techniques: Eye movements are behavioral responses from the oculomotor system, while ERPs are indicators of neural activity. On the other hand, fixation durations and N400 amplitudes are clearly associated with central reading processes. First, both measures are modulated by word difficulty: Fixation durations as well as N400 amplitudes decrease with high frequency and predictability of words. Second, they mirror relatively late stages of word recognition. Fixation durations mark the point in time, when the eyes leave a stimulus, i.e., when lexical processing relying on visual input from a letter string is terminated. Similarly, N400 amplitudes probably denote one of the final stages of lexico-semantic processing, as they are sensitive to lexical but also to post-lexical properties. Thus, fixation durations and N400 amplitudes possibly get input from a common stage of word recognition. If this is true, we should be able to find substantial covariation between the two measures.

We explored the relationship between eye movements and ERPs in path analyses addressing immediacy, lag, and successor effects. For immediacy effects, we expected correlations between fixation durations and N400 amplitudes suggesting that both measures are sensitive to the same word recognition processes. If so, frequency and predictability of the corresponding word represent likely determinants for the covariation as both mirror processing difficulty. Conversely, joint sensitivity of eye movements and ERPs to frequency and predictability questions a strict assignment to either lexical or post-lexical processes and favor rather hybrid functions of fixation durations and N400 amplitudes.

Considering lag effects, it is important to note that the N400 usually peaks at a latency when fixation during normal reading is already on the next word. As the N400 reflects processing of its eliciting stimulus, a significant relation between N400 amplitudes and the next fixation would indicate that word recognition continues after the eyes moved on. Tracing this relation to word frequency would then provide a physiological explanation for the lag effect in eye movements, namely that ongoing processing interferes with recognition of the next word (Kliegl et al., 2006; see also Bouma & de Voogd, 1974; Kolers, 1976). At the same time, support for the lag effect as reflection of incomplete processing of prior words holds important implications for the comprehension of reading processes. Several words can be processed simultaneously and influence recognition of each other. Thus, models of oculomotor control [e.g., *SWIFT*, (Engbert, Krampe, Kurths, & Kliegl, 2002; Engbert et al., 2005); *E-Z Reader*, (Pollatsek, Reichle, & Rayner, 2006; Reichle et al., 1998; Reichle, Rayner, & Pollatsek, 2003)] would have to encounter reading as distributed rather than as serial process.

Concerning successor effects, we assumed that predictability of an upcoming word accounts for covariance between eye movements and ERPs. As the cloze task (i.e., the usual procedure to collect predictability norms) explicitly requires the anticipation of a not yet visible word, predictability reflects at least partly the degree of contextual constraint, which determines the certainty of predictions (see also Dambacher et al., 2006). Confident predictions can be made whenever contextual constraint is high, irrespective of the actual identity of the upcoming word. Successor effects have been found as longer fixation durations prior to high predictability words (Kliegl et al., 2006). Also findings on ERPs point to predictions about upcoming words (DeLong et al., 2005; Van Berkum et al., 2005; Wicha, Bates, Moreno, & Kutas, 2003; Wicha, Moreno, & Kutas, 2003; Wicha et al., 2004). Considering fixation durations and N400 amplitude, joint successor effects would indicate that online predictions are made during reading and that a word is potentially retrieved from memory before it is fixated.

3.2 Methods

Detailed methods on acquisition of eye movement as well as EEG data are published elsewhere (see Kliegl et al., 2006 and Dambacher et al., 2006, respectively).

3.2.1 Stimuli

The Potsdam Sentence Corpus 1 (PSC1; see Appendix A) served as stimulus set in the eye movement and the ERP study. The PSC1 comprises 144 German sentences (1138 words) with a large variety of grammatical structures. Mean sentence length is 7.9 words with a range from 5 to 11 words. Values for frequency (based on *Das Digitale Wörterbuch der deutschen Sprache des 20. Jahrhunderts*, http://www.dwds.de, 2006; Geyken, 2007; Kliegl et al., manuscript in preparation) and predictability (collected in an independent cloze task; see Kliegl et al., 2004) were available for all corpus words, along with other independent variables such as word length and ordinal position of the word in the sentence.

3.2.2 Eye movements

3.2.2.1 Participants

Eye movement data were collected from 125 German speakers (16 to 56 years) with normal or corrected-to-normal vision. They were paid or received study credit at the University of Potsdam.

3.2.2.2 Procedure

Participants (seated 60 cm from the screen; head positioned on a chin rest) were instructed to read the sentences for comprehension. After validation of the accuracy of a standard nine-point grid calibration, a fixation spot appeared in the center-line on the left side of the monitor. If the eye tracker detected a valid fixation on the spot, a sentence was presented so that the midpoint between the beginning and the center of the first word was positioned at the location of the fixation spot. Sentences (font: New Courier 12; visual angle: 0.35° per letter) were shown until participants looked to the lower right corner of the screen. An extra calibration was carried out if the tracker did not detect the eye at the initial fixation point within two seconds.

3.2.2.3 Recording and data processing

Eye movements were recorded with EyeLink I and II systems (SR Research, Osgoode, ON, Canada) with sampling rates of 250 Hz and 500 Hz, respectively, and an eye position resolution of 20 sec-arc. Calibrated eye position was recorded accurately at the level of letters. Data were collected in two laboratories with identical equipment and setup.

Eye movement data were screened for loss of measurement and blinks. Data of sentences without problems were reduced to a fixation format after detecting saccades as rapid binocular eye movements (Engbert & Kliegl, 2003). Only single fixations (i.e., words exactly fixated once) with durations between 50 ms and 750 ms entered analyses. Finally the first word of each sentence was removed. This screening resulted in a total of 42,847 data points.

3.2.3 ERPs

3.2.3.1 Participants

Fifty subjects (19 to 35 years; 43 right-handed) were paid for participation at the Catholic University of Eichstätt-Ingolstadt. All were native German speakers and had normal or corrected-to-normal vision.

3.2.3.2 Procedure

Participants were positioned 60 cm from the monitor and were instructed to read the sentences for comprehension. A fixation-cross indicated the position of the first word on the screen. A sentence was then presented word by word (font: New Courier 12). Each stimulus together with the adjacent punctuation was displayed for 250 ms and a stimulus onset asynchrony (SOA) of 700 ms in black on a white screen (Rapid Serial Visual Presentation; RSVP). Sentence order was randomized.

3.2.3.3 Recording and data processing

EEG data were collected with an electrode cap (ElectroCap International) on 26 locations corresponding to the revised 10/20 International System. Amplified voltages (.1-100 Hz; sampling rate: 256 Hz) originally referenced to one electrode on the left mastoid were converted offline to average reference. Two horizontal and two vertical EOG electrodes recorded bipolarly eye movements and blinks. Impedances of scalp electrodes were kept below $5k\Omega$.

Data of two subjects had to be excluded from further processing, one because of data loss and one because of a former neurological disease. Due to artifact contamination, a total of 11.43% of the data from the remaining 48 subjects was eliminated. The continuous EEG recording was divided into 800 ms epochs beginning 100 ms before stimulus onset. Data were baseline-corrected relative to a 100 ms pre-stimulus interval.

3.2.4 Data reduction

In the EEG data, we identified the N400 component in the time window from 300 to 500 ms over centro-occipital electrodes (CZ, C3, C4, CP5, CP6, PZ, P3, P4, P7, P8, O1, O2) as in the study of Dambacher et al. (2006). They chose this epoch and these channels for N400 analyses after visual inspection and in accordance with previous reports (cf., Kutas et al., 2006). N400 amplitudes were

Table 3.1: Word statistics. Descriptive statistics for words n-1, n, and n+1: Number of open- and closed-class words together with mean and standard deviation (SD) of word frequency and predictability.

	Open-Class Words			Closed-Class Words		
	N	Mean	SD	N	Mean	SD
Word n-1						
Frequency	209	1.52	.98	134	3.66	.72
Predictability	209	−2.10	.72	134	−1.11	.99
Word n						
Frequency	343	1.54	1.00			
Predictability	343	−1.77	.96			
Word n+1						
Frequency	154	1.61	1.06	189	3.64	.65
Predictability	154	−1.87	.85	189	−.70	1.09

computed by collapsing voltages across selected electrodes, across sampling points in the 200 ms interval, and across subjects. Thus, we obtained one average N400 amplitude for each corpus word. For analyses we specified N400 amplitudes of the currently presented word n ($N400_n$) together with N400 amplitudes of the previous word n-1 ($N400_{n-1}$).

Likewise, fixation durations were collapsed across participants resulting in one average single-fixation duration for each word in the PSC1. In addition to the fixation duration associated with a currently fixated word n (FD_n) we also determined the fixation duration on the preceding word n-1 (FD_{n-1}) and on the succeeding word n+1 (FD_{n+1}).

In the ERP as well as in the eye movement data set, word n was restricted to the category of open-class words (e.g., nouns, verbs). Closed-class words (e.g., determiners, pronouns) were excluded. Note that this selection criterion did not pertain to word n-1 or word n+1: While FD_n as well as $N400_n$ were derived from open-class words, FD_{n-1}, $N400_{n-1}$, and FD_{n+1} could correspond to either open-class or closed-class words. Moreover, sentence-initial and sentence-final words were excluded. We also made sure that neither FD_{n-1} nor $N400_{n-1}$ stemmed from the sentence-initial word, and likewise that FD_{n+1} was not from sentence-final position. Therefore, word n varied between the third position from the beginning and the third word from the end of a sentence. The data reduction resulted in a total of 343 open-class words n each comprising a unique value for $N400_{n-1}$, $N400_n$, FD_{n-1}, FD_n, and FD_{n+1} (see Tab. 3.1 for word statistics).

3.3 Results

3.3.1 Fixation durations and N400 amplitudes

The immediacy effect in ERPs and eye movements is visualized as function of word frequency (left panel) and predictability (right panel) of word n (Fig. 3.2). The bins were computed by dividing continuous frequency and predictability values into five quantiles each comprising approximately 20% of the data. As the high proportion of words not predictable at all could not be further split up into categories (i.e., 42.9% shared the lowest predictability value of -2.55), the first and second quantile merged such that only four bins are displayed on the right panel. Error bars reflect 99% confidence intervals.

Fixation durations (FD_n) as well as N400 amplitudes ($N400_n$) are sensitive to frequency and predictability of word n. Moreover, a comparison of the curves for eye movements and ERPs reveals striking similarity. FD_n and $N400_n$ decrease as word frequency increases following a quadratic trend: Differences are larger in the low frequency than in the high frequency range [the higher-order trends are illustrated in Kliegl et al., 2006, Fig. 3 and in Dambacher et al., 2006, Fig. 4 as well (cf., Chapter 2, Fig. 2.4)]. Importantly, both curves show similar disordinalities: The largest drop appears from the first to the second quantile. In the fourth quantile both measures slightly increase, while they decrease again in the fifth quantile. Concerning the right panel, FD_n and $N400_n$ linearly decline as predictability augments.

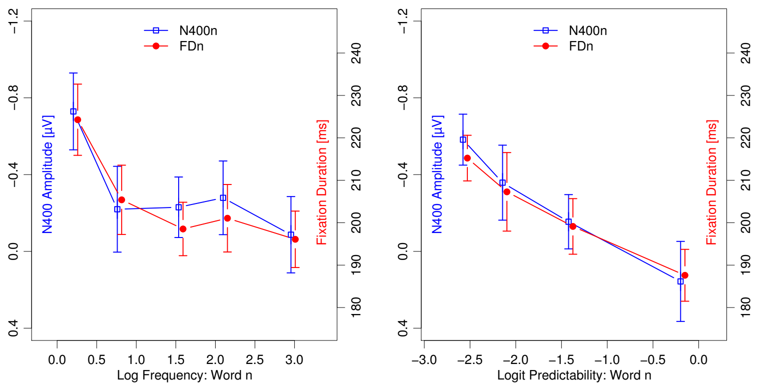


Figure 3.2: Immediate relations: Word n effects on FD_n and $N400_n$. Mean fixation durations (FD_n) and N400 amplitudes ($N400_n$) of word n as function of frequency (left panel) and predictability (right panel) of word n. Data points were calculated on the basis of quantiles for frequency and predictability. Error bars reflect 99% confidence intervals. Eye movement data are from Kliegl et al. (2006) and EEG data are from Dambacher et al. (2006).

In addition to the immediate influence of word n, lagged frequency and predictability affect fixation durations (cf., Kliegl et al., 2006). Figure 3.3 illustrates that FD_n declines as frequency and predictability of the *prior* word n-1 increase. Unsurprisingly, also N400 amplitudes of word n-1 ($N400_{n-1}$) drop with frequency and predictability of word n-1. Thus, Figure 3.3 uncovers covariation of FD_n and $N400_{n-1}$ as a function of word n-1 as well. Although the visual impression of the lagged relation is weaker than the one for the immediate relation (Fig. 3.2), the temporal coincidence of $N400_{n-1}$ and FD_n suggests functional relationship between the two variables (see below).

In summary, fixation durations and N400 amplitudes are strongly modulated by frequency and predictability. Therefore, a similar shape of the lines in Figures 3.2 and 3.3 is not unexpected. Note however, that ERPs and eye movements stem from independent experiments differing in subjects (125 vs. 48), paradigm (normal

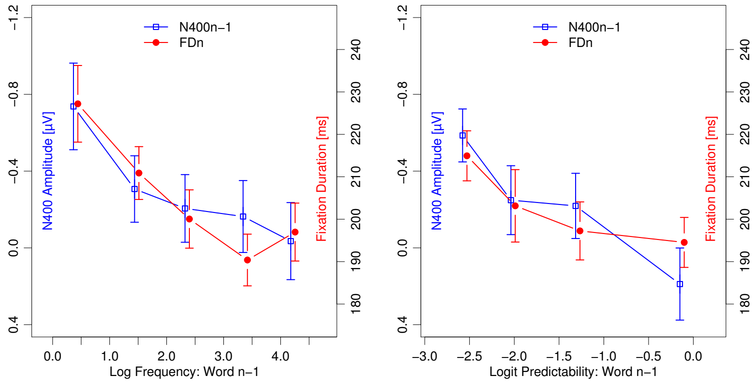


Figure 3.3: Lagged relations: Word n-1 effects on FD_n and $N400_{n-1}$. Mean fixation durations on word n (FD_n) and N400 amplitudes on word n-1 ($N400_{n-1}$) as function of frequency (left panel) and predictability (right panel) of word n-1. Data points were calculated on the basis of quantiles for frequency and predictability. Error bars reflect 99% confidence intervals. Eye movement data are from Kliegl et al. (2006) and EEG data are from Dambacher et al. (2006).

reading vs. RSVP), and laboratory (University of Potsdam vs. University of Eichstätt-Ingolstadt). Considering that the studies merely shared the stimuli, the high correspondence of the two measures warrants a closer examination of this covariation. The large samples of participants and items constitute a stable and reliable basis for the analyses of otherwise noisy measures of eye movements and ERPs. Furthermore, with identical linguistic material in an item-based analysis, we can control for differences between the studies, which may mask common sources of variance in fixation durations and N400 amplitudes (e.g., large inter-individual differences).

In the following sections we will address several questions: How do fixation durations and N400 amplitudes during sentence reading dynamically relate to each other in a time window including more than the currently fixated word? Is there evidence for mutual influence between fixation durations and N400 amplitudes? Can relationships be traced back to a common stage of word recognition?

3.3.2 Synchronizing the timelines

Before examining the relations between fixation durations and ERPs, the two measures must be mapped to a common time-scale. Figure 3.4 illustrates how fixation durations and N400 amplitudes temporally relate to each other. The lower part of panel ***A*** in Figure 3.4 presents a schematic time course of eye movements corresponding to data from Kliegl et al. (2004, 2006); subjects were normally reading sentences from left to right. When the eyes land on a word, it is fixated for about 200 ms before a saccade brings the eyes to the next word, which again is fixated for approximately 200 ms. The upper part of panel ***A*** in Figure 3.4 illustrates an idealized ERP timeline elicited by word n. This curve is compatible with the present ERP data with words presented in fixed intervals of 700 ms (see Fig. 3.1 and Dambacher et al., 2006). The N400 component peaks at a latency of approximately 400 ms after stimulus onset. The blue-shaded area denotes that both FD_n and $N400_n$ are associated with the same stimulus. The common time scale makes clear that the $N400_n$ occurs at a time when the eyes during normal reading already fixate word n+1.

On the basis of this scheme, we sketch a pattern about the relation between fixation durations and N400 amplitudes. The lower part of panel ***B*** in Figure 3.4 reflects the timeline of normal reading. The upper part shows two ERP curves, one elicited by word n (blue area) and one evoked by word n-1 (red area). In order to synchronize the two timelines, the ERP course is "shrunk", so that the stimulus onset in the ERP experiment corresponds to the fixation onset in the eye movement study. Thus, the two ERP curves now overlap substantially. Note that this temporal overlap of components did *not* occur during the ERP experiment. Due to the SOA of 700 ms in the ERP study N400 amplitudes are uniquely attributable to presentation and processing of the corresponding word. Thus, a unique advantage of the combination of RSVP and regular eye movement statistics is that it allows us to unconfound the influence of successive N400 components on successive reading

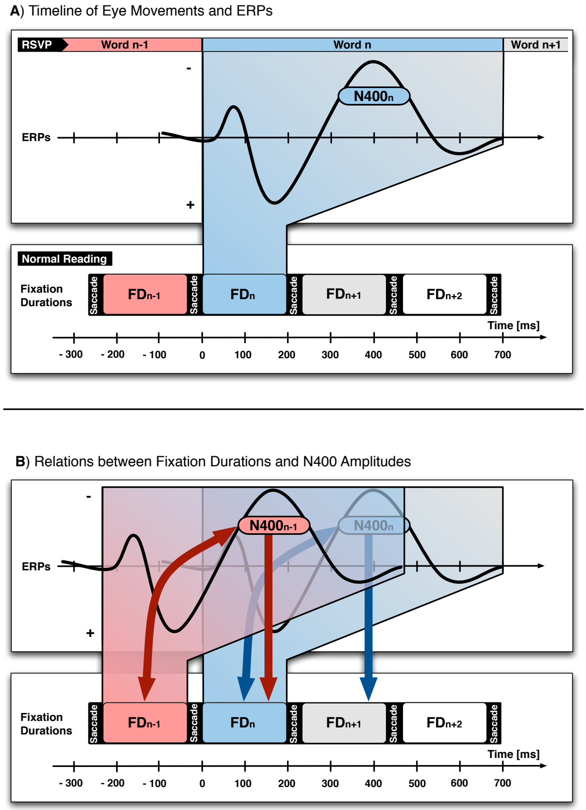


Figure 3.4: Synchronizing the timelines of eye movements and ERPs. Panel **A** illustrates the time-course of fixation durations (FD) during normal reading (bottom) and of ERPs during rapid serial visual presentation (RSVP) of sentences (top). The blue-shaded area denotes that ERP curve as well as FD_n relate to the same word n. Panel **B** sketches expected relations between FD and $N400$ amplitudes across different words: Correlations (double-headed arrows) between FD and $N400$ associated with the same word, and uni-directional influence (directional arrow) from $N400$ on FD on the next word.

fixations. Arrows in panel ***B*** of Figure 3.4 sketch expected relations between the measures together with the direction of influence. First, we assume a correlation between FD_n and $N400_n$ represented by the blue double-headed curved arrow. The blue straight arrow pointing from $N400_n$ to FD_{n+1} reflects the lag effect: $N400_n$ may influence FD_{n+1}, but not the other way round, because word n+1 in the ERP study was presented only after occurrence of $N400_n$ (i.e., 700 ms after word n). In addition, the same pattern of interrelations is expected for measures relating to word n-1 (see red arrows). We predict a covariance between FD_{n-1} and $N400_{n-1}$ as well as a direct influence from $N400_{n-1}$ on FD_n.

3.3.3 Baseline path model

The predictions were tested in a path analysis[3], including also autoregressive paths for fixation durations (i.e., influence from FD_{n-1} on FD_n, and from FD_n on FD_{n+1}). With the simultaneous consideration of relationships between three successive fixation durations together with two corresponding N400 amplitudes we explore reading dynamics in a representative time window. Herein, mutual influence between measures is examined while possible effects of third variables are statistically controlled (e.g., covariance between FD_n and $N400_n$ taking into account influence from $N400_{n-1}$ on FD_n). Moreover, the open-class restriction of word n and class-independence of words n-1 and n+1 grant generalizability across word types.

Path coefficients along with corresponding standard errors and p-values, as well as goodness-of-fit statistics of this *baseline model* are presented in the left part of Table 3.2 (see also Fig. 3.5, panel ***A***). Various goodness-of-fit statistics indicate that the specified model is compatible with the observed variance-covariance matrix, e.g., $\chi^2(4) = 6.4$, $p = .17$. Thus, the results support the hypotheses outlined above: $N400_{n-1}$ (negative voltages) covaries with FD_{n-1} and $N400_n$ covaries with FD_n. Moreover, both lag effects were significant: The more negative the $N400_{n-1}$, the longer FD_n and

[3] All path analyses were conducted with the *sem package* (Fox, 2006) implemented in the *R framework*, a language and environment for statistical computing (R-Development-Core-Team, 2006).

Table 3.2: Path-analytic models. Path coefficients, standard errors (SE), p-values ($p < .05^*$; $p < .01^{**}$), and model fit characteristics for four path models. The baseline model denotes relations between fixation durations and N400 amplitudes. In the immediacy, lag, and successor effect models, these relations are successively dissolved by the add-on of word frequency and predictability, accounting for the covariation of fixation durations and N400 amplitudes.

			Baseline Model				+ Immediacy Effects			
			Coef	SE	p		Coef	SE	p	
Baseline Model										
FD_{n-1}	$\leftrightarrow$	$N400_{n-1}$	−4.077	.944	<.001	**	−2.068	.771	.007	**
$N400_{n-1}$	$\rightarrow$	FD_n	−8.900	2.050	<.001	**	−7.667	1.827	<.001	**
FD_n	$\leftrightarrow$	$N400_n$	−4.645	.931	<.001	**	−.653	.676	.334	
$N400_n$	$\rightarrow$	FD_{n+1}	−4.242	2.024	.036	*	−4.242	2.024	.036	*
FD_{n-1}	$\rightarrow$	FD_n	.040	.052	.449		.065	.048	.171	
FD_n	$\rightarrow$	FD_{n+1}	.166	.051	.001	**	.166	.051	.001	**
Immediacy Effects										
f_{n-1}	$\rightarrow$	FD_{n-1}					.725	1.237	.558	
f_{n-1}	$\rightarrow$	$N400_{n-1}$					.053	.029	.066	
f^2_{n-1}	$\rightarrow$	FD_{n-1}					3.838	.802	<.001	**
f^2_{n-1}	$\rightarrow$	$N400_{n-1}$					−.082	.019	<.001	**
p_{n-1}	$\rightarrow$	FD_{n-1}					−5.413	1.769	.002	**
p_{n-1}	$\rightarrow$	$N400_{n-1}$					.264	.041	<.001	**
f_n	$\rightarrow$	FD_n					.992	1.805	.583	
f_n	$\rightarrow$	$N400_n$					−.006	.047	.902	
f^2_n	$\rightarrow$	FD_n					5.207	1.119	<.001	**
f^2_n	$\rightarrow$	$N400_n$					−.078	.030	.009	**
p_n	$\rightarrow$	FD_n					−9.612	1.297	<.001	**
p_n	$\rightarrow$	$N400_n$					.269	.035	<.001	**
Model Statistics										
χ^2 :			6.4	df : 4			150.0	df : 22		
$Pr(>\chi^2)$:			.17				<.001			
RMSEA Index:			.042	90% CI: (NA, .10)			.130	90% CI: (.11, .15)		
Goodness of Fit Index:			.99				.93			
Adj. Goodness of Fit Index:			.97				.80			
Bentler-Bonnett NFI:			.93				.86			
Tucker Lewis NNFI:			.93				.67			
Bentler CFI:			.97				.87			
BIC:			−17				22			

the more negative $N400_n$, the longer FD_{n+1}. Finally, there was a positive effect from FD_n on FD_{n+1}, but no influence from FD_{n-1} on FD_n (Tab. 3.2: *Baseline Model*).

Clearly, we established a reliable covariance between eye movement and EEG measures during reading over words. Longer fixation durations go along with larger N400 amplitudes on the cor-

Table 3.2: Path-analytic models (continued).

			+ Lag Effects				+ Successor Effects			
			Coef	SE	p		Coef	SE	p	
Baseline Model										
FD_{n-1}	$\leftrightarrow$	$N400_{n-1}$	-2.068	.771	.007	**	-1.861	.758	.014	*
$N400_{n-1}$	$\rightarrow$	FD_n	-1.731	1.737	.319		-1.731	1.737	.319	
FD_n	$\leftrightarrow$	$N400_n$	$-.752$	.601	.211		$-.752$	.601	.211	
$N400_n$	$\rightarrow$	FD_{n+1}	-2.176	1.996	.276		-2.176	1.996	.276	
FD_{n-1}	$\rightarrow$	FD_n	.008	.043	.859		.008	.043	.859	
FD_n	$\rightarrow$	FD_{n+1}	.083	.053	.116		.083	.053	.116	
Immediacy Effects										
f_{n-1}	$\rightarrow$	FD_{n-1}	.725	1.238	.558		.465	1.229	.705	
f_{n-1}	$\rightarrow$	$N400_{n-1}$	.053	.029	.066		.057	.029	.047	*
f^2_{n-1}	$\rightarrow$	FD_{n-1}	3.838	.802	$<.001$	**	4.038	.797	$<.001$	**
f^2_{n-1}	$\rightarrow$	$N400_{n-1}$	$-.082$	.019	$<.001$	**	$-.085$	.019	$<.001$	**
p_{n-1}	$\rightarrow$	FD_{n-1}	-5.413	1.769	.002	**	-6.077	1.767	.001	**
p_{n-1}	$\rightarrow$	$N400_{n-1}$	.264	.041	$<.001$	**	.275	.041	$<.001$	**
f_n	$\rightarrow$	FD_n	$-.275$	1.622	.865		$-.275$	1.615	.865	
f_n	$\rightarrow$	$N400_n$	$-.006$	.048	.902		$-.006$	.047	.902	
f^2_n	$\rightarrow$	FD_n	4.353	.998	$<.001$	**	4.353	.995	$<.001$	**
f^2_n	$\rightarrow$	$N400_n$	$-.078$	.030	.009	**	$-.078$	.030	.009	**
p_n	$\rightarrow$	FD_n	-7.103	1.184	$<.001$	**	-7.103	1.184	$<.001$	**
p_n	$\rightarrow$	$N400_n$	.269	.035	$<.001$	**	.269	.035	$<.001$	**
Lag Effects										
f_{n-1}	$\rightarrow$	FD_n	-7.092	.829	$<.001$	**	-7.092	.829	$<.001$	**
f^2_{n-1}	$\rightarrow$	FD_n	2.949	.641	$<.001$	**	2.949	.641	$<.001$	**
f_n	$\rightarrow$	FD_{n+1}	-4.966	1.842	.007	**	-4.966	1.842	.007	**
f^2_n	$\rightarrow$	FD_{n+1}	1.488	1.216	.221		1.488	1.216	.221	
Successor Effects										
p_n	$\rightarrow$	FD_{n-1}					3.895	1.422	.006	**
p_n	$\rightarrow$	$N400_{n-1}$					$-.062$	.033	.063	
Model Statistics										
χ^2 :			43.2	df : 18			33.5	df : 16		
$Pr(>\chi^2)$:			$<.001$				.006			
RMSEA Index:			.064	90% CI: (.04, .09)			.057	90% CI: (.03, .08)		
Goodness of Fit Index:			.98				.98			
Adj. Goodness of Fit Index:			.92				.93			
Bentler-Bonnett NFI:			.96				.97			
Tucker Lewis NNFI:			.92				.94			
Bentler CFI:			.97				.98			
BIC:			-62				-60			

responding word. Furthermore, neural activity relating to a given stimulus serves as an indicator for fixation durations on the next word. Obviously, language processing is not over once the eyes have left a word but continues while subsequent text is scanned and influences succeeding reading behavior.

3.3.4 Predictor path models

The reliable covariances suggest that fixation durations and N400 amplitudes are sensitive to a common underlying mechanism, presumably related to word processing. Word frequency and predictability are likely candidates to indicate the common source of this covariance, as they are known to affect eye movements as well as ERPs. We tested this hypotheses in three additional path analyses including as exogenous variables *frequency* (f_{n-1}, f_n), *frequency x frequency* (f^2_{n-1}, f^2_n), and *predictability* (p_{n-1}, p_n) of word n-1 and of word n, respectively. We expected that, first, these predictors exhibit influences on both fixation durations as well as on N400 amplitudes, as shown in previous research (see *3.1 Introduction* and Fig. 3.2 and 3.3). Second, if frequency and predictability are responsible for the common modulation of fixation durations and N400 amplitudes and hence reflect the mediating source, they should absorb covariance of the two measures. Therefore, effects shown in the baseline path model should be no longer significant once frequency and predictability are included in the analysis. Specifically, allowing direct influences on fixation duration and N400 amplitude of corresponding words should cancel the covariance between them, a prediction tested in the *immediacy effect* path analysis (Fig. 3.6, panel ***A***). Further, we assumed that lag-frequency is responsible for the influence of N400 amplitudes on fixation durations on the next word. This relation should be absorbed, when frequency is coupled to the N400 amplitude of the current word and to fixation duration on the next word. Additionally, we hypothesized that lag-frequency is also responsible for the influence from FD_n to FD_{n+1}. The *lag effect* model examined these hypotheses (Fig. 3.6, panel ***B***). Finally, the *successor effect* model tested, whether predictability of an upcoming word (p_n) accounts for covariance between fixation durations (FD_{n-1}) and N400 amplitudes ($N400_{n-1}$). Such a result would be compatible with readers' online predictions of a not yet visible word (Fig. 3.6, panel ***C***). Variances, covariances, and correlations of the predictors entering the following analyses are shown in Table 3.3.

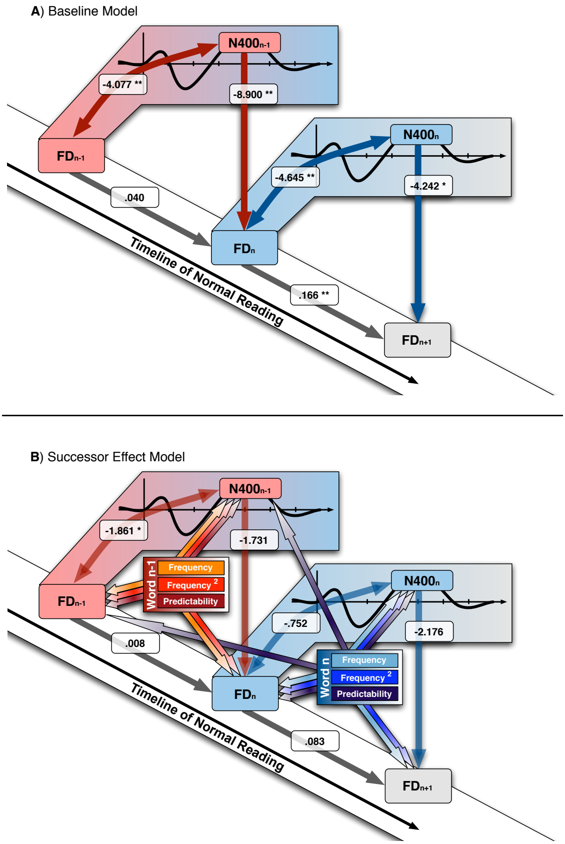


Figure 3.5: Path-analytic models. Visualization of path analyses, together with path coefficients ($p < .05^*$; $p < .01^{**}$). Panel **A** illustrates the baseline model (see also Tab. 3.2), i.e., direct relations between *N*400 amplitudes and fixation durations (*FD*) across word triplets (word n-1, word n, word n+1). Panel **B** shows the successor effect model (see also Tab. 3.2) comprising influence of word frequency and predictability in addition to paths in the baseline model.

In the *immediacy effect model*, frequency and predictability exhibited influence on fixation durations and on N400 amplitudes of the corresponding word. The *baseline model* was expanded by

Table 3.3: Variance-covariance matrix. Variances (*diagonal*), covariances (above diagonal), and correlations (below diagonal) of fixation durations (FD), N400 amplitudes ($N400$), and word properties [frequency (f), frequency x frequency (f^2), and predictability (p)], relating to words n-1, n, and n+1 (indicated by indices).

	FD_{n-1}	FD_n	FD_{n+1}	$N400_{n-1}$	$N400_n$
FD_{n-1}	*664.87*	55.88	−72.54	−4.08	.63
FD_n	.08	*672.08*	130.70	−3.91	−4.53
FD_{n+1}	−.12	.21	*594.50*	−.22	−2.58
$N400_{n-1}$	−.24	−.23	−.01	*.43*	−.01
$N400_n$	.04	−.27	−.16	−.02	*.43*
f_{n-1}	−.10	−.47	.04	.36	.07
f^2_{n-1}	.23	.27	.12	−.18	−.02
p_{n-1}	−.15	−.30	.08	.43	.04
f_n	−.14	−.32	−.32	.03	.26
f^2_n	.02	.39	.30	−.02	−.28
p_n	.08	−.43	−.19	.04	.44

	f_{n-1}	f^2_{n-1}	p_{n-1}	f_n	f^2_n	p_n
FD_{n-1}	−3.46	9.96	−3.82	−3.60	.75	1.96
FD_n	−16.70	12.03	−7.40	−8.46	15.64	−10.65
FD_{n+1}	1.31	4.94	1.82	−7.82	11.37	−4.49
$N400_{n-1}$	.32	−.20	.28	.02	−.03	.03
$N400_n$	.06	−.03	.03	.17	−.29	.28
f_{n-1}	*1.89*	−.12	.81	−.01	−.11	.27
f^2_{n-1}	−.05	*2.86*	.17	−.31	.33	−.13
p_{n-1}	.61	.10	*.93*	.00	−.03	.20
f_n	−.01	−.18	.00	*1.01*	−1.17	.31
f^2_n	−.05	.13	−.02	−.74	*2.45*	−.39
p_n	.20	−.08	.22	.32	−.26	*.92*

paths from f_{n-1}, f^2_{n-1}, and p_{n-1} to FD_{n-1} and $N400_{n-1}$, as well as from f_n, f^2_n, and p_n to FD_n and $N400_n$ (see Fig. 3.6, panel ***A*** for a schematic illustration). Table 3.2 lists path-coefficients, standard error, and p-values of this analysis. The covariance between FD_n and $N400_n$ could be set to zero without loss of fit and the covariance between FD_{n-1} and $N400_{n-1}$ was strongly reduced. The latter is expected because the current model does not account for influences from words further back. Coefficients for predictability significantly affected measures on word n-1 and word n in the expected direc-

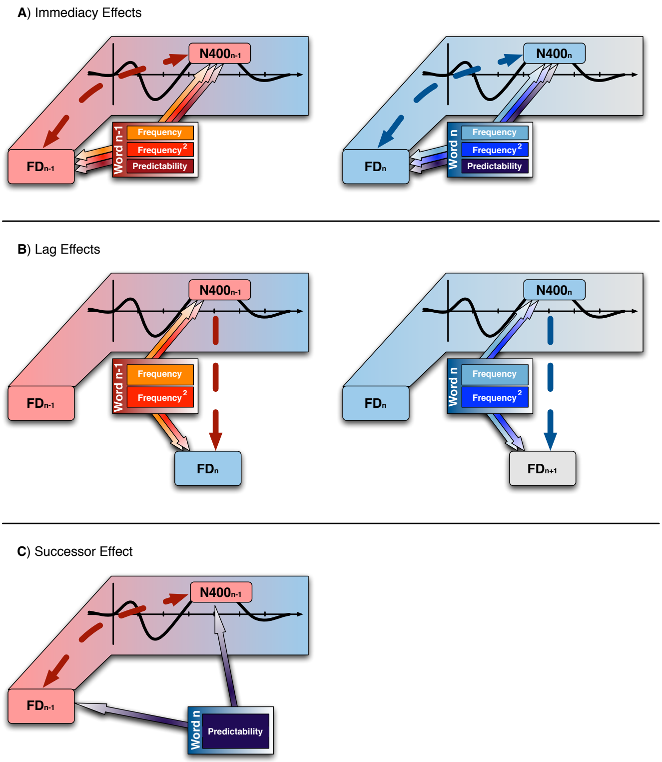


Figure 3.6: Predictor effects. Schematic illustrations of immediacy, lag, and successor effects (see also Tab. 3.2). Word properties frequency and predictability (solid arrows) exhibit influence on fixation durations (*FD*) and *N*400 amplitudes and absorb direct relations between the two measures (dashed arrows). Panel **A** visualizes, how the influence of frequency, frequency^2, and predictability accounts for the correlation between *FD* and *N*400 amplitudes associated with the same word (immediacy effects). Panel **B** shows how frequency explains the influence of *N*400 amplitude on *FD* on the next word (lag effects). Panel **C** sketches, how upcoming predictability accounts for common variance between *FD* and *N*400 amplitude both relating to a previous word (successor effect).

tion: Fixation durations were longer and N400 amplitudes larger as predictability decreased. Similarly, the quadratic trend of word frequency influenced measures on both words; the linear term of word frequency only revealed a statistical trend for $N400_{n-1}$

(Tab. 3.2: *Immediacy effect model*). In sum, including frequency and predictability in the path model accounted for the covariance between FD_n and $N400_n$ and largely reduced the covariance between FD_{n-1} and $N400_{n-1}$. Thus, frequency and predictability of words plausibly are a common source for the correlation between eye movement and EEG records.

While the correlation between fixation durations and N400 amplitudes could be traced to the immediate influence of word frequency and predictability on these measures, the lag effect (i.e., the influence of $N400_{n-1}$ on FD_n and of $N400_n$ on FD_{n+1}) was largely unaffected and still significant. In the *lag effect model*, word frequency was set to "spill over", that is to affect fixation durations on the next word. Specifically, connections from f_{n-1} and f_{n-1}^2 to FD_n and from f_n and f_n^2 to FD_{n+1} were included as predictors in addition to the paths of the *immediacy effect model* (see Fig. 3.6, panel ***B*** for a schematic illustration)[4]. The χ^2 statistic suggested a significant improvement in goodness of fit for the *lag effect model* compared to the *immediacy effect model* ($p < .01$). Importantly, lagged word frequency was sufficient to account for the influence of N400 amplitudes on the succeeding fixation: Neither the coefficient from $N400_{n-1}$ to FD_n nor the one from $N400_n$ to FD_{n+1} were reliable any more. Also the influence from FD_n on FD_{n+1} from the baseline model could be left out of the model. Significant path coefficients indicated that fixation duration was shorter, when the previous word was of high frequency. Concerning quadratic lag-frequency, only the path from f_{n-1}^2 to FD_n was significant.

Starting from the *baseline model*, all but one of the reliable connections between eye movements and ERPs were explained by frequency and predictability, exhibiting immediate and lagged influence. Only the correlation between FD_{n-1} and $N400_{n-1}$ remained significant. In a final path model we examined, whether this covariance could be ascribed to predictability of the upcoming

[4]Additional analyses revealed that predictability did not account for variance in the lag effect: Neither the influence from p_{n-1} on FD_n nor from p_n on FD_{n+1} were significant. Instead, these paths worsened the model fit and were therefore dropped.

word. Compared to the *lag effect model*, additional paths in this *successor effect model* defined influence from p_n on FD_{n-1} and $N400_{n-1}$ (Tab. 3.2; Fig. 3.5, panel ***B*** and Fig. 3.6, panel ***C***). χ^2 statistics confirmed an improved fit for this successor effect model compared to the lag effect model ($p < .01$). Including p_n reduced but did not eliminate the correlation between FD_{n-1} and $N400_{n-1}$. Thus, predictability accounted for common variance of fixation duration and N400 amplitudes of the previous word. The significant path from p_n to FD_{n-1} uncovered that fixation durations are longer when the next word is of high predictability. The path from p_n to $N400_{n-1}$ revealed a trend indicating, that N400 amplitudes are larger as well, when they are succeeded by a high predictability word. Finally, compared to the previous models, the influence of f_{n-1} on $N400_{n-1}$ was enhanced, as indicated by a significant coefficient.

3.3.5 Model fit

In the path models including frequency and predictability as exogenous variables, χ^2 statistics were significant, indicating that the observed variance-covariance matrix was not recovered with the model equations. It is well known, however, that for large sample sizes (as in the present data), the χ^2 statistic tends to reject otherwise acceptable models. The *lag* and *successor effects models* meet the conventional acceptability criteria of derived statistics that "correct" this shortcoming (Tab. 3.2). For instance, root mean square error of approximation (RMSEA) corrects statistics for sample size and model complexity; a model is considered reasonable when RMSEA is below .08 (Loehlin, 2004; Schlösser, Wagner, & Sauer, 2006). Values larger than .90 for various other fit indices lead to the same conclusion.

Model fitting was also strongly guided by theoretical considerations. Starting with a core set of predictors we improved the model by including additional predictors in a stepwise manner. The most parsimonious model (*immediacy effect model*) had a considerably poorer fit than the final ones (*lag* and *successor effect models*), as reflected for example in the substantially lower value of the Bayes-Schwartz Information Criterion (BIC, see Tab. 3.2). In this context, the primary purpose of the present path analyses was to trace relations between eye movements and ERPs to a common source. Therefore, we restricted our analyses to theoretically motivated links that might serve as a common source for the observed relations between fixation durations and N400 amplitudes. Word frequency and predictability lived up the expectation of being plausible candidates. The third candidate, word length, explained variance in only one of the measures (i.e., fixation durations) and was left out of the analyses for reasons of model parsimony[5].

3.4 Discussion

The comparison of eye movement and ERP data from two independent reading studies (i.e., Kliegl et al., 2006 and Dambacher et al., 2006, respectively) utilizing the same sentence material suggested strong relations between fixation durations and N400 amplitudes (Fig. 3.2 and 3.3). After synchronizing timelines of fixation durations from normal reading and N400 amplitudes from word-wise sentence presentation, the *baseline model* established the interdependence of these measures with words as units of analysis. In a second set of analyses, *immediacy*, *lag*, and *successor effects* were traced to the common influence of frequency and predictability in three successive path analyses. We will discuss the findings separately in the following section.

The *baseline model* revealed a correlation between fixation durations and N400 amplitudes, both relating to the same word. Longer fixation durations were associated with larger N400 amplitudes. In the *immediacy effect model*, frequency and predictability were identified as sources of this common modulation, as the inclusion of these variables accounted for the covariance between FD_n and $N400_n$, and reduced substantially the correlation between FD_{n-1}

[5]Word length did not affect N400 amplitudes of the present data set (Dambacher et al., 2006).

and $N400_{n-1}$. The fact that the latter was still significant presumably points to influences from words further back, which were not taken into consideration in the present analyses. This explanation predicts also other relations, e.g., an influence from p_{n-1} to $N400_n$, that was not significant. This could simply be due to insufficient statistical power. It may also mean that our explanation is not sufficient.

In summary, the immediacy effect model demonstrated, that frequency and predictability effects are similarly reflected in two different measures of word recognition: Fixation durations and N400 amplitudes are sensitive to lexical and post-lexical variables. This reveals that both measures are influenced by at least one common stage of word recognition, on which frequency as bottom-up and predictability as top-down variables act together. Given that fixation durations are strongly related to lexical processing, the correspondence between the two measures suggests that N400 amplitudes reflect online lexical processing as well, which is at odds with a purely post-lexical interpretation (e.g., Brown & Hagoort, 1993).

Another result points to a lexical role of the N400. Its peak latency at around 400 ms post-stimulus and its sensitivity to lexical and post-lexical variables denotes that word processing is not completed after a fixation of 200 or 250 ms, but unfolds even when the visual information is no longer accessible. The temporal overlap of N400 amplitudes and fixation durations on the next word suggested a relation between the two measures across word boundaries. Considering eye movement studies showing that fixation durations increase, when the previous word was of low frequency (Kliegl et al., 2006; Schroyens et al., 1999), we tested, whether the temporal coincidence of the ERPs and eye movements accounts for this lag effect. We examined the influence of N400 amplitudes on fixation durations on the consecutive word in the *baseline model*. Indeed, larger N400 amplitudes entailed longer fixation durations. In the *lag effect model*, this relation was traced to the influence of word frequency: Low frequency words elicited larger N400 amplitudes and, at the same time, caused longer fixation durations on the next word. The coherence of N400 amplitudes and longer subsequent fixation durations provides a neurophysiological correlate for the lag effect during reading with frequency as mediating source.

A possible interpretation of this result is reduced efficiency of word recognition during the processing of low frequency words. While lexical access of high frequency words happens fast and automatically within the first 200 ms post-stimulus, identification of low frequency words is much slower and ranges into the N400 time window (Dambacher et al., 2006). Thereby, large N400 amplitudes arise at a time, when the eyes during normal reading usually fixate the next word. This temporal coincidence may cause interference, such that increased N400 activity reduces resources of word recognition and therefore inhibits lexical processing of a fixated word. Consequently, lexical access of a stimulus following a low frequency word is delayed and fixation durations are prolonged.

A second interpretation is even more in line with the cognitive lag-hypothesis assuming that lexical processing continues after saccade execution (Bouma & de Voogd, 1974; Kolers, 1976). Kolers proposed that eye movements are triggered largely independently from word recognition, but that the cognitive systems can intervene when necessary. The present results can be construed in terms of this approach: Concerning eye movements, the word recognition system estimates the additional time necessary to complete word processing when a low frequency word is encountered during normal reading. Accordingly, saccade execution is inhibited and therefore a fixation is prolonged. However, due to the relative slowness of cognitive processes, the inhibition arises with a delay; the increase of inspection time happens to occur only during the next fixation, which presumably is on the next word (e.g., Engbert et al., 2005, for an implementation of this proposal in a computational model of saccade generation during reading). In ERPs, the N400 is known as a sensitive measure for the difficulty of word processing. Also strength of saccade inhibition - or additional fixation time - is presumably calculated on the basis of word difficulty. Thus, it is reasonable to assume that saccade inhibition is to some degree proportional to N400 amplitudes. When saccade inhibition arises during the next fixation, due to temporal delay, inspection time on this word is proportional to the N400 amplitude on the previous stimulus.

The present evidence for the lag effect holds important implications for models of eye movement control in reading. Model architecture has to permit fixation durations to be influenced by properties of a previously fixated word. A mechanism similar to the cognitive lag hypothesis is implemented in SWIFT, a model based on parallel word processing (Engbert et al., 2002, 2005). In SWIFT, an autonomous timer initiates saccades after a randomly chosen interval. When a difficult word is encountered, the lexical processing system is able to inhibit the saccade generator, which entails an increase of fixation duration. However, because the cortical word recognition processes are much slower than the fast brainstem saccade generator, this inhibition process is delayed (e.g., $\tau = 375.7$ ms, Engbert et al., 2005) and potentially arises only during the next fixation. In that case, inspection durations following the critical fixation on a difficult word are prolonged. In contrast, E-Z Reader (Reichle et al., 1998, 2003), a serial attention-shift model of eye movement control, accounts for spillover effects in terms of reduced parafoveal preview rather than in terms of ongoing processing: When word n has been accessed, attention is immediately shifted to word n+1, while saccade execution, which is partially independent from attentional shift, usually occurs later. Thus, fast processing of word n grants more time to process word n+1 parafoveally. Under special situations it is also possible in E-Z Reader that word n+1 is fixated before word n is lexically accessed. However, such "premature saccades" are unlikely and would often result in a regression back to the word that is being processed (Pollatsek et al., 2006). Instead, lexical access even of difficult words is usually completed, before a saccade is executed (see also Fig. 4 in Reichle et al., 2003); consequently, for E-Z Reader spillover due to incomplete processing is presumably not a determinant critically influencing reading behavior. Evidence for lag effects due to ongoing lexical processing of previous words challenges the plausibility of this implementation on a neurophysiological level.

In the final analysis, we addressed the potential influence of an upcoming word on fixation durations and N400 amplitudes. In eye movement research, there is some controversy whether lexical or - if at all - only sublexical information can be extracted from a parafoveal, not yet fixated stimulus during normal reading (Kennedy & Pynte, 2005; Rayner et al., 2003; Vitu et al., 2004). We will not enter this debate here, because parafoveal view was not possible in the present ERP experiment, as sentences were displayed word-by-word. Thus, parafoveal preview cannot be responsible for common modulation of the two measures, neither for successor nor for lag effects (in terms of E-Z Reader). Nonetheless, in the *successor effect model*, predictability accounted for covariance of fixation durations and N400 amplitudes on the previous word. For eye movements, Kliegl et al. (2006) had already reported successor effects with longer fixation durations, when the subsequent word was of high predictability. They proposed that the high predictability word could be retrieved from memory without being fixated and that therefore inspection durations on the previous word increased. In the ERP data, also N400 amplitudes tended to be larger when they preceded a high predictability word; note that N400 amplitudes *following* a high predictability word usually are smaller. This suggests that participants made predictions about the upcoming stimulus, which was reflected in additional neural activity on the previous word. Strong predictions could be made, whenever contextual constraint was high, whereas it was hardly possible to predict the upcoming word in a low constraining context. Considering that the SOA of 700 ms in the present ERP experiment provides unnaturally much time, this effect might even be stronger than in normal reading situations. Admittedly, this interpretation is speculative and needs to be confirmed in further experiments, since the influence of predictability on the previous N400 amplitude only revealed a trend. There is some support for this interpretation from reports of N400 effects on the word before a critical stimulus. DeLong et al. (2005) varied predictability of nouns, half of them starting with a vowel and half of them with a consonant. The nouns were embedded in word-wise presented sentences and were preceded by the phonologically correct article *an* or *a*, respectively. N400 amplitudes measured on the article were (inversely) correlated with the predictability of the subsequent noun; they were larger, when the article *an* was presented, while a consonant-initial noun was expected, and vice versa. Similarly, articles or adjectives, whose gender mismatches the expected succeeding noun, evoked larger N400 or P600 amplitudes (Van Berkum et al., 2005; Wicha, Bates, et al., 2003; Wicha, Moreno, & Kutas, 2003; Wicha et al., 2004). These results, together with the present findings, reveal that readers make online predictions about the identity of an upcoming stimulus, even in the absence of parafoveal visual information, and that these predictions are reflected in fixation durations as well as in ERPs (Kliegl et al., 2006; Kutas et al., 2006).

The present approach of comparing eye movements and ERPs from independent experiments has been used in previous studies. For example, Raney and Rayner (1993) examined changes in eye movements and ERPs, when small text passages were read for the second time. They concluded that re-reading affects multiple lower- and higher-level determinants reflected in both measures. Sereno et al. (1998) collected eye movement data during normal reading using 288 target words embedded into single-line sentences. ERPs were measured employing the same target words together with 192 nonwords in a lexical decision task. The authors proposed a timeline for word recognition on the basis of their results. However, the usage of different stimuli (Raney, 1993; Raney & Rayner, 1995) or different tasks (Sereno et al., 1998) eventually reduces the comparability of the data. As far as we know, the present paper is the first to relate fixation durations and N400 amplitudes from experiments with identical stimuli and tasks to each other and therefore provides optimal data comparability.

Of course, one difference is still that eye movements are recorded in normal reading situations, while sentences in ERP settings are presented word-wise with long intervals between stimuli. Critical researchers doubt that data assessed with this procedure reflect normal reading processes (for a discussion see e.g., Rayner, 1998). This assumption, however, is premise not only for the validity of our conclusions, but also for the generalizability of numerous previous experiments utilizing RSVP paradigms. Although some reports suggest good correspondence between results of RSVP and more natural settings (Hagoort & Brown, 2000a, 2000b; Kutas et al., 1988; Van Berkum, 2004), this issue has to be explicitly addressed in the future. For instance, SOAs in RSVP experiments should be approximated to natural reading rate of four or five words per second. On the one hand, this would prevent ERP data from being contaminated by eye movements and variable fixation onsets. Nevertheless, researchers would have to face the problem of component overlap - unless they do not limit their analyses to sentence-final words, where sentence wrap-up effects reduce generalizability. Very careful selection and strict control of the stimulus material could override this problem. On the other hand, shortening of SOAs would provide evidence, whether word recognition differs at various reading rates. In fact, some studies indicate that SOA manipulation affects language-related ERPs (Hagoort & Brown, 2000a; Van Petten, 1995; Van Petten & Kutas, 1987).

Another straightforward way to examine the soundness of RSVP results and particularly to compare fixation durations and ERPs directly is simultaneous recording of eye movements and EEG signals during normal sentence reading. Both measures are then collected from a subject within the same experiment in one setting. Despite various methodological and technical problems, attempts on this innovative method are promising (Dimigen et al., 2006).

Conclusions

We jointly analyzed eye movements and ERPs and found that fixation durations and N400 amplitudes during sentence reading substantially relate to each other. Both measures are modulated by the same word properties and therefore are presumably influenced by common processes of word recognition. The present paper demonstrates how different methods of psycholinguistic research can be combined and thereby incorporates advantages of both measures. We are confident that future research will strongly benefit from cross-linking eye movements and ERPs.

Acknowledgments

This research was supported by DFG grant KL 655-6. We are grateful to Arthur Jacobs for mediating the use of the ERP lab at the Catholic University of Eichstätt-Ingolstadt. We also thank Petra Grüttner and Markus Hofmann for data acquisition, Mario Braun for technical support, as well as two anonymous reviewers for their valuable and constructive comments.

Copyright

4 The interplay of word frequency, predictability, and SOA in sentence reading: Evidence from event-related potentials

Michael Dambacher[1,2], Mario Braun[2], Kristin Göllner[1], Arthur M. Jacobs[2], and Reinhold Kliegl[1]

[1] Universität Potsdam, Germany
[2] Freie Universität Berlin, Germany

Running Head: Frequency, predictability, and SOA

Abstract

In psycholinguistic research, word frequency is commonly regarded as major bottom-up determinant for the speed of lexical access whereas the temporal role of top-down processes is debated. Context-based predictions about incoming words may affect lexical or solely post-lexical phases of word recognition. In two experiments, we used event-related potentials (ERPs) to delineate bottom-up and top-down processes during sentence reading. Frequency and predictability were independently manipulated on target words embedded in constant sentence frames. In Experiment 1, sentences were displayed word by word with an SOA of 700 ms, compatible with the timing of a large number of ERP reading studies. Experiment 2 approximated normal reading speed of four to five words per second with an SOA of 280 ms. In both experiments we observed larger N400 amplitudes for low than high predictability targets, irrespective of frequency, as well as an interaction of frequency and predictability on ERP amplitudes within 200 ms post-stimulus. Furthermore, the timeline was sensitive to presentation rate: In Experiment 1 (SOA700), frequency effects emerged with a shorter latency for high (90-140 ms) than for low predictability words (240-290 ms). Experiment 2 (SOA280) yielded frequency effects for both predictability conditions in an intermediate epoch (140-190 ms). The results suggest that early lexical processes in sentence reading are responsive to bottom-up and top-down information and that time available for word processing and prediction modulates this interaction. We offer an approach reconciling the present findings in an interactive activation framework.

4.1 Introduction

Arguably, one of the most basic questions of psycholinguistic research is how long it takes to identify a word. Generally, it is assumed that at this moment of lexical access, the mental representation of a word is retrieved from memory and its meaning becomes available. However, despite decades of research, the time course of word identification is not fully understood, even with respect to two major determinants, namely word frequency and word predictability from prior context. Here we show that the timeline of lexical access depends on the interaction of these variables, consistent with assumptions about the interplay of bottom-up input and top-down expectations. Furthermore, differences between ERPs measured with a conventionally slow stimulus onset asynchrony (SOA) of 700 ms and ERPs measured with an SOA of 280 ms, that is approximating normal reading speed, indicate that word recognition critically depends on the presentation rate. These results from slow and normal presentation rates are compatible with predictions derivable from an interactive activation framework of word recognition, and they strongly limit the generalizability of data obtained with artificial reading rates to those of normal reading.

4.1.1 Frequency: Bottom-up processes and lexical access

According to the classical concept of information processing, visual perception is predominantly driven by bottom-up sensory input. Incoming signals travel from the retina to primary visual areas from where they are hierarchically transmitted to higher cortical regions. Ascending this hierarchy, stimulus processing becomes increasingly complex and elaborated until an object is eventually recognized (see Churchland et al., 1994 for a discussion). Consistent with this view, word recognition and specifically lexical access has often been regarded as an automatic bottom-up process (Fodor, 1983; Kintsch & Mross, 1985). Therefore, the identification of a written word depends first and foremost on characteristics of the visual input. In fact, one of the most dominant item properties influencing processing speed is a word's frequency of occurrence in a certain language. Reaction times as well as reading fixations point to faster lexical access for high than for low frequency words (Forster & Chambers, 1973; Inhoff & Rayner, 1986; Kliegl et al., 2004, 2006; Rayner, 1998; Rubenstein et al., 1970; Taft, 1979).

Models of word recognition incorporate the idea of word frequency as the primary agent for the speed of lexical access. For instance, the *Bin Theory*, a serial model of word recognition, implements mental word representations as being sorted in lists (so-called "bins") according to their frequency. The bins are scanned in descending order and when an entry matches the visual input, the information is used to access a fuller description of the word (Forster, 1976; Murray & Forster, 2004). Parallel models, on the other hand, grant an activation advantage for high over low frequency words. In the *Interactive Activation Model* high frequency words hold a higher resting level (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982), while in the *Logogen Model* a virtual threshold for lexical access is lower for high than for low frequency words (Morton, 1969).

Considering the central role of word frequency, the occurrence of the first frequency *effect* in event-related potentials (ERPs) is often regarded as a fingerprint for the achievement of lexical access. Several ERP studies documented differential activation for low and high frequency words within the first 200 ms after presentation (Braun et al., 2009; Dambacher et al., 2006; Hauk & Pulvermüller, 2004; Hauk et al., 2006; Penolazzi et al., 2007; Sereno et al., 1998, 2003). In line with serial as well as parallel views of word recognition, these results suggest that lexical access relies on rapid bottom-up processing of visual properties.

4.1.2 Predictability: Top-down processes and lexical access

Despite the undisputed importance of bottom-up flow of information, other evidence increasingly indicates that a purely hierarchical feedforward perspective cannot fully reproduce the functionality of perception: Sensory input is not passively handed over from low to higher brain regions. Instead, active predictions about upcoming sensory events continuously influence the incoming signal and interact as top-down projections with earliest perceptual processes (Bar, 2007; Carlsson et al., 2000; Churchland et al., 1994; Corbetta & Shulman, 2002; Engel et al., 2001; Enns & Lleras, 2008; Gilbert & Sigman, 2007; Kastner et al., 1999; Kveraga et al., 2007; McClelland & Rumelhart, 1981; Mechelli et al., 2004; O'Connor et al., 2002; Somers et al., 1999; Williams et al., 2008).

In word recognition, top-down processes potentially play a major role. In particular, the anticipation of an upcoming word may influence processing of an input stimulus (see Altmann, 1997; Altmann & Mirkovic, 2009; Elman, 2004; Kliegl et al., 2006; Pickering & Garrod, 2007). For instance, readers presented with a constraining context in a cloze task (e.g., *The Earth takes 365 days to orbit the...*) will often be able to interpret the sentence fragment and to predict the next stimulus, even if it is not displayed. Apparently, visual bottom-up information is not imperative for the activation of mental word representations when sufficient context information grants the anticipation of an upcoming stimulus. The critical question is, however, when the expectation of a specific stimulus interacts with the incoming visual information during reading and, depending on whether the prediction was correct or wrong, helps or hurts word processing.

In general, there is agreement about the facilitative role of supporting contextual information for language comprehension. Reaction times as well as eye movement data from reading point to faster processing of high than of low predictability words (e.g., Ashby et al., 2005; Calvo & Meseguer, 2002; Duffy et al., 1989; Ehrlich & Rayner, 1981; Fischler & Bloom, 1979; Kleiman, 1980; Kliegl et al., 2004, 2006; Rayner et al., 2004; Rayner & Well, 1996; Schuberth & Eimas, 1977; Stanovich & West, 1983; West & Stanovich, 1982). However, there is uncertainty about the temporal locus of context effects, namely whether top-down predictions have an impact on early word recognition, and particularly, on lexical access. There are two alternative views: On the one hand, lexical access is assumed to be a rapid and automatic process that does not involve contextual information. In serial approaches, lexical access is solely driven by bottom-up information. Contextual information operates on a later level influencing post-lexical integration of semantic information into a larger discourse (Fodor, 1983; Forster, 1976; Kintsch & Mross, 1985; Murray & Forster, 2004). On the other hand, predictions are regarded as top-down projections that may affect early processing stages in word recognition. This view is compatible with parallel approaches incorporating simultaneous influences of context and stimulus information at pre-lexical phases. In the *Logogen Model* (Morton, 1969) as well as in the *Interactive Activation Model* (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982), a supportive context increases the activation level of high predictability words and therefore facilitates lexical access. Accordingly, word identification does not only depend on the visual stimulus but can also be influenced by expectations about the identity of the incoming signal.

Behavioral data lend support to both perspectives. Some findings suggested context effects on a purely post-lexical level (e.g., Burgess et al., 1989; Lucas, 1987; Onifer & Swinney, 1981; Swinney, 1979) whereas others pointed to rapid contextual influence on lexical access (Glucksberg et al., 1986; Schvaneveldt et al., 1976; Simpson, 1981; Tabossi, 1988; see Simpson, 1994 for a review). There was hope that the high temporal resolution of ERPs may provide further constraints on these interpretations. In particular, the N400 component, a negative deflection peaking at around 400 ms after stimulus onset, revealed larger amplitudes for low than for high predictability words in numerous studies (Kutas & Hillyard, 1980; for reviews see Barber & Kutas, 2007; Kutas et al., 2006). Given its relatively late appearance in the time course of word identification, the N400 was often considered as a pure indicator of post-lexical processing (e.g., Brown & Hagoort, 1993; Holcomb, 1993; Misra & Holcomb, 2003). However, the exact nature of the N400 is not fully understood yet, since other reports pointed to its sensitivity to lexical processes (e.g., Dambacher et al., 2006; Deacon et al., 2000, 2004; see also Van Petten, 1995).

4.1.3 Predictability and pre-activation

While the question about the temporal role of predictability in word recognition is still unresolved, recent findings reinforced the idea of top-down influences on early levels of language processing. Specifically, with the visual-world paradigm one can demonstrate that predictions about upcoming words direct behavior very rapidly. Participants listen to stories while they are viewing a display with several objects. In a scene containing, for example, a full glass of beer and an empty glass of wine (among other elements), the fragment *the man will drink all of...* entailed more anticipatory saccades to the glass of beer than to the wine glass. The pattern was reversed when subjects heard the sentence *the man has drunk all of...* (Altmann & Kamide, 2007; see also Altmann & Kamide, 1999; Altmann & Mirkovic, 2009; Kamide, Altmann, & Haywood, 2003; Kamide, Scheepers, & Altmann, 2003). These data suggest that contextual information is interpreted even prior to the appearance of a critical stimulus, and that knowledge-based experience guides expectations about forthcoming information.

Further, electrophysiological results indicated that specific representations of highly predictable words are pre-activated before they are encountered. DeLong et al. (2005) presented sentences biasing high predictability of either a vowel-initial or a consonant-initial target word (e.g., *airplane* or *kite*). Each target was preceded by the corresponding indefinite article (*an* or *a*). N400 amplitudes on the article were enhanced, when its phonological form mismatched the initial phoneme of the expected, but not yet visible target word (e.g., *an*, when *kite* was the high predictability noun). Thus, form-specific information about predicted words appears to be available before they are visually presented (see also Otten et al., 2007; Otten & Van Berkum, 2008; Van Berkum et al., 2005; Wicha, Bates, et al., 2003; Wicha et al., 2004).

Together, these findings suggest that the online interpretation of sentence messages affords the anticipation of words. Specific predictions affect behavior even prior to the onset of a critical stimulus. Consequently, there is room for potential interactions between top-down information and early sensory input, such that pre-activated representations of expected words affect bottom-up stimulus processing shortly after the incoming signal is available (cf., Gilbert & Sigman, 2007; Grossberg, 1999; Mumford, 1992; Ullman, 1995).

4.1.4 Present studies

In the present ERP studies, we addressed the temporal relation of top-down expectations and bottom-up input in reading by examining the influence of word predictability on frequency-based indices for lexical access. We hypothesized that if contextual facilitation is of a purely post-lexical nature, as put forward by serial approaches (e.g., Murray & Forster, 2004), lexical access will be independent of predictability. In contrast, the joint influence of frequency and predictability at early latencies (i.e., specific patterns of interactions) would point to the sensitivity of lexical processing to both bottom-up and top-down processes.

Stimuli consisted of pairs of low and high frequency target words that were embedded in neutral sentence frames. Target predictability was manipulated by a preceding context sentence biasing expectancy either of the low or of the high frequency word. Thus, frequency and predictability varied orthogonally in otherwise identical sentence frames.

Experiment 1 followed up previous work on the influence of contextual information in word processing. Neutral sentences were presented word by word with a stimulus onset asynchrony (SOA) of 700 ms, mirroring the timing used in the majority of ERP reading studies. This timing, however, is much slower than the normal processing rate of written language. During natural left-to-right reading, the eyes fixate around four to five words per second. Since the influence of input rate on the interplay of bottom-up and top-down processes in word recognition is largely unknown, the second experiment examined whether the results from artificial presentation rates of Experiment 1 generalize to the timeline of word recognition in a more normal reading condition. Thus, we accelerated presentation rate in Experiment 2 and approximated natural reading speed by employing an SOA of 280 ms.

4.2 Experiment 1

Earlier ERP research either examined influences of frequency or of predictability, but rarely considered the joint impact of both determinants. As one exception, Van Petten and Kutas (1990) made use of ordinal word position in sentences as a proxy for increasing contextual information and reported an interaction of frequency and position on the N400 component. Indeed, the influence of word position could be linked to predictability in a later experiment with a large sentence corpus containing norms of frequency and predictability for each single word (Dambacher et al., 2006). Accordingly, this study confirmed the interaction of frequency and predictability on N400 amplitudes. Contextual influences were absent in an earlier interval in which P200 amplitudes were gradually sensitive to word frequency norms from the high frequency range.

Evidence for early context effects was found by Penolazzi et al. (2007) who orthogonally manipulated frequency and predictability in sentences. In the time window from 110 to 130 ms, word length interacted both with frequency and with predictability, but notably, there was no interaction of frequency and predictability throughout the ERP time course. Thus, despite the indication of early contextual processing, these findings do not point to mutual influences between top-down and bottom-up processes. Instead, the authors argued that frequency-driven lexical access and context-based semantic integration are rapid and parallel processes that operate on functionally dissociable systems.

Interactive patterns of context with early lexical processes were demonstrated by Sereno et al. (2003). From 132 to 192 ms, ERPs to ambiguous words were similar to those of low frequency control words, when context biased their low frequency meaning. Conversely, ERP amplitudes resembled those of high frequency control words in a neutral context that was believed to activate the high frequency meaning of the ambiguous stimulus. Therefore, it was proposed that context information supported the selection of the appropriate meaning early in the time course (see also Van Petten, 1995). Furthermore, a marginal context effect on low frequency controls pointed to contextual influences on lexical access of unambiguous words.

In summary, the role of frequency and predictability in word recognition is not yet resolved. Contextual influence on lexical processing has been found early and late in the time course, but purely additive effects have been reported as well. Employing highly controlled sentence materials with strong experimental manipulations of frequency and predictability we aimed at contributing to a clearer picture of the relation between top-down and bottom-up processes in reading. In general, an interaction of frequency and predictability early in the ERP time course would indicate the sensitivity of lexical processes to contextual top-down information. Specifically, according to parallel models of word recognition, a supportive context grants a temporal advantage for lexical access (McClelland & Rumelhart, 1981; Morton, 1969; Rumelhart & McClelland, 1982). Thus, the first frequency effect as an index for lexical access may appear earlier for high than for low predictability words. In contrast, serial models predict facilitative context effects on a post-lexical level (Fodor, 1983; Forster, 1976; Murray & Forster, 2004). Accordingly, early ERP frequency effects should be independent of word predictability.

4.2.1 Methods

4.2.1.1 Participants

Thirty-two participants (28 female; 28 right-handed; mean age: 23.34, SD: 6.01) received course credit for participation. All were

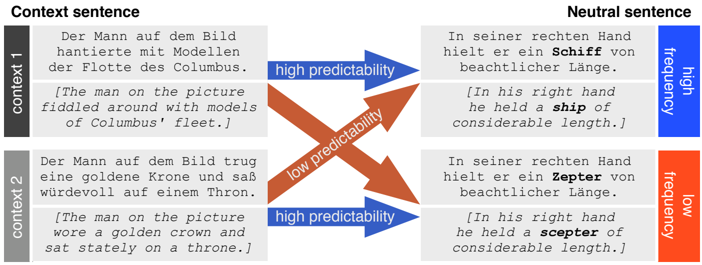


Figure 4.1: Stimulus example. Pairs of low and high frequency target words were embedded in neutral sentence frames. A preceding context sentence triggered high predictability either of the high or of the low frequency target, while its counterpart was of low predictability. A total of 144 sentence units set up a two-by-two factorial manipulation of frequency and predictability.

native German readers and had normal or corrected-to-normal vision. They reported no history of neurological diseases.

4.2.1.2 Materials

A total of 144 sentence units (*Potsdam Sentence Corpus 3*; see Appendix B) formed the stimulus materials (see Fig. 4.1 for an example). Each unit comprised two context sentences and one neutral sentence. Pairs of high (e.g., *ship*) and low frequency (e.g., *scepter*) target words were embedded in the neutral sentences. Predictability on target words was triggered by the prior context sentence: High frequency targets were of high predictability in context 1 and of low predictability in context 2. In turn, low frequency targets were of low predictability in context 1 and of high predictability in context 2. Thus, we realized an orthogonal manipulation of frequency and predictability within otherwise identical sentences frames. The randomized stimuli were divided into lists according to a Latin square design such that every participant was presented with only one version of each sentence unit. Further details on the stimuli are depicted in the following paragraphs (see also Tab. 4.1).

Frequency norms. Target word pairs consisting of a high and a low frequency open-class word were selected from the DWDS data base (Geyken, 2007). High frequency words comprised lemma and word form frequencies greater than 100 and 10 occurrences per million, respectively. For low frequency words, lemma and word form frequencies amounted to less than 10 per million. High and low frequency words from one pair were members of the same class (i.e., nouns, verbs, or adjectives) and, where possible, shared the same number of letters; they differed in one letter in 19 of the 144 cases, in two letters in 4 cases and in three letters in 1 case. Target length varied between three and eight letters and was matched across conditions.

Neutral sentences. A neutral sentence was then constructed for each of the 144 target pairs. This sentence was identical for the two words from one pair. Targets occurred at position six, seven, or eight and were always followed by at least two more words, such that they never appeared at the sentence-final position. Neutral sentence length ranged from 9 to 12 words (mean: 10.47; SD: .82).

Context sentences. Two context sentences were created for each neutral sentence. Context 1 biased high predictability of the high frequency target word, while the low frequency word was of low predictability. Context 2 triggered high predictability of the low frequency word, while the high frequency word was of low predictability. Context sentences had a length of 3 to 18 words (mean: 11.48; SD: 2.81).

Predictability norms. A total of 151 volunteers took part in an independent cloze task for the collection of predictability norms; none of them participated in the EEG experiments. Every participant worked through a part of the stimulus materials, such that each sentence unit was rated by at least 30 judges. For the cloze procedure, stimuli were divided into two lists so that each subject was presented with only one context together with the correspond-

Table 4.1: Descriptive statistics of target words.

	High frequency				Low frequency			
	High pred.		Low pred.		High pred.		Low pred.	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Word form freq.	155.58	194.63	155.58	194.63	3.76	2.08	3.76	2.08
Lemma freq.	362.19	875.30	362.19	875.30	4.87	2.68	4.87	2.68
Predictability	.84	.13	.01	.02	.83	.13	.01	.02
Length	5.36	1.16	5.36	1.16	5.32	1.11	5.32	1.11
Word position	6.94	.76	6.94	.76	6.94	.76	6.94	.76
Word class	noun pairs: N=92; verb pairs: N=37; adjective pairs: N=15							

ing neutral sentence. Sentences were visually presented up to the word prior to the target. Participants were then asked to write at least one and no more than three words probably occurring on the next position. Predictability was computed as proportion of participants correctly predicting the target word with one of their answers. Sentence units entered stimulus materials only if both low and high frequency words reached cloze values larger than .5 in their high predictability contexts and, at the same time, did not exceed .1 in their low predictability conditions.

4.2.1.3 Procedure

Participants were seated at a distance of 60 cm from the monitor in a dimly lit room and were asked to silently read the two-sentence stories for comprehension. A trial started with the message "Bereit machen..." *["Get ready..."]* for 1000 ms, followed by a 500 ms blank screen. A context sentence was then displayed in its entirety in one or two lines until participants pressed a button. Thereafter, a fixation cross (preceded and followed by 500 ms blank screens) indicated for 1000 ms the required fixation position in the center of the monitor. The stimuli of the neutral sentence together with their adjacent punctuation were then presented word by word (RSVP) with a stimulus onset asynchrony (SOA) of 700 ms (i.e., 250 ms stimulus duration; 450 ms blank screen). After another 500 ms blank, either the next trial was initiated (66.67%) or a three-alternative multiple-choice question tested sentence comprehension (33.33%). Questions referred equally often to the content of the context and of the neutral sentence, but never to the target word itself.

Participants were asked to avoid eye movements and blinks during the phase of word-wise sentence presentation. Eight practice trials familiarized them with the task; they took a short break after half of the main experiment. Sentence units (font: Courier New; size: 18pt) were presented in black on a white background and in randomized order.

4.2.1.4 Apparatus

Stimuli were presented on a Belinea 21-inch monitor (resolution: 1024 x 768 pixel; refresh rate: 100 Hz) controlled by a PC (AMD Sempron 2600+; 1.83 GHz; Windows XP Professional). A 64-channel elastic electrode cap (ElectroCap Int.) and a 64-channel amplifier (Porti-S/64, TMS Int.) were used to assess EEG data, which were recorded on another PC (Pentium III, 1.0 GHz; Linux).

4.2.1.5 EEG recording

EEG data were recorded from 50 scalp locations (Fp1, Fp2, AF3, AFz, AF4, F7, F5, F3, F1, Fz, F2, F4, F6, F8, FC5, FC3, FCz, FC4, FC6, T7, C5, C3, C1, Cz, C2, C4, C6, T8, CP5, CP3, CPz, CP4, CP6, P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO7, PO3, POz, PO4, PO8, O1, Oz, O2) corresponding to the 10/20 international system. Impedances were kept below $10k\Omega$. All scalp electrodes and one channel on the right mastoid (M2) originally referenced to the left mastoid (M1) were re-referenced offline to the average of scalp electrodes. Two horizontal and two vertical (above and below the left eye) EOG electrodes recorded bipolarly oculomotor signals and blinks. Data continuously recorded with a sampling rate of 512 Hz and were down-sampled offline to 256 Hz. Amplifier settings cut of frequencies below .01 and above 100 Hz online. Data were bandpass filtered offline from .1 to 30 Hz (24dB; 50 Hz notch).

4.2.1.6 Data processing and analyses

EEG data contaminated by muscular artifacts and drifts were rejected offline via visual inspection. Independent component analysis (Vision Analyzer, Brain Products GmbH, Germany) was used to remove oculomotor artifacts and blinks. Additionally, an automatic algorithm rejected segments with an absolute amplitude value larger than 90 μV in at least one channel. The continuous EEG signal was divided into epochs from 200 ms before and 700 ms after target word onset. Data were corrected relative to a 200 ms pre-stimulus baseline. Artifact correction resulted in a loss of 3.54% of target epochs (low frequency - low predictability: 3.04%; low frequency - high predictability: 3.39%; high frequency - low predictability: 4.77%; high frequency - high predictability: 2.95%). From the remaining data, single-subject average ERPs were generated for each condition.

For analyses, mean ERP amplitudes were computed in five successive time windows, i.e., 50-90 ms, 90-140 ms, 140-190 ms, 190-240 ms, and 240-290 ms. N400 amplitudes were examined in the epoch from 300 to 500 ms. Global analyses of variance (ANOVAs) with within-subject factors frequency (2), predictability (2), and electrode (50) were calculated in each of the time windows. Additionally, frequency effects for low and high predictability words were examined in separate ANOVAs with the factors frequency (2) and electrode (50). Note that the average reference sets mean amplitudes across all scalp electrodes to zero, such that only effects in interaction with the factor electrode are meaningful in these ANOVAs. Main effects of electrode are not reported because they are not of theoretical interest.

Results of the global ANOVAs were scrutinized in local post-hoc analyses on electrode clusters after grouping the 50 scalp electrodes into nine regions according to a grid of three sagittal (left, midline, right) and three coronal (anterior, central, posterior) fields (see

Fig. 4.2). ERP amplitudes were collapsed across electrodes in each region. In all ANOVAs, the Huynh-Feldt correction was applied to adjust degrees of freedom (rounded down) and P-values for violations of the sphericity assumption.

4.2.1.7 Reduction of subject sample

Surprisingly, visual inspection of grand averages from the 32 subjects suggested amplitude differences in an interval prior to the analyzed epochs from 50 ms onwards. Starting shortly before stimulus onset up to approximately 50 ms post-stimulus, ERP amplitudes at frontal sites were more negative for high than for low frequency words in the low predictability condition; the pattern was reversed for high predictability words (see Fig. 4.5, panel ***A***). Indeed, an ANOVA with the factors frequency (2), predictability (2), and electrodes (50) in the epoch from -10 to 50 ms confirmed a significant three-way interaction [$F(5, 163) = 2.879$; $P = .014$]. Although the subsequent interval from 50 to 90 ms revealed no significant amplitude differences, we were concerned about the possibility that differential brain-electrical activity around stimulus onset propagated forward in time and distorted the later ERP course.

To eliminate this possible confound and to run conservative tests on the timeline, data from 12 subjects yielding the strongest amplitude differences from -10 to 50 ms (Fig. 4.5, panel ***C***) were precluded in the following analyses. Exclusion criteria and possible reasons for effects around stimulus onset are discussed below. Importantly, the pattern of critical results did not change for the entire sample of 32 subjects (see Appendix C). Yet, the 20 subjects entering analyses provided a set of uncontaminated data; the ANOVA in the interval from -10 to 50 ms on this reduced sample did not reveal any significant effects on ERP amplitudes [frequency x electrode: $F(3, 71) = .540$; $P = .696$; predictability x electrode: $F(3, 67) = 1.417$; $P = .241$; frequency x predictability x electrode: $F(5, 105) = .394$; $P = .869$; (Fig. 4.5, panel ***B***)].

4.2.2 Results

Figure 4.2 shows grand average ERP curves for the four experimental conditions of frequency (low/high) and predictability (low/high) on 50 scalp electrodes. Target words evoked a prominent positive component at posterior sites peaking after 110 ms. A negative component at 180 ms was followed by a broad positive peak at around 280 ms and finally a negative deflection (N400 component).

4.2.2.1 Global analyses

Results of ANOVAs with frequency (2), predictability (2), and electrodes (50) as within-subject factors in five consecutive time windows as well as in the N400 epoch are listed in Table 4.2. The table also shows results of separate ANOVAs on frequency (2) and electrode (50) within low and high predictability categories in the intervals.

In the epoch from 50 to 90 ms no effects including the factors frequency or predictability were significant (all Ps $> .10$). In contrast, from 90 to 140 ms, the interaction of frequency x predictability x electrode was reliable ($P = .020$). ANOVAs within predictability classes uncovered a significant frequency x electrode interaction for high ($P = .009$) but not for low predictability words ($P = .454$). Amplitudes in the high predictability condition were more pronounced for low than high frequency targets at posterior electrodes. The subsequent intervals from 140 to 190 ms and from 190 to 240 ms did not yield reliable amplitude differences (all Ps $> .05$). From 240 to 290 ms, frequency ($P = .012$) interacted with electrode. In this time window, within-predictability class ANOVAs revealed a significant frequency x electrode effect for low ($P = .012$) but not for high predictability ($P = .171$) words. Here, in the low predictability condition, amplitudes at posterior channels were more pronounced for high than for low frequency targets. Finally, in the epoch from 300 to 500 ms, an interaction of predictability x electrode ($P < .001$) pointed to a strong N400 predictability effect.

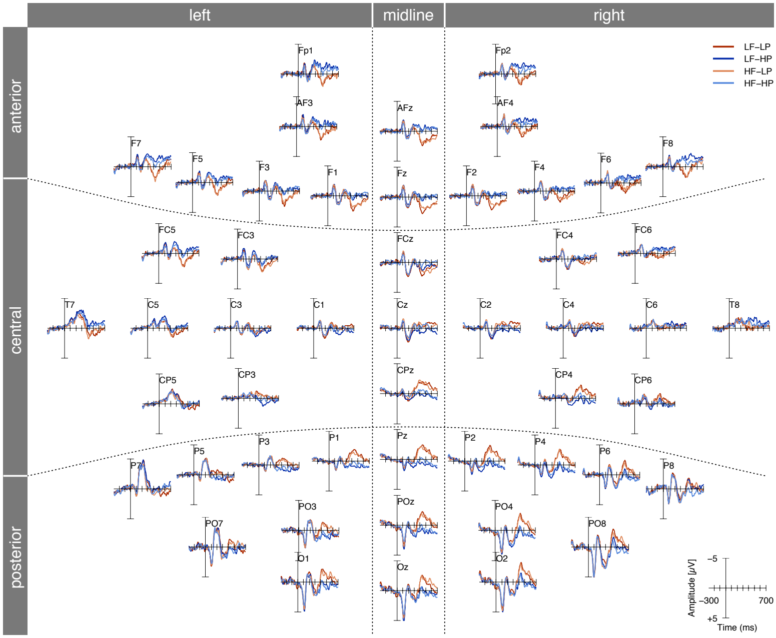


Figure 4.2: Grand average curves for target words in Experiment 1. ERPs illustrate four experimental conditions of frequency (low: LF; high: HF) and predictability (low: LP; high: HP) on 50 scalp electrodes.

Neither the effects of frequency x electrode (P = .330) nor of frequency x predictability x electrode (P = .229) were significant in this time window.

Consistent with numerous previous reports, low predictability evoked large N400 amplitudes from 300 to 500 ms. Importantly, analyses on five preceding intervals revealed additional influences of predictability earlier in the time course. From 90 to 140 ms, the interaction of frequency and predictability pointed to the sensitivity of early word recognition processes to contextual information. Analyses within predictability categories in this interval uncovered a frequency effect for high but not for low predictability words. The first frequency effect for low predictability words was found

Table 4.2: Global analyses of Experiment 1. Three-way ANOVAs (columns 1 to 3) on the factors frequency (2), predictability (2), and electrodes (50) as well as within-predictability class two-way ANOVAs (columns 4 and 5) on the factors frequency (2) and electrodes (50). Analyses were performed in six intervals on data from $N = 20$ subjects.

Interval [ms]	Frequency x Electrode	Predictability x Electrode	Frequency x Predictability x Electrode	Frequency x Electrode: Low Pred.	Frequency x Electrode: High Pred.
50-90	$P = .138$ $F(3,60) = 1.890$	$P = .887$ $F(3,74) = .281$	$P = .799$ $F(2,50) = .306$	$P = .516$ $F(2,45) = .717$	$P = .140$ $F(3,72) = 1.805$
90-140	$P = .105$ $F(3,61) = 2.097$	$P = .838$ $F(5,97) = .421$	**P = .020** $F(4,76) = 3.086$	$P = .454$ $F(3,66) = .909$	**P = .009** $F(3,65) = 3.977$
140-190	$P = .302$ $F(2,55) = 1.245$	$P = .652$ $F(4,76) = .619$	$P = .256$ $F(4,82) = 1.349$	$P = .585$ $F(3,60) = .667$	$P = .095$ $F(3,72) = 2.080$
190-240	$P = .092$ $F(3,75) = 2.081$	$P = .450$ $F(6,129) = .976$	$P = .593$ $F(3,64) = .667$	$P = .354$ $F(3,67) = 1.114$	$P = .146$ $F(3,68) = 1.792$
240-290	**P = .012** $F(4,80) = 3.364$	$P = .057$ $F(3,65) = 2.538$	$P = .228$ $F(4,90) = 1.415$	**P = .012** $F(4,79) = 3.357$	$P = .171$ $F(3,75) = 1.649$
300-500	$P = .330$ $F(3,64) = 1.170$	**P < .001** $F(4,93) = 37.937$	$P = .229$ $F(4,89) = 1.414$	$P = .576$ $F(3,66) = .700$	$P = .127$ $F(4,79) = 1.840$

150 ms later, from 240 to 290 ms. Thus, it seems that predictability modulates the time point at which a transient frequency effect can be detected in ERPs.

4.2.2.2 Local analyses

To scrutinize the findings from the global ANOVAs on all electrodes, we divided the 50 scalp channels into nine regions according to a grid of three sagittal (left, midline, right) and three coronal (anterior, central, posterior) fields (see Fig. 4.2). Word frequency effects for low and high predictability conditions were examined separately in the epochs yielding the earliest significant effects, i.e., from 90 to 140 ms for high predictability and from 240 to 290 ms for low predictability words. In the interval from 300 to 500 ms we explored the influence of predictability on N400 amplitudes.

High predictability frequency effect (90 - 140 ms). In the epoch from 90 to 140 ms, a two-way ANOVA for high predictability words with frequency (2) and region (9) as factors yielded an effect of region [$F(1,35) = 30.998$; $P < .001$], and an interaction of frequency x region [$F(2,41) = 4.935$; $P = .010$]. The main effect of frequency was not significant [$F(1,19) = .428$; $P = .521$].

Post-hoc t-tests in each of the nine scalp regions confirmed larger negative amplitudes for low than for high frequency words at anterior left [$t(19) = 2.665$; $P = .016$], anterior midline [$t(19) = 2.338$; $P = .030$], and central left [$t(19) = 2.138$; $P = .046$] sites. ERPs were more positive for low than for high frequency words at posterior right [$t(19) = -2.575$; $P = .019$] and posterior midline [$t(19) = -3.035$; $P = .007$] regions, where the effect was strongest (Fig. 4.3, panels ***A-B***).

Low predictability frequency effect (240 - 290 ms). From 240 to 290 ms, the main effects of frequency [$F(1,19) = 6.826$; $P = .017$] and region [$F(1,30) = 5.216$; $P = .016$] were significant in the two-way ANOVA for low predictability words with frequency (2) and region (9) as factors. The interaction of frequency x region revealed a statistical trend [$F(2,44) = 2.990$; $P = .052$].

t-Tests in the nine regions yielded significant differences with more negative amplitudes for high than for low frequency words at central midline [$t(19) = -2.916$; $P = .009$] and central right [$t(19) = -2.107$; $P = .049$] regions; the anterior right site [$t(19) = -1.770$; $P = .093$] revealed a trend. The effect was strongest on a positive component at the posterior left region [$t(19) = 3.498$; $P = .002$]. Here, amplitudes were more positive for high than for low frequency words (Fig. 4.3, panels ***B-C***).

N400 predictability effect (300 - 500 ms). In the N400 time window, an ANOVA with predictability (2) and region (9) yielded no significant main effects [predictability: $F(1,19) = .837$; $P = .372$; region: $F(1,30) = .452$; $P = .596$], but a highly reliable interaction of predictability x region [$F(2,47) = 47.455$; $P < .001$].

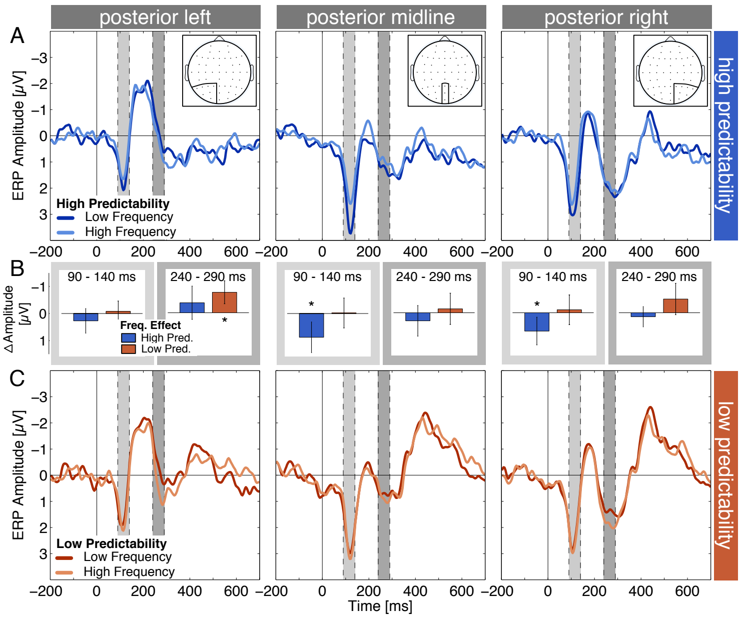


Figure 4.3: Frequency effects in Experiment 1. Grand averages across three posterior electrode clusters for low and high frequency targets in (**A**) the high predictability and (**C**) the low predictability condition. (**B**) Mean amplitude differences in time windows yielding the first significant frequency effect within the high and low predictability conditions; error bars reflect 95% confidence intervals.

Post-hoc comparisons attested significant predictability effects in seven of the nine regions [anterior left: $t(19) = -9.243$, $P < .001$; anterior midline : $t(19) = -8.041$, $P < .001$; anterior right: $t(19) = -8.156$, $P < .001$; central left: $t(19) = -1.471$, $P = .158$; central midline: $t(19) = 3.598$, $P = .002$; central right: $t(19) = -.118$, $P = .908$; posterior left: $t(19) = 5.796$, $P < .001$; posterior midline: $t(19) = 7.752$, $P < .001$; posterior right: $t(19) = 5.895$, $P < .001$]. At posterior electrodes, amplitudes were more negative for low than for high predictability words (Fig. 4.4). The N400 analyses were restricted to the epoch from 300 to 500 ms, however the ERP

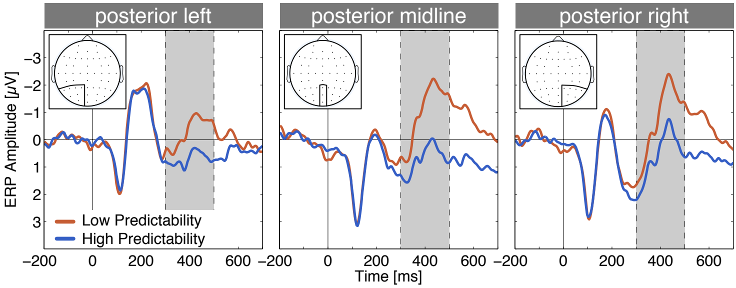


Figure 4.4: Predictability effect in Experiment 1. Grand average curves for low and high predictability target words on three posterior scalp regions. The N400 effect is prominent on all three clusters.

curves suggested an earlier onset of amplitude differences. We will return to this issue below.

4.2.2.3 Additional analyses: Context effects and reduction of subject sample

As noted before, in the full sample of 32 participants, ERP amplitudes started to differ slightly before stimulus onset. The pattern translated into an interaction of frequency and predictability in the interval from -10 to 50 ms (Fig. 4.5, panels ***A-C***). Given this early onset, amplitude differences did not emerge from visual processing of the target word but must have been evoked before. Because words preceding the target in the neutral sentence were identical across experimental conditions, differential visual input prior to the target cannot serve as an explanation for the effect. Notably, however, the conditions differed in the context preceding the neutral sentence (see also Fig. 4.1). Thus, we considered the possibility that the context biasing target predictability was already itself the source for the differential amplitudes around target onset.

In particular, the presentation with context 1 (e.g., *The man on the picture fiddled around with models of Columbus' fleet.*) triggered expectation of a high frequency target word (e.g., *ship*) in the neutral sentence. In congruent trials this prediction matched the actually presented target word (condition high frequency - high predictability), whereas in incongruent trials a low frequency word appeared instead (e.g., *scepter*; condition low frequency - low predictability). Analogously, when context 2 (e.g., *The man on the picture wore a golden crown and sat stately on a throne.*) preceded the neutral sentence, congruent trials comprised a low frequency target (e.g., *scepter*; condition low frequency - high predictability), whereas in incongruent trials the high frequency counterpart was displayed (e.g., *ship*; condition high frequency - low predictability).

Importantly, because the real identity of the upcoming target is unknown before onset, every context should prompt equal predictions irrespective of target congruency, as long as no visual information is available[1]. Thus, given that expected words are pre-activated prior to their appearance (e.g., DeLong et al., 2005) different electrophysiological responses at stimulus onset may point to context-triggered predictions of an upcoming word. To test this hypothesis, we created the factor *contex*t by collapsing ERPs from congruent and incongruent trials in context 1 as well as in context 2. Indeed an ANOVA with the factors context (2) and electrode (50) from -10 to 50 ms yielded a significant effect [context x electrode: $F(5, 163) = 2.837$; $P = .016$] for the sample of 32 subjects (Fig. 4.5, panel ***D***).

In order to strengthen the hypothesis that the context effect was specific to predictions of targets, we examined ERPs on preceding words. These stimuli were identical across experimental conditions and did not undergo intentional predictability manipulations by the context sentence. Therefore, they should not show a systematic influence of context if the observed effect resulted from specific expectations of a high or a low frequency target. Indeed, ANOVAs

[1] In a control analyses, the comparison of ERPs from congruent and incongruent targets in the interval from -10 to 50 ms did not reveal significant differences within context 1 [congruent/incongruent (2) x electrode (50): $F(3, 96) = 1.630$; $P = .186$] or context 2 [congruent/incongruent (2) x electrode (50): $F(3, 116) = .737$; $P = .560$], pointing to similar electrophysiological responses within each context. Of course, we cannot draw any strong conclusions from the absence of effects, except that these results are not incompatible with our explanation.

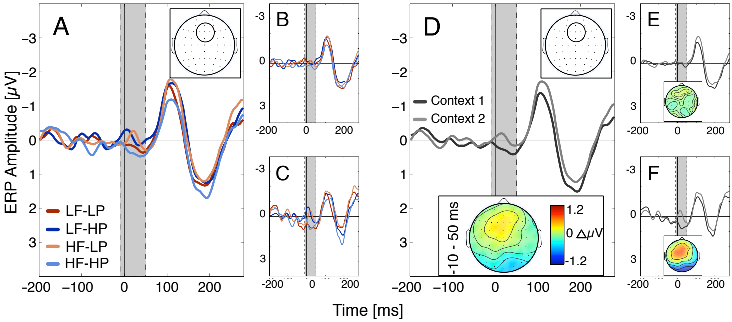


Figure 4.5: Stimulus onset effect. (**A**) Grand average ERPs from the full subject sample ($N = 32$) in a cluster of five anterior electrodes (AFz, F1, Fz, F2, FCz). ERPs to target words reveal an interaction of frequency and predictability from -10 to 50 ms. (**B**) Amplitude differences at stimulus onset are reduced for a sample of 20 participants after precluding (**C**) data from 12 subjects (cf., panels **D-F**). (**D-F**) The interaction at stimulus onset translates into a main effect of context with an anterior distribution for (**D**) the full sample of 32 subjects. (**E**) The effect is absent for data from 20 participants after excluding (**F**) a subset of 12 data sets revealing the strongest context effect.

with the factors context (2) and electrode (50) in the interval from -10 to 50 ms did not reveal significant interactions of context x electrode for the word one position before the target [$F(3, 93) = 2.837$; $P = .324$] nor two positions before the target [context x electrode: $F(3, 122) = .802$; $P = .525$].

Together, these results are compatible with the idea that amplitude differences around stimulus onset resulted from participants' predictions of the upcoming target: Depending on the context sentence, either a low (context 2) or a high frequency (context 1) word was expected at the target position. Since the SOA during word-wise sentence presentation was constant throughout the experiment stimulus onset could be reliably predicted. These predictions may have evoked differential neural responses shortly before the target occurred (cf., Ruz & Nobre, 2008; Dale, Simpson, Foxe, Luks, & Worden, 2008). Note, however, that we did not have a priori hypotheses for these effects. Clearly, this explanation is tentative and needs to undergo further investigation before drawing strong inferences.

This set of analyses, however, provided an objective basis for the selection of uncontaminated data around stimulus onset, such that effects later in the timeline are unbiased with respect to prior epochs. Across all scalp electrodes, we computed single-subject root-mean square amplitudes for ERPs following context 1 and context 2 and identified 12 subjects showing the strongest amplitude differences in the interval from -10 to 50 ms relative to target word onset. An ANOVA on the 12 data sets confirmed a robust influence of context [context x electrode: $F(5, 57) = 4.120$; $P = .003$] with a fronto-central distribution (Fig. 4.5, panel ***F***).

Critically, after excluding these 12 participants, the remaining data from 20 subjects did not show any influence of context x electrode at stimulus onset, neither on the target [$F(5, 106) = .389$; $P = .874$; Fig. 4.5, panel ***E***] nor on the words prior to the target [one word before target: $F(5, 105) = 1.174$; $P = .326$; two words before target: $F(4, 94) = .698$; $P = .625$]. Therefore, this data subset provided an unbiased basis for the analyses of frequency and predictability effects on the ERP course.

4.2.3 Discussion

The ERP time course of Experiment 1 revealed three major results. First, an interaction of frequency and predictability from 90 to 140 ms translated into a frequency effect for high but not for low predictability words. Second, ERPs for low predictability words were modulated by frequency in the interval from 240 to 290 ms. Third, predictability affected N400 amplitudes from 300 to 500 ms. In the following, we discuss the results in detail.

The present experiment primarily focused on the temporal relationship of word frequency and predictability. While frequency as a bottom-up variable is generally accepted as major determinant for the speed of lexical access the role of predictability has often been regarded as post-lexical (e.g., Fodor, 1983; Forster, 1976; Murray & Forster, 2004). According to this view, contextual information is used only after a word has been identified, e.g., for semantic integration. However, considering that predictability is generated prior to the onset of a critical word (Altmann & Kamide, 1999, 2007; DeLong et al., 2005; Kamide, Altmann, & Haywood, 2003; Kamide, Scheepers, & Altmann, 2003; Kliegl et al., 2006; Otten et al., 2007; Otten & Van Berkum, 2008; Van Berkum et al., 2005; Wicha, Bates, et al., 2003; Wicha et al., 2004), we argued that expectancy-based top-down projections potentially have an early influence on lexical processing. The present results are in agreement with this hypothesis. Frequency and predictability interacted in an early interval from 90 to 140 ms, challenging their conceptual separation into lexical and post-lexical variables. Instead the interplay points to a joint influence on a common stage of word recognition where top-down information acts in concert with bottom-up processing. This result adds evidence to recent reports of early context effects. Penolazzi et al. (2007) found additive effects of frequency and predictability in time intervals from 110 to 130 ms and from 170 to 190 ms. Sereno et al. (2003) showed that context biased the selection either of the low or of the high frequency meaning of ambiguous words in an interval from 132 to 192 ms. The present data demonstrate that early lexical processing is substantially affected by context-based predictions about the incoming word.

Moreover, the results permit further insights into the timeline of word recognition. Parallel models (McClelland & Rumelhart, 1981; Morton, 1969; Rumelhart & McClelland, 1982) claim an activation advantage for words in a supportive context, resulting in faster lexical access for high than for low predictability words. In line with this assumption, the interaction of frequency and predictability in the early interval from 90 to 140 ms translated into a frequency effect for high but not for low predictability words. With the first frequency effect as an estimate for lexical access, the data support the idea that word identification is facilitated if the predicted stimulus matches the incoming signal. Conversely, the first frequency effect in the low predictability condition occurred later in the time course, from 240 to 290 ms, when the frequency effect for high predictability words had already dissipated. Thus, word recognition appears to be slowed if a stimulus is unpredictable from the previous context.

In accordance with numerous ERP studies, a robust predictability effect was found on the N400 component. Amplitudes were larger for low than for high predictability words (see Kutas et al., 2006 for a review). The N400 was not affected by word frequency, neither as a main effect nor as an interaction with predictability. This is at odds with previous reports of interactive patterns between context and frequency on the N400 component (Dambacher et al., 2006; Van Petten & Kutas, 1990). Van Petten and Kutas reported larger amplitudes for low than for high frequency words at early positions in sentences; the effect disappeared as sentences unfolded. Taking ordinal word position as an estimate for sentential information, the authors concluded that frequency affects N400 amplitudes predominantly when contextual constraint is weak, as at the beginning of sentences. In the present experiment, sentences always biased a specific target occurring at the sixth to eighth word position. Guiding strong expectations about the identity of targets, the sentences set up a highly constraining context that may have neutralized the influence of frequency on the N400. Further, our targets achieved a strong and factorial manipulation of frequency and predictability in highly controlled sentences, whereas the corpus-analytic studies from Van Petten and Kutas, and Dambacher et al. employed natural variations of intercorrelated word properties, potentially resulting in larger temporal variance of effects. After all, the influence of frequency on the N400 is not resolved yet since there are more studies revealing amplitude modulations (e.g., Penolazzi et al., 2007; Rugg, 1990) whereas others don't (e.g., Brown, Hagoort, & ter Keurs, 1999; Hauk & Pulvermüller, 2004).

A puzzling issue in the present data was the reliable amplitude differences around stimulus onset. The effect occurred too early to relate to visual processing of target words. Since sentence frames were identical across conditions, visual encoding is effectively ruled out as an explanation. A potential reason for the effect is that the preceding context sentences differed systematically between conditions. Either of two contexts biased high predictability of a high or of a low frequency target. Thereby, the relatively long SOA of 700 ms may have induced strong predictions about the identity as well as about the temporal onset of the target. In line with the demonstration of pre-activation of highly expected words (DeLong et al., 2005; Otten et al., 2007; Otten & Van Berkum, 2008; Van Berkum et al., 2005; Wicha, Bates, et al., 2003; Wicha et al., 2004) we considered the possibility that amplitude differences were evoked by context-based predictions about the upcoming target. Indeed the interaction of frequency and predictability in the interval from -10 to 50 ms translated into a main effect of context. Further, the absence of effects in control analyses on preceding words and within context conditions was compatible with the idea of target-specific pre-activation; we wish to stress, however, that such null-results do not allow strong conclusions. We are not aware of another study reporting ERP frequency effects at stimulus onset as a consequence of predictability experimentally induced in an earlier sentence. If replicable, the finding indicates that the anticipation of low and high frequency words is expressed in distinct neural activity before visual information is available. In any case, the effect clearly needs to be further examined before inferences about underlying processes are warranted. Most critically for the present study, however, was that the strength of the context effect varied between participants. After excluding data from 12 subjects showing the strongest effects no amplitude differences were found at stimulus onset for the remaining ERP records.

In summary, Experiment 1 yielded interactions of top-down predictions about upcoming words with lexical bottom-up processing. Electrophysiological indices for frequency-based access emerged earlier when the incoming stimulus matched the expected word form. Moreover, context influenced later phases of word processing as revealed by a modulation of N400 amplitudes.

4.3 Experiment 2

In the vast majority of ERP reading studies, stimuli have been displayed at a rate of one to two words per second. Experiment 1 was carried out in this tradition. Compared to normal reading, however, this timing is unnaturally slow. When skilled readers move their eyes across a text, words are fixated for about 200 to 250 ms on average before inter-word saccades of 20 to 30 ms bring the next string to the fovea (Kliegl et al., 2006; Rayner, 1998, 2009). Consequently, natural word recognition appears to be optimized for an input rate that is substantially faster than those from most experimental ERP settings. Of course, the relatively slow timing in ERP studies has methodological reasons. It prevents EEG signals from being overlaid by brain electrical responses to preceding and following stimuli. This is particularly critical when properties of pre- and post-target stimuli are hard to control across experimental conditions, as it is the case in psycholinguistic research. Here, a superposition of signals would be problematic for the interpretation of ERPs because neural activity could not be uniquely attributed to the processing of a target word (cf., Dambacher & Kliegl, 2007). While the reduction of presentation speed largely circumvents this problem, little is known about the influence of presentation rate on word recognition processes.

It is an open question whether inferences based on data from slow SOAs generalize to natural reading. Indeed, a few studies point to a good agreement of data assessed under different presentation modes (cf., Van Berkum, 2004), but there are also reports revealing differences in ERPs as a consequence of input rates (e.g., Camblin, Ledoux, Boudewyn, Gordon, & Swaab, 2007; Hagoort & Brown, 2000b; Kotz, Von Cramon, & Friederici, 2005). For instance, syntactic violations yielded comparable responses on the P600/SPS component when words were displayed at SOAs of 600 ms and 258 ms, but only the long SOA produced increased N400 amplitudes on words immediately following the syntactic violation. The authors proposed that the fast SOA caused a temporal shift of semantic integration processes in relation to the input rate (Hagoort, Brown, & Groothusen, 1993; Hagoort & Brown, 2000b). Similarly, other studies showed increased N400 latencies for rapid input speeds (Kutas, 1987; Robichon, Besson, & Habib, 2002; Rossell, Price, & Nobre, 2003). Considering that the N400 is particularly sensitive to semantic processes (see Kutas et al., 2006 for a review), these findings suggest that contextual influences on word recognition may well depend on presentation rate.

With an SOA of 700 ms in Experiment 1, temporally distinct frequency effects for high and low predictability words pointed to faster lexical processing in a supportive compared to a misleading context. However, this picture of the interplay between predictability and frequency may be distorted since the slow input rate granted participants unnaturally much time not only to process the currently displayed stimulus but also to predict the upcoming word. At a normal reading speed, top-down expectations may not be generated fast enough or may be insufficiently elaborated to affect early visual processing of the next word. Consequently, mutual influences of top-down expectations and bottom-up input were possibly stronger in Experiment 1 than in normal reading.

In Experiment 2, we examined influences of frequency and predictability at a near-natural reading rate. Stimulus presentation durations of 250 ms and inter-stimulus intervals of 30 ms approximated the duration of fixations and inter-word saccades in normal reading, respectively (Rayner, 2009). We used the same stimuli as in Experiment 1 where critical target words are embedded in identical sentence frames. Thus, the problem of overlapping components from consecutive stimuli at fast rates is minimized since words preceding and following the targets are physically equal in all conditions.

Because little is known about effects of presentation rate on lexical processing, we took into account several possible outcomes concerning the interplay of frequency and predictability. First, because the rapid input speed affords less time for word processing and prediction, the cross-talk of top-down and bottom-up processes may be attenuated or even completely dissolved. The disappearance of predictability effects on early lexical stages would revive the idea of word recognition as serial process under near-normal reading conditions (Fodor, 1983; Forster, 1976; Murray & Forster, 2004). Second, and in contrast to the first hypothesis, parallel models expect an interaction of frequency and predictability also in near-natural reading (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982). However, compared to slow rates, higher cognitive demands and attenuated expectation strength for upcoming words may lead to a temporal shift of the interplay of bottom-up and top-down processes.

4.3.1 Methods

4.3.1.1 Participants

Thirty-two native German readers (24 female; 29 right-handed; mean age: 27.28, SD: 6.77) received course credit for participation. They had normal or corrected-to-normal vision and reported no history of neurological diseases. None of the participants took part in Experiment 1.

4.3.1.2 Stimuli and procedure

Stimuli were adopted from Experiment 1 (*Potsdam Sentence Corpus 3*; for details see *4.2.1 Methods* of Experiment 1). Context and neutral sentences formed 144 sentence units. Within each unit, frequency and predictability were manipulated on target words in neutral sentences. Context sentences appeared in one or two lines until subjects pressed a button. Thereafter, words of the neutral sentences were successively displayed for 250 ms in the center of the screen. The presentation of consecutive words was separated by a 30 ms blank screen, resulting in an SOA of 280 ms. Timing was the only difference to Experiment 1 (i.e., 450 ms blank screen and 700 ms SOA).

4.3.1.3 Apparatus, EEG recording, data processing, and analyses

Apparatus and recording procedures were identical to Experiment 1. Data were processed and analyzed analogously (for details see *4.2.1 Methods* of Experiment 1). After artifact rejection, resulting in an elimination of 3.17% of trials (low frequency - low predictability: 2.78%; low frequency - high predictability: 2.17%; high frequency - low predictability: 3.82%; high frequency - high predictability: 3.91%), continuous data from 50 scalp electrodes were divided into intervals from 200 ms before to 700 ms after target word onset and were corrected to a 200 ms pre-stimulus baseline. As for the analyses of Experiment 1, mean single average ERPs from five successive time windows (50-90 ms, 90-140 ms, 140-190 ms, 190-240, 240-290 ms) and the N400 interval (300-500 ms) were submitted to global ANOVAs with within-subject factors frequency (2), predictability (2), and electrode (50). Furthermore, frequency effects were examined within predictability classes in separate ANOVAs with the factors frequency (2) and electrode (50). Significant results were scrutinized in local post-hoc analyses performed on a grid of three sagittal (left, midline, right) and three coronal (anterior, central, posterior) scalp regions. Where appropriate, degrees of freedom (rounded down) and P-values were adjusted for violations of the sphericity assumption according to the Huynh-Feldt correction.

4.3.2 Results

The grand average curves for target words showed a small negative peak at 70 ms at posterior electrodes. Thereafter, a positive component reached its maximum at around 110 ms. ERPs flattened at 170 ms before a negative deflection peaked at 230 ms. The subsequent broad positivity was followed by a negative-going component between 420 and 560 ms. Presumably, this morphology differed from ERPs in Experiment 1 because of the higher presentation rate (Fig. 4.6).

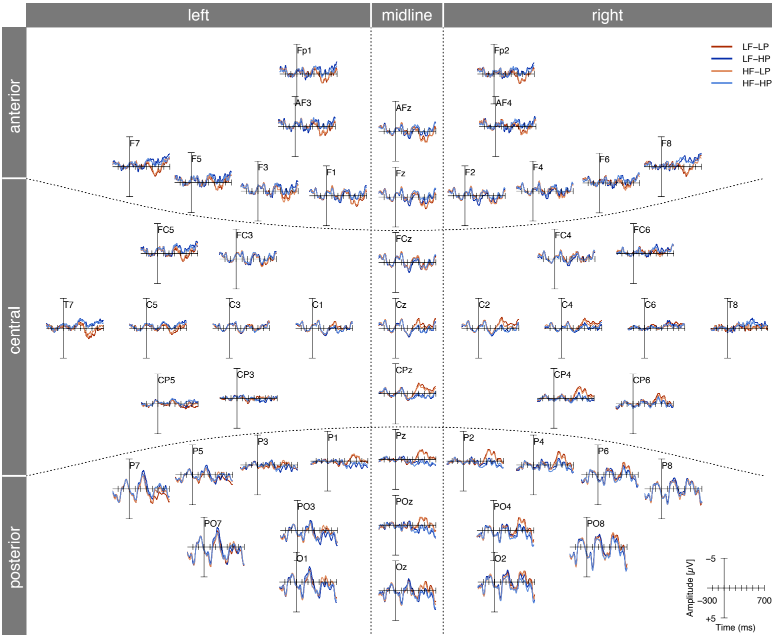


Figure 4.6: Grand average curves for target words in Experiment 2. ERPs illustrate four experimental conditions of frequency (low: LF; high: HF) and predictability (low: LP; high: HP) on 50 scalp electrodes.

4.3.2.1 Global analyses

ANOVAs with the factors frequency (2), predictability (2), and electrodes (50) as well as within-predictability class analyses on frequency (2) and electrodes (50) are summarized in Table 4.3. From 50 to 90 ms, predictability interacted with electrode site ($P = .019$). No other effects were significant in this period (all Ps $> .15$). Amplitude differences were not reliable for any factor in the subsequent time window from 90 to 140 ms (all Ps $> .10$). From 140 to 190 ms, the three-factor interaction of frequency x predictability x electrode ($P = .002$) was significant. Post-hoc ANOVAs yielded significant frequency x electrode effects within the low ($P = .046$)

Table 4.3: Global analyses of Experiment 2. Three-way ANOVAs (columns 1 to 3) on the factors frequency (2), predictability (2), and electrodes (50) as well as within-predictability class two-way ANOVAs (columns 4 and 5) on the factors frequency (2) and electrodes (50). Analyses were performed in six intervals.

Interval [ms]	Frequency x Electrode	Predictability x Electrode	Frequency x Predictability x Electrode	Frequency x Electrode: Low Pred.	Frequency x Electrode: High Pred.
50-90	$P = .288$ $F(4,125) = 6.854$	**$P = .019$** $F(4,132) = 2.973$	$P = .478$ $F(4,142) = .898$	$P = .780$ $F(4,135) = .461$	$P = .178$ $F(4,125) = 1.598$
90-140	$P = .172$ $F(4,126) = 1.620$	$P = .244$ $F(2,69) = 1.438$	$P = .504$ $F(2,89) = .779$	$P = .688$ $F(3,93) = .494$	$P = .120$ $F(3,122) = 1.874$
140-190	$P = .824$ $F(3,97) = .316$	$P = .078$ $F(2,83) = 2.421$	**$P = .002$** $F(3,115) = 4.789$	**$P = .046$** $F(3,108) = 2.620$	**$P = .038$** $F(3,112) = 2.731$
190-240	$P = .144$ $F(3,97) = 1.833$	$P = .310$ $F(2,91) = 1.212$	$P = .365$ $F(4,145) = 1.093$	$P = .454$ $F(3,95) = .884$	**$P = .049$** $F(5,156) = 2.277$
240-290	**$P < .001$** $F(3,106) = 7.056$	**$P = .038$** $F(2,75) = 3.164$	$P = .185$ $F(4,139) = 1.548$	$P = .070$ $F(3,109) = 2.317$	**$P < .001$** $F(3,115) = 6.912$
300-500	$P = .236$ $F(4,147) = 1.384$	**$P < .001$** $F(2,88) = 17.387$	$P = .631$ $F(5,168) = .706$	$P = .495$ $F(5,159) = .885$	$P = .288$ $F(4,150) = 1.253$

as well as within the high predictability ($P = .038$) condition; the latter was reliable throughout the next two time windows. From 240 to 290 ms, frequency x electrode ($P < .001$) and predictability x electrode ($P = .038$) were significant. The predictability x electrode effect spread into in the N400 epoch ($P < .001$), whereas frequency x electrode ($P = .236$) and the three-way interaction ($P = .631$) were not significant.

Analogous to Experiment 1, significant epochs were scrutinized in local analyses on nine scalp regions. First, we examined the early predictability effect in the epoch from 50 to 90 ms. Second, the first frequency effects for high as well as for low predictability conditions were analyzed in the window from 140 to 190 ms. Finally, the predictability effect in the N400 epoch was explored.

4.3.2.2 Local analyses

Predictability effect (50 - 90 ms). The main effect of region [$F(1,52) = 13.555$; $P < .001$] and the interaction of predictability x region [$F(2,77) = 3.646$; $P = .022$] were significant in the two-way ANOVA with predictability (2) and region (9) as factors; the main effect of predictability was not significant [$F(1,31) = 1.652$; $P = .208$].

Post-hoc t-tests in each region confirmed significant predictability effects at anterior midline [$t(31) = 2.216$; $P = .034$], anterior right [$t(31) = 2.217$; $P = .034$], central right [$t(31) = 3.160$; $P = .004$], and posterior left [$t(31) = -3.350$; $P = .002$] regions. The posterior midline region revealed a trend [$t(31) = -1.847$; $P = .074$]. The strongest effect occurred at posterior left sites where a negative deflection peaked for high but not for low predictability words (Fig. 4.8). This finding is described elsewhere in detail (Dambacher, Rolfs, Göllner, Kliegl, & Jacobs, 2009).

High predictability frequency effect (140 - 190 ms). In the interval from 140 to 190 ms, the ANOVA for high predictability words with frequency (2) and region (9) as factors yielded a significant main effect of region [$F(2,78) = 10.019$; $P < .001$] and an interaction of frequency x region [$F(2,64) = 3.628$; $P = .030$]. The main effect of frequency was not reliable [$F(1,31) = 2.251$; $P = .144$].

Post-hoc tests confirmed more positive ERPs for low than for high frequency words at anterior left [$t(31) = -2.184$; $P = .037$], anterior midline [$t(31) = -2.211$; $P = .035$], and anterior right [$t(31) = -2.312$; $P = .028$] regions. The strongest effect was observed at posterior right sites [$t(31) = 2.374$; $P = .024$] where amplitudes of a negative component were larger for low than for high frequency words (Fig. 4.7). Posterior midline sites revealed a trend [$t(31) = 1.781$; $P = .085$].

Low predictability frequency effect (140 - 190 ms). Within the low predictability condition, the two-way ANOVA with factors frequency (2) and region (9) in the epoch from 140 to 190 ms revealed a significant main effect of region [$F(2,82) = 6.425$; $P = .001$] and an interaction of frequency x region [$F(1,59) = 3.335$; $P = .045$]. The main effect of frequency was not significant [$F(1,31) = 1.064$; $P = .310$].

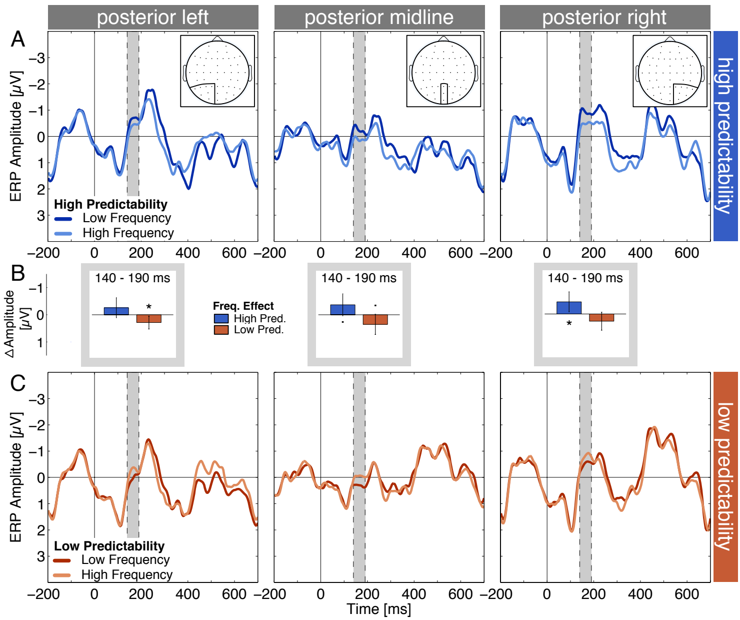


Figure 4.7: Frequency effects in Experiment 2. Grand averages across three posterior electrode clusters for low and high frequency targets in (**A**) the high predictability and (**C**) the low predictability condition. (**B**) Mean amplitude differences in time windows yielding the first significant frequency effect within the high and low predictability conditions; error bars reflect 95% confidence intervals.

t-Tests uncovered more positive amplitudes for high than for low frequency words at anterior right [$t(31) = 2.895$; $P = .007$] sites. The anterior midline region was marginally significant [$t(31) = -2.008$; $P = .053$]. At the posterior left region [$t(31) = -2.368$; $P = .024$], amplitudes of a negative-going deflection were larger for high than for low frequency words (Fig. 4.7). The posterior midline region revealed a trend in this direction [$t(31) = -1.858$; $P = .073$].

N400 predictability effect (300 - 500 ms). The two-way ANOVA with the factors predictability (2) and region (9) yielded signifi-

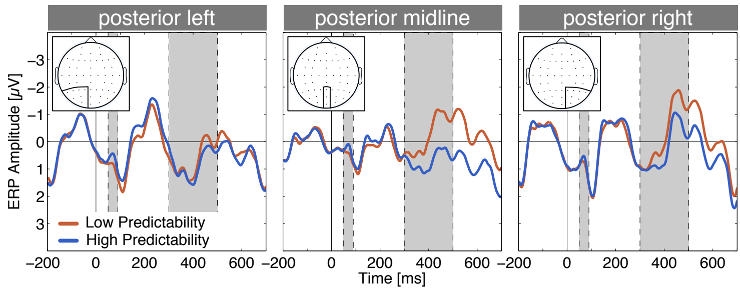


Figure 4.8: Predictability effects in Experiment 2. Grand average curves for low and high predictability target words on three posterior scalp regions. The N400 effect is prominent on posterior midline and right sites. In addition, posterior left electrodes reveal more negative amplitudes for high than for low predictability words in an interval from 50 to 90 ms (see also Dambacher et al., 2009).

cant effects of region [$F(2,72) = 8.870$; $P < .001$], predictability [$F(1,31) = 20.730$; $P < .001$], and predictability x region [$F(1,54) = 15.220$; $P < .001$].

Post-hoc t-test revealed predictability effects in eight of the nine regions [anterior left: $t(31) = -3.760$, $P = .001$; anterior midline: $t(31) = -2.530$, $P = .017$; anterior right: $t(31) = -5.038$, $P < .001$; central left: $t(31) = -2.715$, $P = .011$; central midline: $t(31) = 9.822$, $P < .001$; central right: $t(31) = 2.460$, $P = .020$; posterior left: $t(31) = 1.304$, $P = .202$; posterior midline: $t(31) = 4.537$, $P < .001$; posterior right: $t(31) = 2.795$, $P = .009$]. At posterior sites, low predictability words evoked larger negative amplitudes than high predictability words (Fig. 4.8).

4.3.2.3 Comparison between the studies (SOA effects)

Compatible with the majority of ERP studies on sentence reading, Experiment 1 had employed a relatively slow SOA of 700 ms. To investigate whether data from this rather artificial timing generalize to word processing at natural reading speed, Experiment 2 examined effects of frequency and predictability under a near-normal

SOA of 280 ms. With the exception of presentation rate, both experiments used identical stimuli, procedures, and setups. The comparison of the two data sets provides insights about influences of presentation rate on the time course of word recognition.

Frequency effects for high predictability words were found from 90 to 140 ms in Experiment 1 and from 140 to 190 ms in Experiment 2. Influences of frequency for low predictability words emerged from 240 to 290 ms in Experiment 1 and from 140 to 190 ms in Experiment 2. Notably, besides these distinct timelines, visual differences in the scalp topographies of frequency effects between the studies point to distinct underlying processes (Fig. 4.9, panels ***A-D***). Between-study differences were also evident in the topographical maps of N400 predictability effects (Fig. 4.9, panels ***E-H***). In the following, we compare the respective effects between the two experiments.

High predictability frequency effect. In Experiment 1 the first frequency effect for high predictability words yielded positive amplitude differences between low and high frequency words at posterior sites (positive deflection) with a slight trend towards the right hemisphere; the frontal effect showed a negative polarity and was prominent over the left hemisphere (Fig. 4.9, panel ***A***). In Experiment 2, the frequency effect for high predictability words revealed an inverse pattern: Amplitude differences were positive at anterior sites and, with an emphasis over the right-hemispheric channels, negative at posterior sites (negative deflection; Fig. 4.9, panel ***B***).

To describe these dissimilarities statistically, single-subject difference ERPs between amplitudes for low and high frequency words were calculated in epochs of the first word frequency effects, i.e., from 90 to 140 ms for Experiment 1 and from 140 to 190 ms in Experiment 2. Difference scores were scaled by the single-subject root-mean-square (McCarthy & Wood, 1985). An ANOVA with electrodes (50) as within- and SOA (2) as between-subject factor revealed a significant interaction of electrode x SOA

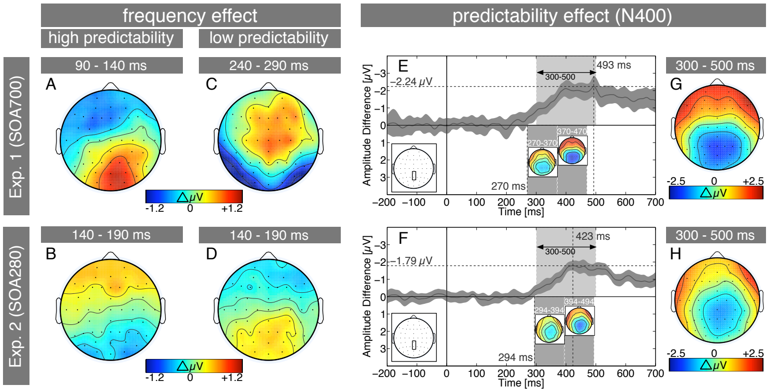


Figure 4.9: Comparison between experiments. (**A-D**) Frequency effects (low minus high) on 50 scalp electrodes in time intervals showing the first significant amplitude differences for high predictability targets in (**A**) Experiment 1 (90-140 ms) and (**B**) Experiment 2 (140-190 ms), as well as for low predictability targets in (**C**) Experiment 1 (240-290 ms) and (**D**) Experiment 2 (140-190 ms). (**E-F**) N400 difference curves (low minus high predictability) from a cluster of two electrodes (CPz, Pz) illustrate an earlier onset and more pronounced effect in (**E**) Experiment 1 as compared to (**F**) Experiment 2. (**G-H**) Scalp distribution of the N400 predictability effect in an interval from 300 to 500 ms in (**G**) Experiment 1 and (**H**) Experiment 2.

[$F(5, 260) = 30.316$; $P < .001$] confirming the visual impression of different scalp distributions between the experiments.

Low predictability frequency effect. The first frequency effect for low predictability words in Experiment 1 showed positive amplitude differences over central and frontal sites and a negative polarity at occipito-temporal sites (positive deflection) with largest differences at posterior left sites (Fig. 4.9, panel ***C***). In Experiment 2, the low predictability frequency effect yielded negative differences at anterior right sites, and a positive effect at posterior electrodes (negative deflection ; Fig. 4.9, panel ***D***).

Difference scores between low and high frequency words were computed in intervals from 240 to 290 ms in Experiment 1 and from 140 to 190 ms in Experiment 2. The ANOVA with electrodes (50) and SOA (2) as factors yielded significant differences of the scalp distribution [$F(5,299) = 3.478$; $P = .002$].

N400 predictability effects. Although the scalp maps of the predictability effect from 300 to 500 ms suggested greater similarities between the two experiments than the topographies of the frequency effects, the N400 appeared to be shifted towards anterior sites at the fast presentation rate (Fig. 4.9, panels ***G-H***). At SOA280 the effect centered around the CPz electrode, whereas at SOA700, differences were distributed around the Pz electrode. In fact, an ANOVA with electrode (50) and SOA (2) as factors confirmed a significant difference between the scalp maps [$F(5,290) = 4.951$; $P < .001$].

Moreover, the comparison of amplitudes suggested a smaller N400 effect in Experiment 2 (Fig. 4.9, panels ***E-F***; cf. Rossell et al., 2003). For statistical analyses, we computed mean amplitudes for N400 predictability effects in the epoch from 300 to 500 ms from jackknifed averages (Miller, Patterson, & Ulrich, 1998) for a cluster of five electrodes (CPz, P1, Pz, P2, POz). Error terms were corrected for the reduction of error variance due to the jackknifing procedure (Ulrich & Miller, 2001). An ANOVA with electrodes (50) as within- and SOA (2) as between-subject factor confirmed a larger predictability effect for Experiment 1 [mean amplitudes: Exp. 1: -1.74 μV vs. Exp. 2: -1.15 μV; $F(1,50) = 6.285$, $P = .016$].

Similar to previous studies pointing to increased N400 onset latencies at high presentation rates (Kutas, 1987; Robichon et al., 2002; Rossell et al., 2003), grand average curves also suggested a delay of the N400 in Experiment 2. We determined the onset of the predictability effect from the average of Pz and CPz electrodes, showing the strongest N400 effects in Experiments 1 and 2, respectively. On the basis of single-subject difference ERPs we computed 95% confidence intervals from 1000 bootstrap samples. Sampling points were considered as significant on the 5% level, when upper and lower bound of the confidence band shared algebraic signs.

The N400 onset was determined as the first time stamp in an interval of at least 25 successive significant data points. This procedure yielded an onset at 270 ms for Experiment 1 and at 294 ms for Experiment 2. Given this latency gap of 24 ms, we considered the possibility that differences in scalp distributions and amplitudes between the experiments resulted from a temporal shift of the N400 component. We re-ran the comparisons between Experiment 1 and 2, taking their specific N400 onsets as starting point for epochs of 100 ms each. Indeed the first 100 ms interval (i.e., 270-370 ms for Exp. 1 and 294-394 ms for Exp. 2) revealed no differences in scalp topographies [$F(6,300) = 1.549$; $P = .162$] or mean amplitudes [Exp. 1: -.67 μV vs. Exp. 2: -.94 μV; $F(1,50) = 1.737$; $P = .194$] in the five-electrodes cluster (CPz, P1, Pz, P2, POz). However, in the second 100 ms interval (370-470 ms for Exp. 1 and 394-494 ms for Exp. 2), a significant difference between the scalp topographies pointed to a more anterior distribution of the N400 in Experiment 2 [$F(5,279) = 4.493$; $P < .001$]; the comparison of mean amplitudes revealed a trend indicating a larger predictability effect in Experiment 1 [Exp. 1: -2.03 μV vs. Exp. 2: -1.54 μV; $F(1,50) = 3.401$; $P = .071$].

Thus, N400 differences between the studies can partly be explained in terms of an onset delay caused by a higher reading rate. Taking N400 onset latency into account amplitudes and scalp maps were similar in the initial phase, whereas a later segment pointed to a smaller effect and a shift towards anterior sites at a fast SOA.

4.3.3 Discussion

In Experiment 2, we employed a rapid SOA of 280 ms per word. In contrast to the SOA of 700 ms in Experiment 1, this timing approximated rates of four to five words per second during normal left-to-right reading. The major findings of the ERP time course in Experiment 2 settled in three intervals. First, a main effect of predictability emerged from 50 to 90 ms, i.e., at a considerably shorter latency than in Experiment 1. Second, influences of word frequency showed up as an interaction with predictability from 140 to 190 ms. In this epoch, low and high frequency words evoked differential amplitudes in both predictability conditions. Finally, the N400 was strongly modulated by word predictability, whereas it was unaffected by frequency. The findings are discussed in the following.

In the interval from 50 to 90 ms, we observed a reliable main effect of predictability that was strongest over posterior left electrodes (see Dambacher et al., 2009 for a discussion on this effect). This result is striking since previous reports mostly yielded predictability effects in later N400 intervals (e.g., Barber & Kutas, 2007; Kutas & Hillyard, 1980; Kutas et al., 2006); only a few reading studies found influences of predictability in early epochs between 100 to 200 ms post-stimulus (Penolazzi et al., 2007; Sereno et al., 2003). To the best of our knowledge, the data from Experiment 2 are the first to demonstrate electrophysiological evidence for contextual influences in visual word recognition before 90 ms. Considering the short latency it is unlikely that the effect reflects post-lexical processes of semantic integration. Furthermore, its independence from word frequency challenges a lexical interpretation. Instead, we propose a rapid verification between pre-activated mental representations of expected words and the actual physical input; that is, shortly after the visual signal reaches the cortex, neural activity differentiates predictions matching the incoming visual signal from those producing a mismatch (Dambacher et al., 2009; cf., DeLong et al., 2005; Gilbert & Sigman, 2007; Grossberg, 1999; Mumford, 1992; Ullman, 1995; Van Berkum et al., 2005; Wicha, Bates, et al., 2003; Wicha et al., 2004).

Notably, and consistent with numerous ERP studies on predictability effects in sentence reading, the effect was absent in Experiment 1. Why do those studies fail to reveal an early influence of predictability? An obvious difference is that most of them, including Experiment 1, used SOAs that are slower than normal reading rates of four to five words per second. However, word recognition is presumably adapted to a high presentation rate, such that most efficient performance is observed under near-optimal conditions. Similarly, in sentences presented at normal speaking rates, ERPs to predicted and unpredicted adjective inflections differed no later than 50 ms after onset (Van Berkum et al., 2005). These findings line up with evidence that early processes are primarily engaged when perceptual load and task requirements are high (Fründ et al., 2008; Handy & Mangun, 2000; Lavie, 1995, 2005; Lavie & Tsal, 1994; Luck et al., 2000).

The earliest index for frequency-based processing emerged in the interval from 140 to 190 ms. The epoch is compatible with previous reports of frequency effects within 200 ms after stimulus onset (Dambacher et al., 2006; Hauk & Pulvermüller, 2004; Penolazzi et al., 2007; Sereno et al., 1998, 2003). Importantly, the frequency effect showed up as an interaction with predictability. Thus, consistent with Experiment 1, these findings point to the joint influence of bottom-up and top-down processes on early word recognition and corroborate assumptions from parallel models (McClelland & Rumelhart, 1981; Morton, 1969; Rumelhart & McClelland, 1982). The interactive pattern in the interval from 140 to 190 ms translated into frequency effects within both low and high predictability conditions. Considering the first influence of frequency as an estimate for lexical access, the data suggest that high and low predictability words are identified in a common time range.

In the interval from 300 to 500 ms, a robust N400 effect with larger amplitudes for low than for high predictability words was observed in Experiment 2. Consistent with results from Experiment 1, frequency did not influence the N400. This corroborates the notion that, in the present stimulus materials frequency has no detectable impact on N400 amplitudes, presumably because of high contextual constraints on target positions (cf., Van Petten & Kutas, 1990; see Discussion of Experiment 1).

In summary, the approximation of normal reading speed in Experiment 2 (SOA of 280 ms) uncovered an early predictability effect suggesting the rapid comparison of top-down and bottom-up information. Furthermore, an interaction of frequency and predictability pointed to frequency-based access of low and high predictability words in a common latency range. Finally, a strong N400 predictability effect was in accordance with the literature as well as with Experiment 1.

4.4 General discussion

Perception is an active process. This has been demonstrated in numerous cases and in several domains (e.g., Bar et al., 2006; Bays, Flanagan, & Wolpert, 2006; Carlsson et al., 2000; Corbetta & Shulman, 2002; Enns & Lleras, 2008; Kastner et al., 1999; Kveraga et al., 2007; Mechelli et al., 2004; O'Connor et al., 2002; Pickering & Garrod, 2007; Sigman et al., 2005; Simmons, Martin, & Barsalou, 2005; Somers et al., 1999; Williams et al., 2008). Accordingly, vision does not only rely on passive bottom-up transfer of sensory input to higher cognitive levels, but continuous top-down predictions about our environment interact with early sensory processes to support fast and smooth perception (Bar, 2007; Churchland et al., 1994; Engel et al., 2001; Gilbert & Sigman, 2007; Grossberg, 1999; Mumford, 1992; Ullman, 1995).

Although the anticipation of future events appears to be a substantial property of brain functionality, the influence of top-down predictions on early word recognition is not well established. We addressed this issue in two studies examining interactions of word predictability with the earliest markers for lexical access. Both experiments revealed interactions of frequency and predictability within 200 ms of the ERP time course. The rapidness of this interplay points to the lexical role of predictability and calls for the amenability of top-down information at early levels of word recognition. This view converges with recent evidence of contextual information affording the pre-activation of specific word representations prior to their occurrence. Words evoke increased brain-electrical responses, when their forms mismatch those of expected upcoming stimuli (DeLong et al., 2005; Van Berkum et al., 2005; Wicha, Bates, et al., 2003; Wicha et al., 2004). In eye movements, biasing contexts prompt anticipatory saccades to goals representing likely continuations of stories (Altmann & Kamide, 1999, 2007; Kamide, Altmann, & Haywood, 2003; Kamide, Scheepers, & Altmann, 2003). Moreover, in natural reading, high predictability words are fixated shorter and skipped more often than words of low predictability; thus, a supporting context facilitates word processing within a fixation duration of usually less than 250 ms or even renders inspections of high predictability stimuli dispensable (Ashby et al., 2005; Ehrlich & Rayner, 1981; Kliegl et al., 2004, 2006; Rayner et al., 2004). The present data line up with these results pointing to the involvement of active top-down predictions in early language processing. Word recognition is not a passive accumulation of sensory input, but lives from continuous predictions that rapidly interact with incoming information to grant lexical access.

4.4.1 Influences of presentation rate

Despite the demonstration of early interactions between frequency and predictability in the two experiments, there were substantial differences between the timelines. In Experiment 1, the first indices for lexical access occurred fairly early for high (90-140 ms) and in a later interval for low predictability words (240-290 ms). The SOA of 700 ms in this setup is in the range of rates traditionally used in ERP reading studies. Advantageously, this procedure prevents brain-electrical activity to consecutive items from overlapping. The timing, however, gives readers unnaturally much time to process the current and to predict the upcoming word. In contrast, the SOA of 280 ms in Experiment 2 approximated natural reading rates and therefore simulated input speed that word recognition presumably is optimized for. Indices for frequency-based access in the high and low predictability conditions evolved in a single time window (140-190 ms), signaling the retrieval of word representations within 200 ms post-stimulus. Notably, this result is compatible with eye movement recordings from normal reading where words are fixated for around 200 to 250 ms (e.g., Kliegl et al., 2006). A comparison of the ERP course from Experiment 2 and the timeline from eye movement measurements suggests that, on average, the eyes move on to the next word shortly after a word has been accessed. In contrast, the slow display rate of Experiment 1 yields a time course that does not intuitively match eye movement behavior. Here, frequency effects indicate access of high predictability words at around 100 ms before the eyes move on, whereas low predictability words are identified at a time, when the eyes already have proceeded to subsequent stimuli. Of course, such a pattern is possible in principle since word processing can exceed the duration of a fixation (Dambacher & Kliegl, 2007). Nevertheless, the data from near-normal reading speed yielding evidence for lexical processing within the duration of a fixation fit eye movement behavior more plausibly (cf., Sereno & Rayner, 2003).

Additional evidence for the influence of SOA on word recognition comes from the comparison of scalp topographies. Similar amplitude distributions of frequency effects at different presentation rates would point to comparable neural generators. However, the two experiments clearly revealed topographical differences for the first frequency effects in the high as well as in the low predictability conditions. On the one hand, of course, the inhomogeneity of topographies is not surprising since the between-study analyses compared effects on different components occurring at distinct latencies. On the other hand, the results make clear that neither latencies nor brain-electrical sources are invariant in lexical processing. Although no strong inferences about neural generators can be drawn on the basis of the present ERP data, the results demonstrate that word recognition is a dynamic and interactive process that depends on environmental influences as well as on internal brain states.

Influences of presentation rate were also evident on the N400 component from 300 to 500 ms. In Experiment 2, the predictability effect was smaller and the scalp distribution was shifted towards anterior sites. Further, in line with previous reports, the N400 onset was delayed at a fast compared to a slow presentation rate (Kutas, 1987; Robichon et al., 2002; Rossell et al., 2003). The differences manifested particularly during the later phases of the N400. An explanation can presumably be found in processing demands (cf., Hinojosa, Martin-Loeches, & Rubia, 2001). With a short SOA, word processing as well as generation of predictions are subject to high time constraints. Conversely, the long SOA grants much time to integrate the current and to anticipate the next word in the sentence. Consequently, predictions may entail a stronger dissonance between high and low predictability words and cause more pronounced N400 effects with a slow than with a fast presentation rate.

Certainly further research is necessary to examine the relations between language processing and the rate of sensory input. In any case, differences between the two experiments demonstrate the relevance of presentation rate for the timeline of word recognition. In particular, the sensitivity of frequency effects to presentation rate suggests a major influence on early lexical processing. After all, data assessed with artificial SOAs must be interpreted carefully in terms of their generalizability to natural reading since processes or strategies for word recognition may change with reading rates.

4.4.2 Integrative account

As discussed before, the present interactions of frequency and predictability are in line with assumptions from parallel models predicting an interplay of bottom-up and top-down information during word recognition (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982; see also Grainger & Jacobs, 1996). In their seminal work on the *Interactive Activation Model* (IAM), McClelland and Rumelhart (1981) specified and implemented conceptions on the processing of written words. Although the IAM primarily accounts for behavioral data from isolated word recognition, Rumelhart and McClelland (1982) also predicted how the model would work in the context of sentences. On the basis of these notions, we propose five principles setting up a theoretical framework that shall reconcile the present data on a larger scale.

As a first principle, we presume that perception is interactive. Top-down and bottom-up processes operate simultaneously and influence each other such that knowledge and hypotheses about stimuli interact with incoming sensory information. Second, at every point in time, a certain activation level can be ascribed to a word's mental representation, or word *node*. Inactive nodes usually lie on their specific resting levels which may differ between words. For instance, resting levels are higher for high than for low frequency words, granting an activation advantage for more familiar stimuli. Nodes are considered as active when their level surpasses an activation threshold. Third, word nodes are interconnected with each other. Active nodes emit inhibitory signals that lower activation levels of other nodes. Inhibition strength increases with activation of the operating node. In an inactive state, nodes do not send inhibitory signals. Fourth, a node's activation level increases with time as long as the total input received from other sources is excitatory. Excitation comes from bottom-up input when a node shares features with the visual stimulus. Further, top-down signals increase the activation level of an expected node. Fifth, lexical access is achieved, when activation of a node is sufficiently high to provide evidence about stimulus identity. Here, we assume a theoretical threshold being surpassed for lexical access (cf. Grainger & Jacobs, 1996; Jacobs et al., 1998; Morton, 1969). On the basis of these principles, we attempt to outline a time course of lexical access taking into account the present evidence about influences of frequency, predictability, and SOA. We address the findings from high and low predictability conditions of Experiment 1 and 2 successively.

In Experiment 1 with words presented at an SOA of 700 ms, a frequency effect from 90 to 140 ms pointed to rapid lexical access of high predictability words (Fig. 4.10, panel *A*). In the present framework, this short latency is explained by high contextual constraints that trigger pre-activation of expected target words prior to exposure (cf., DeLong et al., 2005). Since the slow presentation rate grants a long interval to anticipate the upcoming word (cf., Altmann & Kamide, 2007), the pre-activation of high predictability targets virtually reaches a high level such that, at stimulus onset, the activation difference necessary to surpass the threshold for lexical access is small. Consequently, sensory input matching the expected pattern elicits additional excitatory bottom-up activation and rapidly drives the pre-activated node beyond the threshold of lexical access. Low predictability candidates, on the other hand, are not activated at any time in the high predictability condition but are inhibited as soon as the high predictability node becomes active.

Different from the rapid frequency effect for high predictability words in Experiment 1, evidence for lexical access in the low predictability condition emerged later, from 240 to 290 ms. Importantly, both predictability conditions comprised identical stimulus materials, such that context sentences in the low predictability condition also biased the expectation of a high predictability candidate. However, contrary to the prediction, an unexpected word was presented instead. Hence, analogous to the high predictability condition, top-down predictions pre-activate the expected word node whereas the low predictability word is inhibited as long as no visual information reveals the true identity of the upcoming word (Fig. 4.10, panel ***B***). Only after stimulus onset, bottom-up input provides excitatory information for the low predictability word and activates the corresponding node. Due to lateral inhibition between active nodes, the high activation level of the expected word suppresses the unpredicted word at early phases. Over time the accumulation of bottom-up input increases and forces the high predictability node down. Finally, the low predictability visual input presumably wins the competition and reaches the threshold for lexical access. Yet, the mismatch between predictions and physical input led to a conflict that retarded word identification.

In Experiment 2 with a faster presentation rate of 280 ms per word, frequency effects from 140 to 190 ms pointed to lexical access for low and high predictability words in a common time interval. Consistent with the interpretation of Experiment 1, these results are compatible with the pre-activation of expected target nodes prior to stimulus onset. Here, the fast rate limits the time to predict

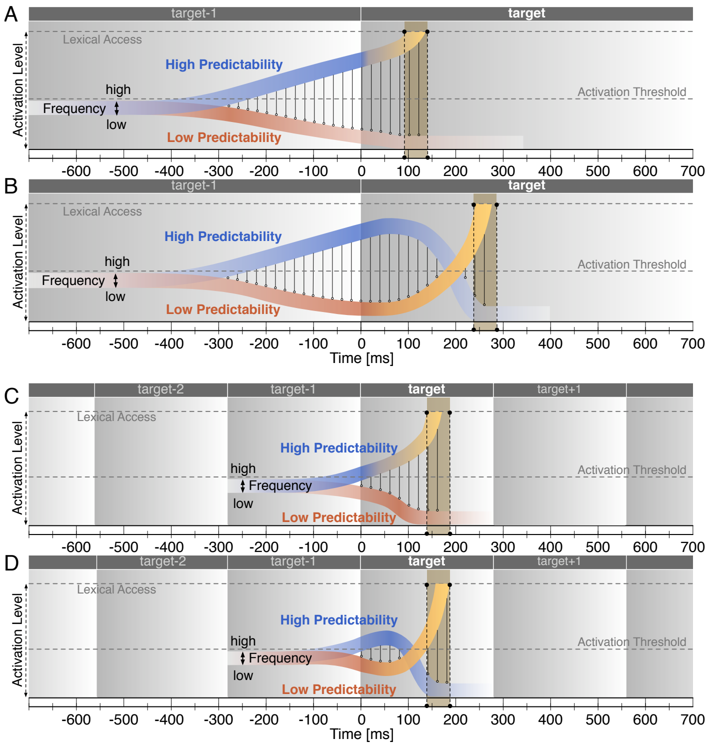


Figure 4.10: Integrative account. Schematic illustration of the timeline of word recognition in the light of an interactive activation framework. (**A-B**) Progress of target word activation in (**A**) the high predictability and (**B**) the low predictability condition at a slow SOA of 700 ms (Experiment 1). (**C-D**) Devolution of activation for (**C**) high predictability and (**D**) low predictability target words at a near-normal SOA of 280 ms (Experiment 2).

an upcoming stimulus such that pre-activation is lower than at the slow SOA (cf. Altmann & Kamide, 2007). Consequently, at a fast SOA, the pre-activation benefit in the high predictability condition is reduced, resulting in later access than at the slow presentation rate of Experiment 1 (Fig. 4.10, panel *C*). Analogously, in the low predictability condition, the moderate pre-activation of high predictability nodes entails only minor interference between the expected and the actual input. Hence, low predictability words reach the threshold for lexical access more quickly than in Experiment 1 (Fig. 4.10, panel ***D***). Thus, because facilitatory as well as inhibitory influences of context on lexical processing are reduced, low and high predictability words can be accessed in a comparable time range at a fast presentation rate.

In summary, the present framework qualitatively reconciles the timelines of lexical access from the present sentence reading experiments taking into account effects of frequency, predictability, and SOA. Our approach lines up with assumptions of the IAM on a sentence level (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982) and integrates model predictions and neurophysiological evidence (Barber & Kutas, 2007; Braun et al., 2006; Jacobs & Carr, 1995). Of course, more work is necessary to validate the present claims and to provide further insights about the dynamics in word recognition. In particular, the computational implementation of the proposed approach will afford quantitative and falsifiable predictions about the timeline of lexical access in sentence reading. Moreover, the simultaneous recording of EEG and eye-movements appears as a valuable technique for the investigation of lexical access in sentence reading under natural reading conditions. In contrast to the word-wise presentation traditionally used in ERP studies, participants read sentences normally from left to right on their individual pace. Despite serious methodological and theoretical difficulties, considerable progress has been made recently (Baccino & Manunta, 2005; Dimigen et al., 2006; Hutzler et al., 2007).

4.4.3 Further suggestions

In addition to the time courses of frequency effects, the present experiments yielded further results that can be discussed in terms of the interactive framework. First, we found an influence of context sentences in Experiment 1. At the time around stimulus onset, ERP amplitudes differed according to the contextual bias of high frequency words in context 1 (e.g., *The man on the picture fiddled around with models of Columbus' fleet. In his right hand he held a...*) and of low frequency words in context 2 (e.g., *The man on the picture wore a golden crown and sat stately on a throne. In his right hand he held a...*). In line with the present approach, we suggested that both context conditions pre-activated corresponding high predictability candidates prior to their exposure. Since the constant SOA afforded reliable predictions about stimulus onset and because the slow presentation rate permitted a high level of pre-activation, differential neural responses may have evolved from the anticipation of either high or low frequency words (Fig. 4.5). We stress again, however, that this interpretation is ad-hoc and needs to undergo further research before any conclusions can be drawn.

Second, a main effect of predictability from 50 to 90 ms post-stimulus emerged in Experiment 2. We proposed that top-down expectations and bottom-up input are compared at an early stage of visual processing; thereby, neural responses to mismatching information differ from those to matching signals (Dambacher et al., 2009). Considering the short latency of this predictability effect, top-down hypotheses about the incoming signal were presumably available prior to stimulus onset, which is in line with the pre-onset activation of highly expected words. Notably, although the pre-activation was arguably higher at the slow than at the fast SOA, the lack of evidence for rapid verification in Experiment 1 suggests that early interactions of top-down and bottom-up processes are involved especially at high presentation rates. Clearly, also here more work is needed for a comprehensive picture of rapid verification processes as well as of their relation to reading speed and lexical access.

Finally, the N400 predictability effect had a later onset and was weaker at the fast SOA of Experiment 2. In the present framework, a fast presentation rate results in lower pre-activation levels of expected words and, at the same time, in less inhibition of unexpected words. Thus, N400 differences between the studies potentially point to a reduced activation dissonance between low and high predictability words at a fast SOA.

4.5 Conclusions

We conducted two ERP experiments to examine the interplay of word frequency, predictability, and SOA in sentence reading. The major findings converge to two conclusions. First, early word recognition relies on interactions of top-down and bottom-up processes. In constraining contexts, predictions about incoming stimuli affect language processing at early lexical levels. Second, the timeline of word recognition is sensitive to presentation rates of stimuli. Frequency effects point to temporally distinct lexical processing for high and low predictability words at a slow, but not at a near-normal reading rate.

We reconciled the data in a descriptive interactive framework incorporating the pre-activation of predicted word representations prior to their occurrence. In accordance with the present ERP results, the approach suggests that lexical processing does not rely on passive accumulation of sensory input, and that lexical access is not anchored at a fixed component or latency. Instead, the active cross-talk between top-down and bottom-up streams affords the integration of information from multiple levels to grant rapid elaboration of incoming signals.

The present findings line up with increasing evidence that the interaction of top-down and bottom-up processes is fundamental to brain functionality. Hence, this principle is not unique to the processing of written language but holds for various domains in visual perception as well as for other modalities (Bar, 2007; Carlsson et al., 2000; Davidson & Wolpert, 2003; Gilbert & Sigman, 2007; Mechelli et al., 2004; Simmons et al., 2005; Van Berkum et al., 2005).

Acknowledgments

We thank Olaf Dimigen, Ralf Engbert, Markus Hofmann, Lars Kuchinke, Konstantin Mergenthaler, Antje Nuthmann, Martin Rolfs, Sascha Tamm, Hans Trukenbrod, Christiane Wotschack, and Kay-Michael Würzner for their support and valuable comments. This research was supported by Deutsche Forschungsgemeinschaft, grants FOR868/1 and KL655/6-1

5 Event-related potentials reveal rapid verification of predicted visual input

Michael Dambacher[1,2], Martin Rolfs[3], Kristin Göllner[1], Reinhold Kliegl[1], and Arthur M. Jacobs[2]

[1] Universität Potsdam, Germany
[2] Freie Universität Berlin, Germany
[3] Université Paris Descartes, France

Running Head: Verification of predictions

published 2009 in *PLoS ONE, 4*(3), e5047.
doi:10.1371/journal.pone.0005047

Abstract

Human information processing depends critically on continuous predictions about upcoming events, but the temporal convergence of expectancy-based top-down and input-driven bottom-up streams is poorly understood. We show that, during reading, event-related potentials differ between exposure to highly predictable and unpredictable words no later than 90 ms after visual input. This result suggests an extremely rapid comparison of expected and incoming visual information and gives an upper temporal bound for theories of top-down and bottom-up interactions in object recognition.

5.1 Introduction

Perception is not the result of passive bottom-up transmission of physical input (Churchland et al., 1994). Instead active top-down projections continuously interact with earliest stages of sensory analysis. This insight increasingly influences our understanding of cognitive efficiency (Bar, 2007; Engel et al., 2001; Gilbert & Sigman, 2007; Kveraga et al., 2007). For instance, attention enhances neural responses to visual stimuli in extrastriate and striate visual cortices (Somers et al., 1999), and already on the subcortical level in the LGN (O'Connor et al., 2002). In fact, studies using functional magnetic resonance imaging (fMRI) revealed modulations in cortical and subcortical areas even prior to sensory input of expected stimuli (Carlsson et al., 2000; Kastner et al., 1999; O'Connor et al., 2002). We regard such anticipatory activity as top-down predictions engaging lower-level areas involved in sensory processing to grant fast and smooth perception of forthcoming stimuli. Given that the quantity of feedback connections to primary sensory areas even outnumbers pure feedforward input (Kveraga et al., 2007) the interplay of top-down and bottom-up flow appears as a major principle of perception.

Beyond fMRI-based evidence about spatial characteristics of neural activity, temporal information contributes to the comprehension of bottom-up and top-down processes. Employing the high temporal resolution of electroencephalography (EEG), research predominantly focused the influence of attention on the time course of visual perception (Luck et al., 2000). For instance, spatial attention modulates alpha band activity over occipital areas prior to the appearance of an expected target (Sauseng et al., 2005; Worden, Foxe, Wang, & Simpson, 2000). After stimulus onset, amplitudes on the P1 component evolving at around 70 ms are enhanced for stimuli appearing at attended compared to unattended locations (Di Russo, Martinez, & Hillyard, 2003; Mangun, Hillyard, & Luck, 1993; Martinez et al., 1999, 2001). Influences of object- and feature-based attention have typically been observed later with a post-stimulus onset at 100 to 150 ms (Anllo-Vento & Hillyard, 1996;

Hillyard & Anllo-Vento, 1998; Hopf, Boelmans, Schoenfeld, Luck, & Heinze, 2004; Pitts, Gavin, & Nerger, 2008; Schoenfeld et al., 2007; Valdes-Sosa, Bobes, Rodriguez, & Pinilla, 1998).

However, despite the undisputed role for top-down control, attention cannot be equated with feedback flow per se. Gilbert and Sigman (2007) expanded the traditional concept of *attention*-based top-down influences and denominated *expectations* and *perceptual task* as further forms. Although these concepts are strongly overlapping and can hardly be separated, the critical distinction lies in the amount of information top-down streams carry. For example, directing attention to a certain location presumably contains less information than a task affording predictions about the identity of an upcoming stimulus at that position. In particular, strong expectations of a certain stimulus may involve a form of hypothesis testing that compares characteristics of the incoming signal to stored representations even prior to object identification (Gilbert & Sigman, 2007). This idea is implemented in models integrating bottom-up and top-down processes, such that feedforward streams transmitting sensory information converge with feedback activity carrying knowledge and hypotheses about stimuli. For instance, McClelland and Rumelhart (1981; Rumelhart & McClelland, 1982) proposed that word identification is driven by the interaction of linguistic and context-based knowledge with incoming featural information. Indeed, the amount of top-down feedback can be quantified at the level of individual participants (Ziegler, Rey, & Jacobs, 1998). Grossberg (1999) suggested that stimulus-related signals are enhanced, when top-down predictions are correct and match sensory inputs (cf., Di Lollo et al., 2000; Mumford, 1992; Rao & Ballard, 1999; Ullman, 1995). According to such theories, the congruence of prediction and input facilitates stimulus processing, potentially at early perceptual levels. An open question is, however, at what point in time perception benefits from the comparison of top-down and bottom-up processes, when strong predictions are involved.

The present study used event-related potentials (ERPs) to delineate the earliest interaction between expectations about the identity of incoming signals and input-driven information in visual word recognition. Sentence reading is perfectly suited to investigate the issue. As a well-overlearned everyday activity, it involves highly optimized object recognition processes ranging from individual letters and sublexical units to whole words, thereby engaging both early and higher levels of the visual system (Vinckier et al., 2007). Critically, earliest visual cortices were found to be selectively sensitive to trained, letter-like shapes (Sigman et al., 2005). Furthermore, during normal reading, rapid input rates of four to five words per second require high perceptual efficiency and encourage fast stimulus processing. This is crucial since modulations of early sensory processes are primarily engaged, when task demands and perceptual load are high (Lavie, 1995; Lavie & Tsal, 1994; Luck et al., 2000). Finally, sentence contexts afford strong and form-specific predictions for upcoming words. Indeed, increased neural activity was measured on articles (i.e., *a/an*) when their phonological form mismatched the initial phoneme of a highly predictable but not yet presented noun (e.g., *airplane/kite*; DeLong et al., 2005; see also Van Berkum et al., 2005).

We manipulated predictability of target words in sentences to investigate at what point in time after visual onset expectations about upcoming stimuli are verified. To push the necessity of efficient visual processing and to measure neural responses under near-normal conditions, words were presented at a high rate approximating natural reading speed (Kliegl et al., 2006; Rayner, 1998). Provided that match and mismatch of stimulus and prediction evoke distinct neural responses (Kveraga et al., 2007), an early difference between ERPs for predictable and unpredictable words represents an upper bound for the latency of top-down and bottom-up interactions.

5.2 Methods

5.2.1 Participants

Thirty-two native German readers (24 female; 29 right-handed; mean age: 27.3, SD: 6.8), recruited at Freie Universität Berlin, received course credit for participation. They had normal or corrected-to-normal vision and reported no history of neurological diseases. The experiment was performed in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki. In agreement with the ethics and safety guidelines at the Freie Universität Berlin, we obtained a verbal informed consent statement from all individuals prior to their participation in the study. Potential participants were informed of their right to abstain from participation in the study or to withdraw consent to participate at any time without reprisal.

5.2.2 Materials

A total of 144 sentence units formed the stimulus materials (see Appendix B). Each unit comprised two context sentences and one neutral sentence. The latter was identical across conditions except for target words setting up a two-by-two factorial design of frequency and predictability (Fig. 5.1, panel ***A***).

144 pairs of high (e.g., Schiff [*ship*]) and low frequency (e.g., Zepter [*scepter*]) open-class words served as targets. High frequency words comprised lemma and word form frequencies greater than 100 and 10 occurrences per million, respectively. For low frequency words, lemma and word form frequencies were lower than 10 per million. Frequency norms were taken from the DWDS data base (Geyken, 2007). High and low frequency words from one pair were members of the same class (i.e., nouns, verbs, or adjectives) and, where possible, shared the same number of letters; they differed in one letter in 19 of the 144 cases, in two letters in 4 cases and in three letters in 1 case. Target length varied between three and eight letters and was matched across conditions.

Target pairs were embedded at the sixth to eighth word position in neutral sentence frames and were always followed by at least two more words. Two context clauses preceding the neutral sentences triggered predictability of target words: High frequency targets were of high predictability in context 1 and of low predictability in context 2. For low frequency targets the pattern was reversed.

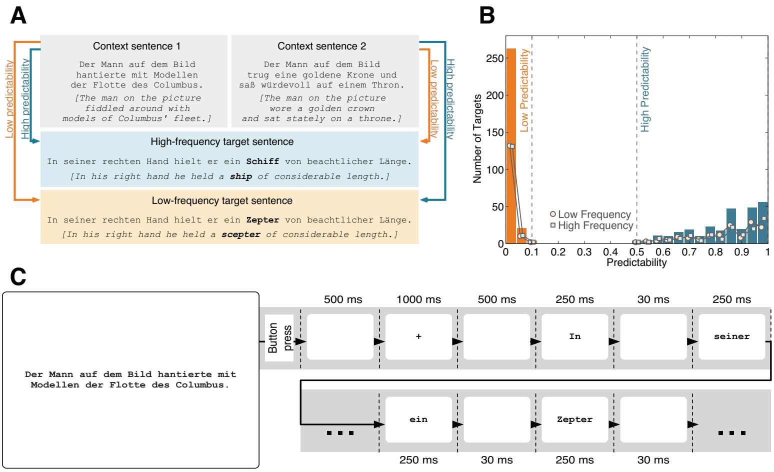


Figure 5.1: **(A)** Stimulus example. High (*ship*) and low frequency (*scepter*) targets were embedded in a neutral sentence frame. Two context sentences triggered low or high predictability of target words. **(B)** Distribution of predictability values. Bars illustrate the distribution of target predictability across the stimulus material. Low predictability targets (orange) include cloze probabilities no larger than .1. High predictability words (blue) comprise cloze values of at least .5. Lines reflect the dispersion of predictability norms within low (light orange circles) and high (light blue squares) frequency categories. Note that the entire corpus comprises a total of 576 predictability values, since each of the 144 sentence units involves a low and a high frequency target that both serve as low and as high predictability word. **(C)** Presentation sequence. A context sentence was fully displayed until participants pressed a button. After a fixation cross, the neutral sentence was presented word by word at monitor center. Each word was displayed for 250 ms and followed by a 30 ms blank screen.

Predictability norms were assessed in an independent cloze task performed by a total of 151 voluntary participants; none of them took part in the EEG experiment. In the cloze procedure, a context sentence was presented together with words of the corresponding neutral sentence up to the position prior to the target. Participants then guessed the word that would most likely continue the sentence fragment. They were asked to write at least one, but no more

Table 5.1: Descriptive statistics of target words.

	LF-LP		LF-HP		HF-LP		HF-HP	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Word form freq.	3.76	2.08	3.76	2.08	155.58	194.63	155.58	194.63
Lemma freq.	4.87	2.68	4.87	2.68	362.19	875.30	362.19	875.30
Predictability	.01	.02	.83	.13	.01	.02	.84	.13
Length	5.32	1.11	5.32	1.11	5.36	1.16	5.36	1.16
Word position	6.94	.76	6.94	.76	6.94	.76	6.94	.76

Note. Target word norms [mean and standard deviation (SD)] according to the 2 x 2 experimental manipulation of frequency (low: LF; high: HF) and predictability (low: LP; high: HP). 144 target word pairs consisted of 92 noun-, 37 verb-, and 15 adjective-pairs.

than three guesses per sentence. Each participant was presented with only one context per sentence unit and worked through a part of the stimuli. In total, every sentence was rated by at least 30 subjects. Predictability was computed as the proportion of participants correctly predicting the target word with one of their guesses. In the 144 sentence units entering the stimulus materials both low and high frequency words reached cloze values of at least .5 in the high predictability conditions while not exceeding .1 in the low predictability conditions. Target word statistics are depicted in Table 5.1.

Panel ***B*** in Figure 5.1 illustrates the distribution of predictability values in the categories. Most low predictability targets had cloze values of zero; in the high predictability condition the number of targets increased with predictability. Cloze values were similarly distributed for low and high frequency words.

For the ERP study, randomized stimuli were divided into lists such that each participant was presented with every sentence unit only once. A Latin square design provided that each version of a sentence unit was presented to the equal number of participants. This resulted in 72 high and 72 low predictability trials per subject, with 36 high and low frequency words in either category.

5.2.3 Procedure

Participants were seated at a distance of 60 cm from the monitor in a dimly lit room and were asked to silently read two-sentence stories for comprehension. A trial started with a context sentence that was displayed in its entirety until subjects pressed a button. Thereafter, a fixation cross, preceded and followed by a 500 ms blank interval, indicated for 1000 ms the required fixation position at monitor center. The stimuli of the neutral sentence together with their adjacent punctuation were then presented word by word with a stimulus onset asynchrony (SOA) of 280 ms (i.e., stimulus: 250 ms; blank: 30 ms). The presentation sequence of context and neutral sentences is schematized in panel ***C*** of Figure 5.1. After the neutral sentence, either the next trial was initiated (66.67%) or a three-alternative multiple-choice question was inserted to test sentence comprehension (33.33%). Questions referred to the content either of the context or the neutral sentence, but were never related to the target word.

Participants were asked to avoid eye movements and blinks during the interval of word-wise sentence presentation. After eight practice trials and 72 sentence units of the main experiment, they took a short break. Stimuli (font: Courier New; size: 18 pt) were presented in black on a white background.

5.2.4 Electrophysiological recording and data processing

EEG data were recorded from 50 scalp locations corresponding to the 10/20 international system. Impedances were kept below $10k\Omega$. All scalp electrodes and one channel on the right mastoid originally referenced to the left mastoid were re-referenced offline to the average of scalp electrodes. Two horizontal and two vertical EOG electrodes recorded bipolarly oculomotor signals and blinks. Data continuously recorded with a sampling rate of 512 Hz were re-sampled offline to 256 Hz. Amplifier settings cut off frequencies below .01 and above 100 Hz. Data were bandpass filtered offline from .1 to 30 Hz (24dB; 50 Hz notch).

EEG data contaminated by muscular artifacts and drifts were rejected offline via visual inspection. Independent component analysis (Vision Analyzer, Brain Products GmbH, Germany) was used to remove oculomotor artifacts and blinks. Additionally, an automatic algorithm rejected segments with an absolute amplitude larger than 90 μV in at least one channel. The rejection procedure resulted in the exclusion of 3.17% of all target intervals (low frequency - low predictability: 2.78%; low frequency - high predictability: 2.17%; high frequency - low predictability: 3.82%; high frequency - high predictability: 3.91%). In the remaining data, the continuous EEG signal was divided into epochs from 200 ms before to 700 ms after the target. Epochs were corrected relative to a 200 ms pre-stimulus baseline.

Effect onset was detected on the basis of 95% confidence intervals computed from 5000 bootstrap samples of single-average difference curves. Sampling points were considered as significant at the 5%-level, when upper and lower bound of the confidence band shared algebraic signs for an interval exceeding 10 ms. ERP amplitudes collapsed across sampling points in the epoch from 50 to 90 ms were examined in repeated-measures analyses of variance (ANOVA). The Huynh-Feldt correction was applied to adjust degrees of freedom (rounded down) and p-values for violations of the sphericity assumption.

5.3 Results

Grand average ERPs for low and high predictability target words are illustrated in panel ***A*** of Figure 5.2 for a sample of nine scalp electrodes. Curves are displayed for the interval from 200 ms before target onset up to the appearance of the target-succeeding word at 280 ms. Inspection of the data suggested amplitude differences at a surprisingly early latency - well before 100 ms.

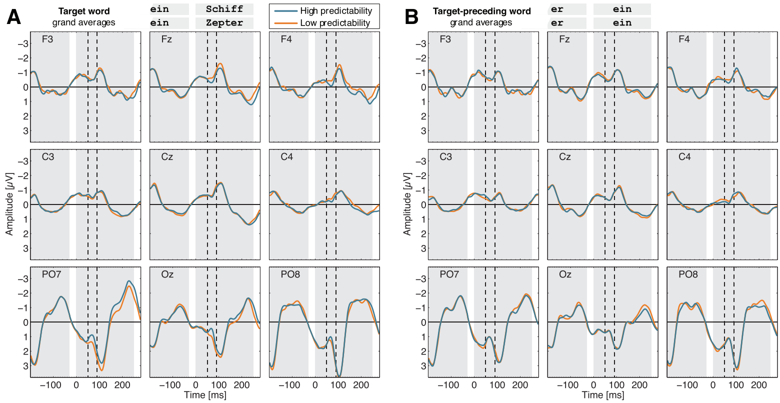


Figure 5.2: Grand average curves for low (orange) and high (blue) predictability target-word conditions when **(A)** the target word or **(B)** the target-preceding word was presented. Background shading illustrates the stimulus sequence (gray: word-present; white: blank screen). Dashed lines border the interval from 50 to 90 ms.

Amplitudes for high compared to low predictability words were more negative at posterior left locations and more positive at anterior right sites.

The visual impression was corroborated in statistical analyses examining temporal onsets and durations of the first predictability effect (Fig. 5.3, panel ***A***). From 0 to 100 ms, a total of 19 out of 50 scalp electrodes revealed significant amplitude differences with an average onset latency of 60 ms (SD: 4 ms) and a mean duration of 28 ms (SD: 16 ms). The earliest effect emerged at 52 ms post-stimulus. The topographical latency map (Fig. 5.3, panel ***B***) identified early predictability effects at right anterior and left posterior sites.

Based on these results, we conducted statistical tests on mean amplitudes in the epoch from 50 to 90 ms after stimulus onset

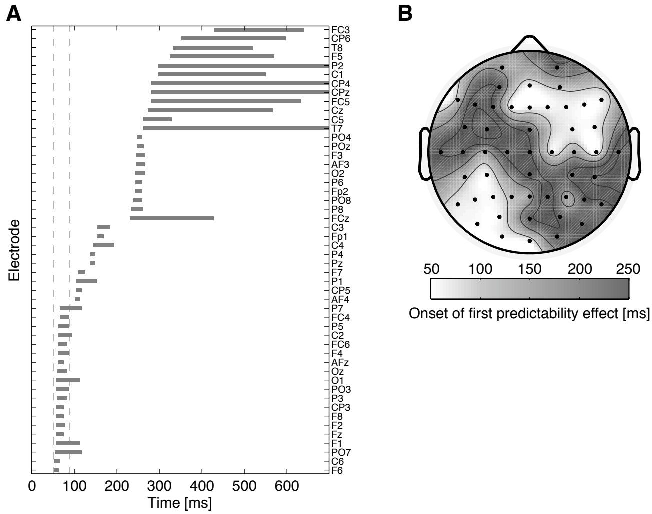


Figure 5.3: Latencies of the first predictability effect on target words. **(A)** Gray bars illustrate onset and duration of the first significant predictability effect on 50 scalp electrodes. In the interval from 50 to 90 ms (dashed lines), the effect emerges on 19 channels. **(B)** The onset topography reveals early predictability effects at right anterior and left posterior sites.

(dashed lines in Fig. 5.3, panel *A*). An ANOVA[1] with frequency (2), predictability (2), and electrode (50) as within-subject factors yielded a main effect of electrode [$F(2,70) = 14.66$; $p < .001$; $\eta_p^2 = .321$] and, critically, an interaction of predictability x electrode [$F(4,132) = 2.97$; $p = .019$; $\eta_p^2 = .098$]. Neither the interaction of frequency x electrode ($p = .298$) nor the three-way interaction ($p = .478$) was significant.

In order to strengthen evidence that the observed predictability effect was related to the experimental manipulation of targets, we examined ERPs for the two words prior to the target. These stimuli were identical across all conditions and were not subject to the predictability modulation from context sentences. Hence,

[1]Because the average reference sets mean amplitudes across scalp channels to zero, only interactions with the factor electrode are meaningful in this ANOVA.

amplitudes should not reveal any significant differences in the critical interval from 50 to 90 ms. ANOVAs with frequency (2), predictability (2), and electrode (50) as factors yielded no reliable effects for frequency, predictability, or the interaction of frequency x predictability (all Fs < 1)[2]. Grand average ERPs for the target-preceding word are displayed in panel ***B*** of Figure 5.2.

To scrutinize the predictability effect on the target word we grouped the 50 scalp electrodes into nine regions according to a grid of three sagittal (left, midline, right) and three coronal (anterior, central, posterior) fields (see Fig. 5.4, panel ***A***). ERP amplitudes were collapsed across electrodes in corresponding regions and submitted to an ANOVA with the factors frequency (2), predictability (2), and region (9). The main effect of region [$F(1, 51) = 13.27$; $p < .001$; $\eta_p^2 = .300$] and the interaction of predictability x region [$F(2, 80) = 3.36$; $p = .028$; $\eta_p^2 = .098$] were significant. No other factors were statistically reliable (all ps $> .15$). Post-hoc two-way ANOVAs with the factors frequency (2) and predictability (2) in each of the nine regions yielded significant predictability effects at anterior-midline [$F(1, 31) = 4.47$; $p = .043$; $\eta_p^2 = .126$], anterior-right [$F(1, 31) = 4.73$; $p = .037$; $\eta_p^2 = .132$], central-right [$F(1, 31) = 9.43$; $p = .004$; $\eta_p^2 = .233$], and posterior-left sites [$F(1, 31) = 10.67$; $p = .003$; $\eta_p^2 = .256$; shown in Fig. 5.4, panel ***B***]. The main effect of frequency and the interaction of frequency x predictability were not reliable in any of the nine regions (all ps $> .10$).

Finally, we conducted separate analyses for low and high frequency words in the posterior-left region, which yielded the strongest effect (Fig. 5.4, panels ***A-C***). As shown in panel ***C*** of Figure 5.4, we consistently found more negative amplitudes for high than for low predictability words within the low frequency

[2]On each of the two words preceding the target, additional ANOVAs with frequency (2), predictability (2), and electrodes (50) were performed in seven successive epochs of 40 ms each, ranging from 0 to 280 ms after stimulus onset. None of these intervals on the two words revealed significant effects involving the factors frequency, predictability, or the interaction of frequency x predictability (all ps $> .15$).

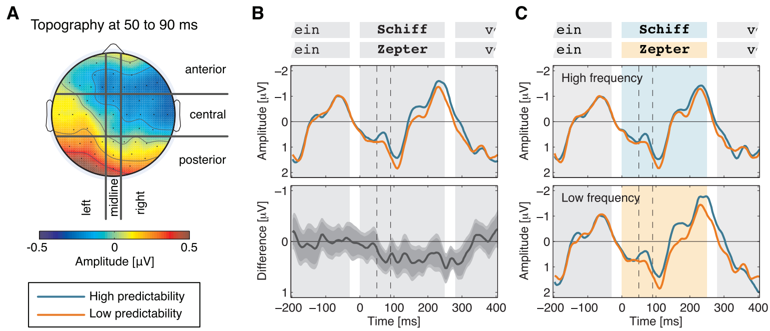


Figure 5.4: Grand average ERPs. **(A)** Topography of mean amplitude differences (low minus high predictability) in the epoch from 50 to 90 ms. Nine regions of scalp electrodes are delimited by black borders. **(B)** Mean amplitudes from seven electrodes at the posterior left region. In the interval from 50 to 90 ms (dashed lines), amplitudes are more negative for high (blue) than for low predictability (orange) words. The lower panel shows the difference waveform (low minus high predictability). Mid-gray and light-gray error bands depict 95% and 99% confidence intervals, respectively, computed from 5000 bootstrap samples. Background shading illustrates the stimulus sequence (gray: word-present; white: blank screen). **(C)** Within-frequency class ERPs at the posterior left region. The early effect of predictability is independent from target frequency. Background shading reflects the stimulus sequence (shaded: word-present; white: blank screen).

($t(31) = -2.25$; $p = .032$) as well as within the high frequency condition ($t(31) = -2.54$; $p = .016$).

5.4 Discussion

The present study examined the earliest index for the interplay between expectancy-based top-down and stimulus-driven bottom-up processes in sentence reading. ERPs to predictable and unpredictable words differed in an interval from 50 to 90 ms after stimulus onset, a latency that is considerably faster than most previous reports of interactions between top-down and bottom-up information in visual perception. It should be noted that other target properties cannot serve as an explanation for the effect because low and high predictability conditions utilized the same words in identical sentence frames; only preceding context sentences rendered targets expected or unexpected. Words prior to the target did not evoke differential ERPs across frequency and predictability conditions, corroborating the view that the observed effect resulted from the experimental manipulation of the target word. Importantly, the predictability effect held across levels of word frequency (Fig. 5.4, panel ***C***) pointing to the reliability of the result. Furthermore, the independence from frequency rules out visual word familiarity as an explanation. We therefore propose that ERP differences have emerged from a rapid match of form-specific predictions with incoming visual patterns.

The finding contributes to the idea that active top-down predictions play a major role in early visual processing (Bar, 2007; Di Lollo et al., 2000; Engel et al., 2001; Gilbert & Sigman, 2007; Grossberg, 1999; McClelland & Rumelhart, 1981; Mumford, 1992; Rao & Ballard, 1999; Rumelhart & McClelland, 1982; Sigman et al., 2005; Ullman, 1995; Worden et al., 2000). As was noted previously, the large amount of feedback connections warrants projections to early cortical regions (e.g., Kveraga et al., 2007). Accordingly, fMRI studies have revealed top-down activations of primary sensory areas prior to the occurrence of expected stimuli (Kastner et al., 1999; O'Connor et al., 2002). In visual word recognition, predictions were shown to pre-activate form-specific patterns of expected words (e.g., DeLong et al., 2005). The present data indicate, that these predictions are verified very rapidly with the actual incoming stimulus, i.e., before 90 ms after visual onset.

Notably, the predictability effect occurred substantially earlier than in previous research. We consider two explanations why top-down effects at comparable latencies have been rarely reported before. First, we presume that powerful top-down projections are required to produce measurable influences at early latencies. In previous studies, effects potentially were indiscoverable or absent as a consequence of insufficiently strong feedback information. For example, effects of spatial attention were usually found from around 70 ms on P1 amplitudes, whereas the C1 component from 50 to 90 ms was unaffected (Di Russo et al., 2003; Mangun et al., 1993; Martinez et al., 1999, 2001). However, variable SOAs inducing temporal uncertainty may have reduced the strength of attention towards upcoming stimuli. By contrast, with fixed SOAs and individual differences taken into account, attention effects on the C1 were found after 57 ms (Kelly, Gomez-Ramirez, & Foxe, 2008). Beyond that, top-down influences vary in the amount of information they carry (Gilbert & Sigman, 2007). Feedback signals issuing spatial selection are presumably weaker than expectations pre-activating form-specific representations of predicted stimuli (DeLong et al., 2005; Van Berkum et al., 2005). The present data indicate that word predictability afforded top-down modulations that were strong enough to affect earliest perceptual processes.

As a second explanation, we presume that the observation of early top-down modulations depends on the perceptual task (see also Gilbert & Sigman, 2007). In particular, early processes are enforced when task demands and perceptual load are sufficiently high (Lavie, 1995; Lavie & Tsal, 1994; Luck et al., 2000). In word recognition, normal reading speed of four to five words per second sets tight time constraints for stimulus processing. Compared to that, ERP reading experiments typically used slow rates of one or two words per second and potentially missed adequate demands. Those mostly revealed predictability effects from 200 to 500 ms on the N400 component (Dambacher et al., 2006; Kutas & Hillyard, 1984; Kutas et al., 2006); only a few authors reported earlier effects, from 120 to 190 ms (Penolazzi et al., 2007; Sereno et al., 2003). Employing a quasi-normal reading speed, the present setup presumably approximated temporal conditions word recognition is optimized for and encouraged rapid integration of both top-down and bottom-up information. This is comparable to auditory sentence processing at normal speaking rate, where expected and unexpected inflections on adjectives evoked differential ERPs no later than after 50 ms (Van Berkum et al., 2005).

These two proposals are neither exclusive nor exhaustive and, certainly, a number of additional factors will influence the timing of convergence between bottom-up and top-down streams in visual processing. To examine the validity of the present suggestions and to complete the picture of short-latency top-down effects, further research will be necessary. The reconciliation of these findings with feedback modulations occurring later in time will contribute to a comprehensive understanding about the interplay of internal brain states and information from the environment.

Clearly, the present data point to the efficiency of stimulus encoding in visual perception. Evidence from electro- and magneto-encephalography revealed that bottom-up activation spreads in the primary visual cortex at around 50 ms post-stimulus and is rapidly transmitted to higher cortical areas. Activity reaches a large proportion of extrastriate and frontal regions within 70 and 80 ms, respectively (Foxe & Simpson, 2002; Poghosyan & Ioannides, 2007). Can these signals be interpreted and compared to stored information before 90 ms? Converging empirical support comes from visual search. Sigman and colleagues (2005) showed that extensive training with letter-like shapes grants selective responsiveness in earliest visual cortices. Further, complex search patterns that were either predictive or unpredictive with respect to target position evoked differential magneto-encephalographic responses from 50 to 100 ms at occipital sites. Since participants were not aware of the pattern-target associations, this result points to fast elaboration of visual input that rapidly contacts unconscious memory (Chaumon, Drouet, & Tallon-Baudry, 2008). An explanation for the high processing speed of visual input is provided by recent theories proposing that meaningful information is already extracted from the first 1-5% of the bottom-up signal. Thereby, top-down processes, acting as temporal bias, increase stimulus saliency (Guyonneau, VanRullen, & Thorpe, 2004; VanRullen & Thorpe, 2002). Consistent with these ideas, our data indicate that in the presence of strong predictions, the cortex matches pre-activated representations with incoming stimuli shortly after the visual signal is available.

This interpretation is in line with models assuming interactions between feedforward and feedback information (e.g., Di Lollo et al., 2000; Grossberg, 1999; McClelland & Rumelhart, 1981; Mumford, 1992; Rao & Ballard, 1999; Rumelhart & McClelland, 1982; Ullman, 1995). For instance, Di Lollo and co-workers (2000) proposed that early visual processes generate preconscious hypotheses about the identity of an incoming stimulus. These hypotheses reenter low visual areas and are iteratively compared with the input. An affirmative match enhances the signal and affords conscious perception of a stimulus. This interactive view of feedforward and feedback information successfully accounted for findings from backward masking, assuming that top-down hypotheses from a briefly presented target mismatch the visual input after a mask has superseded the bottom-up target signature (Di Lollo et al., 2000; Enns & Di Lollo, 2000). Further, rapid resumption of an interrupted visual search indicates that preprocessed patterns evoke target-specific hypotheses, which are swiftly tested against sensory information (Lleras, Rensink, & Enns, 2005, 2007).

The present data extend this view suggesting that top-down hypotheses also emerge from the interpretation of semantic contexts. Thereby, the instantaneous match with the visual input is compatible with the idea that top-down influences dynamically reconfigure filters in the visual system to grant optimal processing of relevant information from incoming signals (Di Lollo, Kawahara, Zuvic, & Visser, 2001). Thus, visual perception appears as an active process that rapidly compares internal semantic representations with task-relevant aspects of incoming stimuli (Hayhoe, 2000; O'Regan, 1992; O'Regan, Deubel, Clark, & Rensink, 2000).

The observed predictability effect was strongest over posterior electrodes. This region is situated above the left hemispheric occipito-temporal network that is strongly linked to the so-called visual word form area (L. Cohen et al., 2000; McCandliss, Cohen, & Dehaene, 2003). As these cortical structures are gradually sensitive to the processing of word-like stimuli (Vinckier et al., 2007), they reflect a plausible ground for the matching of top-down predictions and incoming signals. Another relevant structure may be the foveal portion of the retinotopic cortex that was shown to receive category-specific feedback information as response to peripherally presented objects. Hence, V1 was proposed to serve as scratch pad for the storage and computation of task-relevant visual information (Williams et al., 2008; see also Gilbert & Sigman, 2007). Note, however, that suggestions about underlying sources of the predictability effect remain speculative, as no strong inferences about localization can be drawn on the basis of the present ERP data.

In conclusion, previous research has shown that predictions about upcoming words pre-activate representations of specific word forms. The present results indicate that, under near-normal reading speed, these predictions are checked in an interval from 50 to 90 ms after the visual input. Though reading is ideally suited to examine this issue, rapid verification of expected physical input is fundamental to many domains, including object recognition in general (Kveraga et al., 2007) and movement control (Davidson & Wolpert, 2003). If replicable across a wide range of tasks, our finding provides a critical temporal constraint for theories of top-down and bottom-up interactions as well as novel insights about the efficiency of stimulus encoding.

Acknowledgments

We thank our lab members at Freie Universität Berlin and Universität Potsdam for their support and Mario Braun for research assistance. Both laboratories contributed equally to this work. We also thank Mariano Sigman and Mark Williams for helpful and constructive comments on an earlier version of the article. This research was supported by Deutsche Forschungsgemeinschaft, grants FOR868/1 and KL655/6-1.

6 General summary and conclusions

6.1 General summary

In psycholinguistic research, the time of lexical access serves as a central marker for the description and comprehension of word recognition: Processes are considered as (pre-)lexical or post-lexical relative to this moment of stimulus identification. Although decades of research have substantially increased the understanding of language processing, core questions about the common role of bottom-up and top-down processes in the timeline of word recognition remained unresolved. Specifically, it was unclear whether top-down expectations provide a rapid source of information that influences early lexical processes, or alternatively, whether they reflect slow operations affecting only late post-lexical levels.

The present work addressed this issue and investigated the impact of top-down predictions on the time course of visual word processing. We demonstrated that the timeline of word recognition is substantially influenced by the interplay of bottom-up and top-down information. This superordinate inference is based on several studies that brought to light various important insights. In the following, five major aspects are discussed: First, top-down and bottom-up processes jointly modulate lexical stages of word recognition. Second, under near-normal reading conditions, top-down information affords rapid verification of expected sensory input. Third, presentation rate is a relevant factor for the timeline of word recognition. Fourth, relations between ERPs and eye movements are mediated by bottom-up and top-down processes. Fifth, interactive models of word recognition account for the present results.

6.1.1 Bottom-up and top-down interactions in lexical processing

Relations of bottom-up and top-down information were investigated on the basis of two core determinants of language processing. Word frequency, the major stimulus-dependent characteristic for the speed of lexical access, was considered as an indicator for bottom-up processing of the visual word form. Predictability, representing internal hypotheses about upcoming words from the interpretation of a previous context, conceptualized top-down information. Influences of the two determinants were examined in three ERP sentence reading studies. The *Potsdam Sentence Corpus 1* (PSC1; see Appendix A) with frequency and predictability norms for each word was employed in Chapter 2. While the PSC1 came with a natural confound of word properties, the *PSC3* in Chapter 4 (see also Chapter 5) realized an orthogonal and strong manipulation of frequency and predictability (see Appendix B).

As a major outcome, interactive patterns consistently pointed to bottom-up and top-down influences on a common stage of word recognition. In PSC1 reading, an interaction of word frequency and predictability on N400 amplitudes suggested top-down influences on the late access of low frequency words. In the PSC3 studies, predictability interacted with frequency before 200 ms at a slow as well as at a near-normal presentation rate. Together, the results provide converging evidence that top-down predictions influence lexical levels of word recognition and therefore co-determine lexical access.

Notably, the data from the two corpora also revealed differences. First, the absence of top-down influences before 200 ms in PSC1 reading contrasts with early interactions of frequency and predictability in the PSC3 experiments. A likely reason is that the PSC1 reflected natural variations of contextual constraint, such that the vast majority of words was of rather low predictability. In fact, according to the classification of PSC3 target words, 76% of the stimuli entering analyses in the PSC1 study were of low predictability, whereas only 7% met PSC3 criteria of high predictability[1]. Given the arguably small size of early ERP effects, top-down influences in PSC1 reading may have been too weak to manifest in amplitude differences at early latencies.

As a second and related difference, ERPs from PSC1 reading revealed an interaction of frequency and predictability on the N400 component, whereas amplitudes were unaffected by frequency in both PSC3 experiments. The finding is compatible with reports of the absence of N400 frequency effects under high contextual constraints (Van Petten & Kutas, 1990). In the PSC3, strong constraints biased expectancy of a particular target word in every sentence. In contrast, the small proportion of very high predictability words in the PSC1 suggests that specific predictions of upcoming stimuli are not always encouraged. However, also the PSC1 data pointed to diminished N400 frequency effects under high constraints, since the influence of frequency was smaller for high predictability words. Thus, although the underlying mechanisms remain unknown and must be addressed in forthcoming research, contextual constraint appears as a critical factor for the impact of frequency on N400 amplitudes.

In summary, we provided evidence that lexical access is driven by the interplay of bottom-up and top-down processes. Certainly, in everyday language, contextual constraints are not always strong, and in many situations the anticipation of upcoming words may be impossible. The present studies demonstrate, however, that top-down information is strongly involved in lexical processing when valid predictions about future events can be derived from the previous context. The findings hold for strong experimental manipulations as well as for natural variations in the language. Thus, the online generation of top-down predictions appears as an essential mechanism in sentence reading.

[1] In the PSC3, low predictability targets did not exceed values larger than .1, while high predictability targets comprised values of at least .5.

6.1.2 Rapid verification

Further evidence for rapid top-down effects was observed in ERPs at a near-normal reading rate (Chapter 5). Amplitudes to low and high predictability words revealed differences in an interval of earliest sensory processing, i.e., from 50 to 90 ms. The finding suggests that, in the presence of strong predictions, top-down hypotheses of incoming patterns are compared with the actual input as soon as visual information becomes available.

Clearly, further research is necessary for a better understanding of mechanisms and neural sources underlying this effect. The replication across several tasks and modalities will provide a more general picture of the interplay of bottom-up and top-down processes on early perceptual levels. Yet, the finding converges with reports of rapid top-down influences on sensory processing (e.g., Chaumon et al., 2008; Van Berkum et al., 2005) and is compatible with the notion of pre-activation of expected word forms (e.g., DeLong et al., 2005). Moreover, the result points to the high efficiency of stimulus encoding, since meaningful information must be extracted from bottom-up signals shortly after they reached primary visual cortices (Foxe & Simpson, 2002; Guyonneau et al., 2004; Poghosyan & Ioannides, 2007; VanRullen & Thorpe, 2002). Thus, a rapid comparison of bottom-up and top-down information provides temporal constraints for models of visual processing (e.g., Di Lollo et al., 2000; Grossberg, 1999; McClelland & Rumelhart, 1981; Mumford, 1992; Rao & Ballard, 1999; Ullman, 1995).

Notably, the early predictability effect was absent at a slow presentation rate (Chapters 2 and 4), suggesting that highly efficient processes are predominantly involved under optimal reading conditions, as approximated with the fast SOA of 280 ms. Interestingly, however, amplitude differences were found around stimulus onset for a subset of data assessed with a slow SOA of 700 ms (Experiment 1, Chapter 4). Although no strong inferences were drawn from this observation, the pattern was compatible with the idea of distinct neural activity in expectation of high and low frequency words. After all, top-down predictions of sensory events appear as a crucial factor for perceptual processes, an insight increasingly calling attention in neuroscientific research (e.g., Bar, 2007; Carlsson et al., 2000; Kastner et al., 1999).

6.1.3 Reading rate matters

More fine-grained evidence about the interplay of bottom-up and top-down processes in the course of word recognition was gained by the manipulation of presentation rate (Chapter 4). Due to methodological reasons, words are presented at a relatively slow pace in the range of 500 to 1000 ms per word in many ERP reading studies (cf., Kutas et al., 2006). However, influences of such rather artificial presentation rates on word recognition have been seldom investigated and are largely unknown. Thus, we contrasted ERPs from a conventional presentation rate with data recorded in a setup that approximated natural reading speed of around four to five words per second (e.g., Kliegl et al., 2006).

In fact, the comparison uncovered distinct timelines of word recognition. At a slow rate (i.e., SOA of 700 ms), frequency-based access emerged early in a supportive context whereas it appeared delayed in a misleading context. In contrast, at a near-normal speed (i.e., SOA of 280 ms), high and low predictability conditions pointed to access in a common, intermediate time interval. The data therefore indicated that lexical processes are not fixed to a certain latency or component in the ERP course but critically depend on timing parameters of stimuli.

Further differences between reading rates were observed on N400 predictability effects. Those occurred earlier and were more pronounced at a slow presentation rate (cf., Kutas, 1987; Robichon et al., 2002; Rossell et al., 2003). As possible explanation, we proposed that a greater dissonance between high and low predictability words at a slow SOA enhanced the effect.

In summary, the findings indicate that word recognition is affected by the time available to process a current and to predict an upcoming word. Clearly, the results call for the consideration of stimulus timing in psycholinguistic experiments and they advise caution on the generalization of data from artificial rates to normal reading. Future experiments taking into account a variety of SOAs will provide more detailed insights about the role of presentation rates and their relation to bottom-up and top-down processes in word recognition.

6.1.4 Eye movements and ERPs

While the present ERP results permit inferences about the timeline of word recognition with excellent temporal precision, eye movements reflect oculomotor processes in an ecologically valid setup and uncover important dynamics of natural reading. In particular, *lag*, *immediacy*, and *successor effects* (Kliegl et al., 2006) make clear that, for a comprehensive understanding of word recognition, influences from past, present, and future words must be taken into account. In Chapter 3 we addressed this issue and examined the link between ERPs and eye movements in a sequence of several words.

Analyses of *immediate* relations between N400 amplitudes and fixation durations revealed a concerted increase with decreasing frequency and predictability. Thus, fixation durations and N400 amplitudes presumably share levels of word recognition that serve as a common ground for both bottom-up and top-down processing of a currently fixated word.

Moreover, a *successor* effect of upcoming word predictability on both measures indicated that top-down hypotheses are reflected in N400 amplitudes and fixation durations. The finding contacts reports of anticipatory responses to expected stimuli in eye movements (Altmann & Kamide, 2007; see also Altmann & Mirkovic, 2009; Altmann & Kamide, 1999; Kamide, Altmann, & Haywood, 2003; Kamide, Scheepers, & Altmann, 2003) and ERPs (DeLong et al., 2005; Otten & Van Berkum, 2008; Van Berkum et al., 2005; Wicha, Moreno, & Kutas, 2003; Wicha, Bates, et al., 2003; Wicha et al., 2004). Together, they provide converging evidence that online predictions about future input are fundamental to language processing.

Influences of N400 amplitudes on fixation durations on the next word provided an electrophysiological correlate for *lag* effects. Given that the N400 evolves at a latency when the eyes during normal reading have moved on to the subsequent stimulus, the relation pointed to ongoing word processing beyond a fixation. That is, increased neural activity in response to a low frequency word temporally overlaps with the next fixation and therefore may interfere with word recognition. Critically, the result also suggested that oculomotor control is at least partly independent from word recognition, since the eyes may leave a word while processing is still incomplete (cf., Engbert et al., 2005).

In summary, the joint consideration of ERPs and eye movements brings together advantages of both methodologies and grants insights beyond each measure alone. Synchronizing the timelines provided valuable information about relations between N400 amplitudes and fixation durations, as well as about frequency and predictability as mediating sources. Moreover, the data demonstrated that reading depends on a complex interplay of information from several words.

Certainly, future research will contribute to a more fine-grained picture concerning lag, immediacy, and successor effects. Importantly, the investigation of relations between eye movements and ERPs from natural reading conditions will add evidence to the present findings. After all, ERPs from PSC1 reading were recorded while sentences were displayed word by word with a non-natural SOA of 700 ms. In fact, the comparison of fixation durations with ERPs from a near-normal reading speed (Chapter 4) suggested that frequency-based access is often achieved within a fixation. Thus, the proportion and nature of processes spilling over to subsequent fixations are important issues to be addressed in upcoming studies.

An even more sophisticated way of taking advantage from the two methods is the simultaneous recording of EEG and eye movements in natural reading. This approach provides neural activity and oculomotor behavior from the same subjects in ecologically valid settings. Although such co-registrations come with severe methodological difficulties, first successful steps have not only demonstrated the feasibility but have already yielded pioneering results about processes in left-to-right reading (Baccino & Manunta, 2005; Dimigen et al., 2006; Hutzler et al., 2007). The co-registration of ERPs and eye movements may contribute to the solution of theoretical controversies that, for instance, are implemented in different models of oculomotor control (e.g., Engbert et al., 2005; Reichle, Warren, & McConnell, 2009). In particular, the examination of influences from past, current, and future words will add insights about the time course of word processing as well as about the uptake of visual information from non-fixated stimuli. At the same time, uncovering relations between eye movements and correlates of mental processes will advance conceptions of oculomotor control. Thus, the combination of ERPs and eye movements appears as a major step forward towards the understanding of natural reading and, more general, of visual perception.

6.1.5 Models of word recognition

Besides evidence from ERPs and eye movements, models enhance the comprehension of language processing. Those explicate assumptions about mechanisms of word recognition and generate testable hypotheses. The present work contrasted two frameworks deriving different predictions about the influence of top-down processes in word recognition. According to a the serial *Bin Theory*, lexical access relies on bottom-up information while top-down modulation acts on a purely post-lexical level (Forster, 1976, 1992; Murray & Forster, 2004). In contrast, the parallel *Interactive Activation Model* (IAM) incorporates rapid influences from higher levels, such that lexical processing is determined by both bottom-up and top-down processes (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982). The present data from three ERP studies consistently lend support to the parallel approach. Predictability effects were observed in time intervals of frequency-based access, suggesting top-down influences on lexical levels of word recognition (Chapters 2 and 4).

On the basis of assumptions of the IAM, we conceived a framework taking into account top-down and bottom-up processes, as well as influences of presentation rate (Chapter 4). In particular, we incorporated the pre-activation of expected visual input as a central principle (DeLong et al., 2005; McClelland & Rumelhart, 1981; Otten et al., 2007; Otten & Van Berkum, 2008; Rumelhart & McClelland, 1982; Van Berkum et al., 2005; Wicha, Moreno, & Kutas, 2003; Wicha et al., 2004). With this qualitative approach, the findings of the present PSC3 studies could be mapped onto a common timeline of word recognition. Forthcoming experiments manipulating the strength of top-down expectations and bottom-up signals as well as presentation rates will examine the validity of the underlying assumptions.

As another step forward, the computational implementation of the proposed model would provide quantitative estimates about the time course of bottom-up and top-down processes that could be tested in ERP studies. Indeed, computational models of the interactive activation family have already been successfully used to account for processes of word recognition on a neural level (cf., Braun et al., 2006; Grainger & Holcomb, 2009; Holcomb, Grainger, & O'Rourke, 2002). Thus, psycholinguistic research will substantially benefit from such multi-methodological strategies combining complementary approaches, like models, ERPs, and eye movements (cf., Barber & Kutas, 2007; Jacobs & Carr, 1995).

6.2 Conclusions

The present thesis focused the common role of bottom-up and top-down information in reading. Beyond all doubt, bottom-up processes play a leading role in visual word recognition. Per definition, written stimuli are a basic prerequisite for reading, and most often, the identification of a word fails in the absence of sufficient visual information.

Despite this fact, the present studies demonstrated that word recognition does not exclusively resort to the accumulation of sensory input. Given an appropriate context, readers are able to interpret this information and to derive online predictions about upcoming words very fast. This process grants elaborated top-down predictions that are involved in earliest levels of perception. We have shown that lexical processing is substantially driven by the influence of both bottom-up and top-down information and that their joint consideration is essential for the understanding of the timeline of word recognition. Further, we provided evidence that word processing is sensitive to influences from present, past, and future words. Accordingly, word recognition is an active process that seems to take information from every source that is available.

The anticipation of upcoming events does not only hold for the case of reading, but is relevant in various domains and modalities. Thus, top-down predictions appear as a major functionality of perception to grant highly efficient processing of sensory information. I therefore conclude with the notion that, besides reading, the ability to predict is an outstanding achievement of the human brain.

References

Altmann, G. T. M. (1997). *The Ascent of Babel. An exploration of language, mind, and understanding*. Oxford: Oxford University Press.

Altmann, G. T. M., & Kamide, Y. (1999). Incremental interpretation at verbs: Restricting the domain of subsequent reference. *Cognition*, *73*(3), 247-264.

Altmann, G. T. M., & Kamide, Y. (2007). The real-time mediation of visual attention by language and world knowledge: Linking anticipatory (and other) eye movements to linguistic processing. *Journal of Memory and Language*, *57*, 502-518.

Altmann, G. T. M., & Mirkovic, J. (2009). Incrementality and prediction in human sentence processing. *Cognitive Science*, *33*, 583-609.

Anllo-Vento, L., & Hillyard, S. A. (1996). Selective attention to the color and direction of moving stimuli: Electrophysiological correlates of hierarchical feature selection. *Perception and Psychophysics*, *58*(2), 191-206.

Ashby, J., Rayner, K., & Clifton, C. (2005). Eye movements of highly skilled and average readers: Differential effects of frequency and predictability. *Quarterly Journal of Experimental Psychology*, *58*(6), 1065-1086.

Assadollahi, R., & Pulvermüller, F. (2001). Neuromagnetic evidence for early access to cognitive representations. *Neuroreport*, *12*(2), 207-213.

Baccino, T., & Manunta, Y. (2005). Eye-fixation-related potentials: Insight into parafoveal processing. *Journal of Psychophysiology*, *19*(3), 204-215.

Balota, D. A., & Chumbley, J. I. (1984). Are lexical decisions a good measure of lexical access? The role of word frequency in the neglected decision stage. *Journal of Experimental Psychology: Human Perception and Performance*, *10*(3), 340-357.

Balota, D. A., Pollatsek, A., & Rayner, K. (1985). The interaction of contextual constraints and parafoveal visual information in reading. *Cognitive Psychology*, *17*(3), 364-90.

Bar, M. (2007). The proactive brain: Using analogies and associations to generate predictions. *Trends in Cognitive Sciences*, *11*(7), 280-289.

Bar, M., Kassam, K. S., Ghuman, A. S., Boshyan, J., Schmidt, A. M., Dale, A. M., et al. (2006). Top-down facilitation of visual recognition. *Proceedings of the National Academy of Sciences of the United States of America*, *103*(2), 449-454.

Barber, H. A., & Kutas, M. (2007). Interplay between computational models and cognitive electrophysiology in visual word recognition. *Brain Research Reviews*, *53*(1), 98-123.

Bays, P. M., Flanagan, J. R., & Wolpert, D. M. (2006). Attenuation of self-generated tactile sensations is predictive, not postdictive. *PLoS Biology*, *4*(2), 281-284.

Becker, C. A. (1979). Semantic context and word frequency effects in visual word recognition. *Journal of Experimental Psychology: Human Perception and Performance*, *5*(2), 252-259.

Becker, C. A. (1980). Semantic context effects in visual word recognition: An analysis of semantic strategies. *Memory and Cognition*, *8*(6), 493-512.

Berg, P., & Scherg, M. (1994). A multiple source approach to the correction of eye artifacts. *Electroencephalography and Clinical Neurophysiology*, *90*(3), 229-241.

Berger, H. (1929). Electroencephalogram in humans. *Archiv für Psychiatrie und Nervenkrankheiten*, *87*, 527-570.

Besson, M., Boaz, T., Fischler, I., & Raney, G. (1992). Effects of automatic associative activation on explicit and implicit memory tests. *Journal of Experimental Psychology: Learning Memory and Cognition*, *18*(1), 89-105.

Bouma, H., & de Voogd, A. H. (1974). On the control of eye saccades in reading. *Vision Research*, *14*, 273-284.

Braun, M., Hutzler, F., Ziegler, J. C., Dambacher, M., & Jacobs, A. M. (2009). Pseudohomophone effects provide evidence of early lexico-phonological processing in visual word recognition. *Human Brain Mapping*, *30*, 1977-1989.

Braun, M., Jacobs, A. M., Hahne, A., Ricker, B., Hofmann, M., & Hutzler, F. (2006). Model-generated lexical activity predicts graded ERP amplitudes in lexical decision. *Brain Research*, *1073*, 431-439.

Brown, C. M., & Hagoort, P. (1993). The processing nature of the N400: Evidence from masked priming. *Journal of Cognitive Neuroscience*, *5*(1), 34-44.

Brown, C. M., Hagoort, P., & ter Keurs, M. (1999). Electrophysiological signatures of visual lexical processing: Open- and closed-class words. *Journal of Cognitive Neuroscience*, *11*(3), 261-281.

Burgess, C., Tanenhaus, M. K., & Seidenberg, M. S. (1989). Context and lexical access: Implications of nonword interference for lexical ambiguity resolution. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *15*(4), 620-632.

Calvo, M. G., & Meseguer, E. (2002). Eye movements and processing stages in reading: Relative contribution of visual, lexical, and contextual factors. *The Spanish Journal of Psychology*, *5*(1), 66-77.

Camblin, C. C., Ledoux, K., Boudewyn, M., Gordon, P. C., & Swaab, T. Y. (2007). Processing new and repeated names: Effects of coreference on repetition priming with speech and fast rsvp. *Brain Research*, *1146*, 172-184.

Carlsson, K., Petrovic, P., Skare, S., Petersson, K. M., & Ingvar, M. (2000). Tickling expectations: Neural processing in anticipation of a sensory stimulus. *Journal of Cognitive Neuroscience*, *12*(4), 691-703.

Chaumon, M., Drouet, V., & Tallon-Baudry, C. (2008). Unconscious associative memory affects visual processing before 100 ms. *Journal of Vision*, *8*(3).

Churchland, P. S., Ramachandran, V. S., & Sejnowski, T. J. (1994). A critique of pure vision. In C. Koch & J. L. Davis (Eds.), *Large-scale neuronal theories of the brain* (p. 23-60). Cambridge MA: MIT Press.

Cohen, J., & Cohen, P. (1975). *Applied multiple regression/correlation analysis for the behavioral sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Cohen, L., Dehaene, S., Naccache, L., Lehericy, S., Dehaene-Lambertz, G., Henaff, M. A., et al. (2000). The visual word form area: Spatial and temporal characterization of an initial stage of reading in normal subjects and posterior split-brain patients. *Brain*, *123*, 291-307.

Coltheart, M., Rastle, K., Perry, C., Langdon, R., & Ziegler, J. (2001). DRC: A dual route cascaded model of visual word recognition and reading aloud. *Psychological Review*, *108*(1), 204-256.

Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews Neuroscience*, *3*(3), 201-215.

Coulson, S., & Federmeier, K. D. (in press). Words in context: ERPs and the lexical/postlexical distinction. *Journal of Psycholinguistic Research*.

Dale, C. L., Simpson, G. V., Foxe, J. J., Luks, T. L., & Worden, M. S. (2008). ERP correlates of anticipatory attention: Spatial and non-spatial specificity and relation to subsequent selective attention. *Experimental Brain Research*, *188*(1), 45-62.

Dambacher, M., & Kliegl, R. (2007). Synchronizing timelines: Relations between fixation durations and N400 amplitudes during sentence reading. *Brain Research*, *1155*, 147-162.

Dambacher, M., Kliegl, R., Hofmann, M., & Jacobs, A. M. (2006). Frequency and predictability effects on event-related potentials during reading. *Brain Research*, *1084*, 89-103.

Dambacher, M., Rolfs, M., Göllner, K., Kliegl, R., & Jacobs, A. (2009). Event-related potentials reveal rapid verification of predicted visual input. *PLoS ONE*, *4*(3), e5047.

Davidson, P. R., & Wolpert, D. M. (2003). Motor learning and prediction in a variable environment. *Current Opinion in Neurobiology*, *13*(2), 232-237.

Deacon, D., Dynowska, A., Ritter, W., & Grose-Fifer, J. (2004). Repetition and semantic priming of nonwords: Implications for theories of N400 and word recognition. *Psychophysiology*, *41*(1), 60-74.

Deacon, D., Hewitt, S., Yang, C. M., & Nagata, M. (2000). Event-related potential indices of semantic priming using masked and unmasked words: Evidence that the N400 does not reflect a post-lexical process.

Cognitive Brain Research, *9*(2), 137-146.

Dehaene, S., Cohen, L., Sigman, M., & Vinckier, F. (2005). The neural code for written words: A proposal. *Trends in Cognitive Sciences*, *9*(7), 335-341.

DeLong, K. A., Urbach, T. P., & Kutas, M. (2005). Probabilistic word pre-activation during language comprehension inferred from electrical brain activity. *Nature Neuroscience*, *8*(8), 1117-1121.

Di Lollo, V., Enns, J. T., & Rensink, R. A. (2000). Competition for consciousness among visual events: The psychophysics of reentrant visual processes. *Journal of Experimental Psychology: General*, *129*(4), 481-507.

Di Lollo, V., Kawahara, J., Zuvic, S. M., & Visser, T. A. W. (2001). The preattentive emperor has no clothes: A dynamic redressing. *Journal of Experimental Psychology: General*, *130*(3), 479-492.

Dimigen, O., Sommer, W., Hohlfeld, A., Jacobs, A. M., Engbert, R., & Kliegl, R. (2006). Concurrent recording of EEG and gaze position: Measuring effects of word predictability during left-to-right reading of normal sentences. *Journal of Cognitive Neuroscience*, *Supplement*, 224.

Di Russo, F., Martinez, A., & Hillyard, S. A. (2003). Source analysis of event-related cortical activity during visuo-spatial attention. *Cerebral Cortex*, *13*(5), 486-499.

Duffy, S. A., Henderson, J. M., & Morris, R. K. (1989). Semantic facilitation of lexical access during sentence processing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *15*(5), 791-801.

Ehrlich, S. F., & Rayner, K. (1981). Contextual effects on word perception and eye movements during reading. *Journal of Verbal Learning and Verbal Behavior*, *20*(6), 641-655.

Elman, J. L. (1990). Finding structure in time. *Cognitive Science*, *14*(2), 179-211.

Elman, J. L. (2004). An alternative view of the mental lexicon. *Trends in Cognitive Sciences*, *8*(7), 301-306.

Engbert, R., & Kliegl, R. (2003). Microsaccades uncover the orientation of covert attention. *Vision Research*, *43*(9), 1035-1045.

Engbert, R., Krampe, R. T., Kurths, J., & Kliegl, R. (2002). Synchronizing movements with the metronome: Nonlinear error correction and unstable periodic orbits. *Brain and Cognition*, *48*(1), 107-116.

Engbert, R., Nuthmann, A., Richter, E. M., & Kliegl, R. (2005). SWIFT: A dynamical model of saccade generation during reading. *Psychological Review*, *112*(4), 777-813.

Engel, A. K., Fries, P., & Singer, W. (2001). Dynamic predictions: Oscillations and synchrony in top-down processing. *Nature Reviews Neuroscience*, *2*(10), 704-716.

Enns, J. T., & Di Lollo, V. (2000). What's new in visual masking? *Trends in Cognitive Sciences*, *4*(9), 345-352.

Enns, J. T., & Lleras, A. (2008). What's next? New evidence for prediction in human vision. *Trends in Cognitive Sciences*, *12*(9), 327-333.

Fischler, I., & Bloom, P. A. (1979). Automatic and attentional processes in the effects of sentence contexts on word recognition. *Journal of Verbal Learning and Verbal Behavior*, *18*(1), 1-20.

Fodor, J. A. (1983). *The modularity of mind*. MIT Press Cambridge, MA.

Forster, K. I. (1976). Accessing the mental lexicon. In R. J. Wales & E. L. Walker (Eds.), *New approaches to language mechanisms: A collection of psycholinguistic studies* (p. 257-287). Amsterdam: North Holland.

Forster, K. I. (1979). Levels of processing and the structure of the language processor. In W. E. Cooper & E. C. T. Walker (Eds.), *Sentence processing: Psycholinguistic studies presented to Merrill Garrett* (p. 25-87). Hillsdale, NJ: Erlbaum.

Forster, K. I. (1992). Memory-adressing mechanisms and lexical access. In R. Frost & L. Katz (Eds.), *Orthography, phonology, morphology, and meaning* (p. 413-425). Elsevier Science Publishers B.V.

Forster, K. I., & Chambers, S. M. (1973). Lexical access and naming time. *Journal of Verbal Learning and Verbal Behavior*, *12*(6), 627-635.

Fox, J. (2006). Structural equation modeling with the sem package in R. *Structural Equation Modeling*, *13*(3), 465-486.

Foxe, J. J., & Simpson, G. V. (2002). Flow of activation from V1 to frontal cortex in humans: A framework for defining "early" visual processing. *Experimental Brain Research*, *142*(1), 139-150.

Frederiksen, J. R., & Kroll, J. F. (1976). Spelling and sound: Approaches to internal lexicon. *Journal of Experimental Psychology: Human Perception and Performance*, *2*(3), 361-379.

Friedman, D., Simson, R., Ritter, W., & Rapin, I. (1975). Late positive component (P300) and information processing in sentences. *Electroencephalography and Clinical Neurophysiology*, *38*(3), 255-262.

Fründ, I., Busch, N. A., Schadow, J., Gruber, T., Körner, U., & Herrmann, C. S. (2008). Time pressure modulates electrophysiological correlates of early visual processing. *PLoS ONE*, *3*(2), e1675.

Geyken, A. (2007). The DWDS corpus: A reference corpus for the German language of the 20th century. In C. Fellbaum (Ed.), *Idioms and collocations: Corpus-based linguistic, lexicographic studies* (p. 23-40). London: Continuum Press.

Gilbert, C. D., & Sigman, M. (2007). Brain states: Top-down influences in sensory processing. *Neuron*, *54*, 677-696.

Glucksberg, S., Kreuz, R. J., & Rho, S. H. (1986). Context can constrain lexical access: Implications for models of language comprehension. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *12*(3), 323-335.

Graf, R., Nagler, M., & Jacobs, A. M. (2005). Factor analysis of 57 variables in visual word recognition. *Zeitschrift für Psychologie*, *213*(4), 205-218.

Grainger, J. (1990). Word frequency and neighborhood frequency effects in lexical decision and naming. *Journal of Memory and Language*, *29*(2), 228-244.

Grainger, J. (2008). Cracking the orthographic code: An introduction. *Language and Cognitive Processes*, *23*(1), 1-35.

Grainger, J., & Holcomb, P. J. (2008). Neural constraints on a functional architecture for word recognition. In P. Cornelissen, P. Hansen, M. Kringelbach, & K. Pugh (Eds.), *The neural basis of reading.* Oxford: Oxford University Press.

Grainger, J., & Holcomb, P. J. (2009). Watching the word go by: On the time-course of component processes in visual word recognition. *Language and Linguistics Compass*, *3*(1), 128-156.

Grainger, J., & Jacobs, A. M. (1996). Orthographic processing in visual word recognition: A multiple read-out model. *Psychological Review*, *103*(3), 518-565.

Grossberg, S. (1999). The link between brain learning, attention, and consciousness. *Consciousness and Cognition*, *8*(1), 1-44.

Guyonneau, R., VanRullen, R., & Thorpe, S. J. (2004). Temporal codes and sparse representations: A key to understanding rapid processing in the visual system. *Journal of Physiology-Paris*, *98*(4-6), 487-497.

Hagoort, P. (2003). Interplay between syntax and semantics during sentence comprehension: ERP effects of combining syntactic and semantic violations. *Journal of Cognitive Neuroscience*, *15*(6), 883-899.

Hagoort, P., Brown, C., & Groothusen, J. (1993). The syntactic positive shift (SPS) as an ERP measure of syntactic processing. *Language and Cognitive Processes*, *8*(4), 439-483.

Hagoort, P., & Brown, C. M. (2000a). ERP effects of listening to speech compared to reading: The P600/SPS to syntactic violations in spoken sentences and rapid serial visual presentation. *Neuropsychologia*, *38*(11), 1531-1549.

Hagoort, P., & Brown, C. M. (2000b). ERP effects of listening to speech: Semantic ERP effects. *Neuropsychologia*, *38*(11), 1518-1530.

Handy, T. C., & Mangun, G. R. (2000). Attention and spatial selection: Electrophysiological evidence for modulation by perceptual load. *Perception and Psychophysics*, *62*(1), 175-186.

Hauk, O., Davis, M. H., Ford, M., Pulvermüller, F., & Marslen-Wilson, W. D. (2006). The time course of visual word recognition as revealed by linear regression analysis of ERP data. *Neuroimage*, *30*(4), 1383-1400.

Hauk, O., & Pulvermüller, F. (2004). Effects of word length and frequency on the human event-related potential. *Clinical Neurophysiology*, *115*(5), 1090-1103.

Hayhoe, M. (2000). Vision using routines: A functional account of vision. *Visual Cognition*, *7*(1-3), 43-64.

Henderson, J. M., & Ferreira, F. (1990). Effects of foveal processing difficulty on the perceptual span in reading: Implications for attention and eye movement control. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *16*(3), 417-429.

Hillyard, S. A., & Anllo-Vento, L. (1998). Event-related brain potentials in the study of visual selective attention. *Proceedings of the National*

Academy of Sciences of the United States of America, *95*(3), 781-787.

Hinojosa, J. A., Martin-Loeches, M., & Rubia, F. J. (2001). Event-related potentials and semantics: An overview and an integrative proposal. *Brain and Language*, *78*(1), 128-139.

Holcomb, P. J. (1993). Semantic priming and stimulus degradation: Implications for the role of the N400 in language processing. *Psychophysiology*, *30*(1), 47-61.

Holcomb, P. J., Grainger, J., & O'Rourke, T. (2002). An electrophysiological study of the effects of orthographic neighborhood size on printed word perception. *Journal of Cognitive Neuroscience*, *14*(6), 938-950.

Hopf, J. M., Boelmans, K., Schoenfeld, M. A., Luck, S. J., & Heinze, H. J. (2004). Attention to features precedes attention to locations in visual search: Evidence from electromagnetic brain responses in humans. *Journal of Neuroscience*, *24*(8), 1822-1832.

Howes, D. H., & Solomon, R. L. (1951). Visual duration threshold as a function of word probability. *Journal of Experimental Psychology*, *41*(6), 401-410.

http://www.dwds.de. (2006). *Das Digitale Wörterbuch der deutschen Sprache des 20. Jahrhunderts.*

Hudson, P. T. W., & Bergman, M. W. (1985). Lexical knowledge in word recognition: Word length and word frequency in naming and lexical decision tasks. *Journal of Memory and Language*, *24*(1), 46-58.

Hutzler, F., Braun, M., Vo, M. L. H., Engl, V., Hofmann, M., Dambacher, M., et al. (2007). Welcome to the real world: Validating fixation-related brain potentials for ecologically valid settings. *Brain Research*, *1172*, 124-129.

Huynh, H., & Feldt, L. S. (1976). Estimation of the box correction for degrees of freedom from sample data in randomized block and split-plot designs. *Journal of Educational Statistics*, *1*, 69-82.

Inhoff, A. W., & Rayner, K. (1986). Parafoveal word processing during eye fixations in reading: Effects of word frequency. *Perception and Psychophysics*, *40*(6), 431-439.

Jacobs, A. M., & Carr, T. H. (1995). Mind mappers and cognitive modelers: Toward cross-fertilization. *Behavioral and Brain Sciences*, *18*(2), 362-363.

Jacobs, A. M., & Grainger, J. (1994). Models of visual word recognition: Sampling the state of the art. *Journal of Experimental Psychology: Human Perception and Performance*, *20*(6), 1311-1334.

Jacobs, A. M., Nuerk, H. C., Graf, R., Braun, M., & Nazir, T. A. (2008). The initial capitalization superiority effect in German: Evidence for a perceptual frequency variant of the orthographic cue hypothesis of visual word recognition. *Psychological Research*, *72*(6), 657-665.

Jacobs, A. M., Rey, A., Ziegler, J. C., & Grainger, J. (1998). MROM-p: An interactive activation, multiple readout model of orthographic and phonological processes in visual word recognition. In J. Grainger & A. M. Jacobs (Eds.), *Localist connectionist approaches to human cognition* (p. 147-188). Mahwah, NJ: Lawrence Erlbaum Associates.

Jung, T.-P., Humphries, C., Lee, T.-W., Makeig, S., McKeown, M., Iragui, V., et al. (1998). Extended ICA removes artifacts from electroencephalographic recordings. In M. Jordan, M. Kearns, & S. Solla (Eds.), *Advances in neural information processing systems* (Vol. 10, p. 894-900). Cambridge MA: MIT Press.

Kamide, Y., Altmann, G. T. M., & Haywood, S. L. (2003). The time-course of prediction in incremental sentence processing: Evidence from anticipatory eye movements. *Journal of Memory and Language*, *49*(1), 133-156.

Kamide, Y., Scheepers, C., & Altmann, G. T. M. (2003). Integration of syntactic and semantic information in predictive processing: Cross-linguistic evidence from German and English. *Journal of Psycholinguistic Research*, *32*(1), 37-55.

Kastner, S., Pinsk, M. A., De Weerd, P., Desimone, R., & Ungerleider, L. G. (1999). Increased activity in human visual cortex during directed attention in the absence of visual stimulation. *Neuron*, *22*(4), 751-761.

Kelly, S. P., Gomez-Ramirez, M., & Foxe, J. J. (2008). Spatial attention modulates initial afferent activity in human primary visual cortex. *Cerebral Cortex*, *18*(11), 2629-2636.

Kennedy, A., & Pynte, J. (2005). Parafoveal-on-foveal effects in normal reading. *Vision Research*, *45*(2), 153-168.

King, J. W., & Kutas, M. (1998). Neural plasticity in the dynamics of human visual word recognition. *Neuroscience Letters*, *244*(2), 61-64.

Kintsch, W., & Mross, E. F. (1985). Context effects in word identification. *Journal of Memory and Language*, *24*(3), 336-349.

Kleiman, G. M. (1980). Sentence frame contexts and lexical decisions: Sentence-acceptability and word-relatedness effects. *Memory and Cognition*, *8*(4), 336-344.

Kliegl, R. (2007). Toward a perceptual-span theory of distributed processing in reading: A reply to Rayner, Pollatsek, Drieghe, Slattery, and Reichle (2007). *Journal of Experimental Psychology: General*, *136*(3), 530-537.

Kliegl, R., Geyken, A., Hanneforth, T., & Würzner, K. (manuscript in preparation). Corpus matters: A comparison of German DWDS and CELEX lexical and sublexical frequency norms for the prediction of reading fixations.

Kliegl, R., Grabner, E., Rolfs, M., & Engbert, R. (2004). Length, frequency, and predictability effects of words on eye movements in reading. *European Journal of Cognitive Psychology*, *16*(1-2), 262-284.

Kliegl, R., Nuthmann, A., & Engbert, R. (2006). Tracking the mind during reading: The influence of past, present, and future words on fixation durations. *Journal of Experimental Psychology: General*, *135*(1), 12-35.

Kolers, P. (1976). Buswell's discoveries. In R. A. Monty & F. W. Senders (Eds.), *Eye movements and psychological processes.* Hillsdale, NJ: Erlbaum.

Kotz, S. A., Von Cramon, D. Y., & Friederici, A. D. (2005). On the role of phonological short-term memory in sentence processing: ERP single case evidence on modality-specific effects. *Cognitive Neuropsychology*, *22*(8), 931-958.

Kutas, M. (1987). Event-related brain potentials (ERPs) elicited during rapid serial visual presentation of congruous and incongruous sentences. In R. Johnson Jr., J. W. Rohrbaugh, & R. Parasuraman (Eds.), *Current trends in event-related potential research* (Vol. (EEG Suppl. 40), p. 406-11). Elsevier Science Publishers B. V.

Kutas, M., & Federmeier, K. D. (2000). Electrophysiology reveals semantic memory use in language comprehension. *Trends in Cognitive Sciences*, *4*(12), 463-470.

Kutas, M., & Hillyard, S. A. (1980). Reading senseless sentences: Brain potentials reflect semantic incongruity. *Science*, *207*(4427), 203-205.

Kutas, M., & Hillyard, S. A. (1983). Event-related brain potentials to grammatical errors and semantic anomalies. *Memory and Cognition*, *11*(5), 539-550.

Kutas, M., & Hillyard, S. A. (1984). Brain potentials during reading reflect word expectancy and semantic association. *Nature*, *307*(5947), 161-163.

Kutas, M., & Van Petten, C. (1994). Psycholinguistics electrified: Event-related brain potential investigations. In M. A. Gernsbacher (Ed.), *Handbook of psycholinguistics* (p. 83-143). San Diego: Academic Press.

Kutas, M., Van Petten, C., & Besson, M. (1988). Event-related potential asymmetries during the reading of sentences. *Electroencephalography and Clinical Neurophysiology*, *69*(3), 218-233.

Kutas, M., Van Petten, C., & Kluender, R. (2006). Psycholinguistics electrified II: 1994-2005. In M. Gernsbacher & M. Traxler (Eds.), *Handbook of psycholinguistics, 2nd edition* (p. 659-724). New York: Elsevier Press.

Kveraga, K., Ghuman, A. S., & Bar, M. (2007). Top-down predictions in the cognitive brain. *Brain and Cognition*, *65*, 145-168.

Lavie, N. (1995). Perceptual load as a necessary condition for selective attention. *Journal of Experimental Psychology: Human Perception and Performance*, *21*(3), 451-468.

Lavie, N. (2005). Distracted and confused?: Selective attention under load. *Trends in Cognitive Sciences*, *9*(2), 75-82.

Lavie, N., & Tsal, Y. (1994). Perceptual load as a major determinant of the locus of selection in visual attention. *Perception and Psychophysics*, *56*(2), 183-197.

Lins, O. G., Picton, T. W., Berg, P., & Scherg, M. (1993). Ocular artifacts in EEG and event-related potentials I: Scalp topography. *Brain Topography*, *6*(1), 51-63.

Lleras, A., Rensink, R. A., & Enns, J. T. (2005). Rapid resumption of interrupted visual search. *Psychological Science*, *16*(9), 684-688.

Lleras, A., Rensink, R. A., & Enns, J. T. (2007). Consequences of display changes during interrupted visual search: Rapid resumption is target specific. *Perception and Psychophysics*, *69*(6), 980-993.

Loehlin, J. (2004). *Latent variable models: An introduction to factor, path, and structural equation analysis*. New Jersey: Lawrence Erlbaum Associates, Inc.

Loftus, G. R., & Masson, M. E. J. (1994). Using confidence intervals in within-subject designs. *Psychonomic Bulletin and Review*, *1*(4), 476-490.

Lorch, R. F., & Myers, J. L. (1990). Regression analyses of repeated measures data in cognitive research. *Journal of Experimental Psychology: Learning Memory and Cognition*, *16*(1), 149-157.

Lucas, M. M. (1987). Frequency effects on the processing of ambiguous words in sentence contexts. *Language and Speech*, *30*, 25-46.

Luck, S. J., Woodman, G. F., & Vogel, E. K. (2000). Event-related potential studies of attention. *Trends in Cognitive Sciences*, *4*(11), 432-440.

Mangun, G. R., Hillyard, S. A., & Luck, S. J. (1993). Electrocortical substrates of visual selective attention. In D. E. Meyer & S. Kornblum (Eds.), *Attention and performance XIV: Synergies in experimental psychology, artificial intelligence, and cognitive neuroscience* (p. 219-243). Cambridge MA: MIT Press.

Martinez, A., Anllo-Vento, L., Sereno, M. I., Frank, L. R., Buxton, R. B., Dubowitz, D. J., et al. (1999). Involvement of striate and extrastriate visual cortical areas in spatial attention. *Nature Neuroscience*, *2*(4), 364-369.

Martinez, A., DiRusso, F., Anllo-Vento, L., Sereno, M. I., Buxton, R. B., & Hillyard, S. A. (2001). Putting spatial attention on the map: Timing and localization of stimulus selection processes in striate and extrastriate visual areas. *Vision Research*, *41*(10-11), 1437-1457.

Matin, E. (1974). Saccadic suppression: Review and an analysis. *Psychological Bulletin*, *81*(12), 899-917.

McCandliss, B. D., Cohen, L., & Dehaene, S. (2003). The visual word form area: Expertise for reading in the fusiform gyrus. *Trends in Cognitive Sciences*, *7*(7), 293-299.

McCarthy, G., & Wood, C. C. (1985). Scalp distributions of event-related potentials: An ambiguity associated with analysis of variance models. *Electroencephalography and Clinical Neurophysiology*, *62*(3), 203-208.

McClelland, J. L. (1987). The case of interactionism in language processing. In M. Coltheart (Ed.), *Attention and performance XII: The psychology of reading* (p. 3-36). Hillsdale, NJ: Erlbaum.

McClelland, J. L., & Rumelhart, D. E. (1981). An interactive activation model of context effects in letter perception: Part 1. An account of basic findings. *Psychological Review*, *88*(5), 375-407.

Mechelli, A., Price, C. J., Friston, K. J., & Ishai, A. (2004). Where bottom-up meets top-down: Neuronal interactions during perception and imagery. *Cerebral Cortex*, *14*(11), 1256-1265.

Miller, J., Patterson, T., & Ulrich, R. (1998). Jackknife-based method for measuring LRP onset latency differences. *Psychophysiology*, *35*(1), 99-115.

Misra, M., & Holcomb, P. J. (2003). Event-related potential indices of masked repetition priming. *Psychophysiology*, *40*(1), 115-130.

Monsell, S. (1990). The nature and locus of word frequency effects in reading. In D. Besner & G. W. Humphreys (Eds.), *Basic processes in reading: Visual word recognition* (p. 148-197). Lawrence Erlbaum Associates.

Monsell, S., Doyle, M. C., & Haggard, P. N. (1989). Effects of frequency on visual word recognition tasks: Where are they? *Journal of Experimental Psychology: General*, *118*(1), 43-71.

Morton, J. (1969). Interaction of information in word recognition. *Psychological Review*, *76*(2), 165-178.

Mumford, D. (1992). On the computational architecture of the neocortex: II. the role of cortico-cortical loops. *Biological Cybernetics*, *66*(3), 241-251.

Münte, T. F., Wieringa, B. M., Weyerts, H., Szentkuti, A., Matzke, M., & Johannes, S. (2001). Differences in brain potentials to open and closed class words: Class and frequency effects. *Neuropsychologia*, *39*(1), 91-102.

Murray, W. S., & Forster, K. I. (2004). Serial mechanisms in lexical access: The rank hypothesis. *Psychological Review*, *111*(3), 721-756.

Nazir, T. A., Jacobs, A. M., & O'Regan, J. K. (1998). Letter legibility and visual word recognition. *Memory and Cognition*, *26*(4), 810-821.

Neville, H. J., Mills, D. L., & Lawson, D. S. (1992). Fractionating language: Different neural subsystems with different sensitive periods. *Cerebral Cortex*, *2*, 244-258.

Nuthmann, A., Engbert, R., & Kliegl, R. (2007). The IOVP effect in mindless reading: Experiment and modeling. *Vision Research*, *47*(7), 990-1002.

O'Connor, D. H., Fukui, M. M., Pinsk, M. A., & Kastner, S. (2002). Attention modulates responses in the human lateral geniculate nucleus. *Nature Neuroscience*, *5*(11), 1203-1209.

Onifer, W., & Swinney, D. A. (1981). Accessing lexical ambiguities during sentence comprehension: Effects of frequency of meaning and contextual bias. *Memory and Cognition*, *9*(3), 225-236.

O'Regan, J. K. (1992). Solving the "real" mysteries of visual perception: The world as an outside memory. *Canadian Journal of Psychology*, *46*(3), 461-488.

O'Regan, J. K., Deubel, H., Clark, J. J., & Rensink, R. A. (2000). Picture changes during blinks: Looking without seeing and seeing without looking. *Visual Cognition*, *7*(1-3), 191-211.

O'Regan, J. K., & Jacobs, A. M. (1992). Optimal viewing position effect in word recognition: A challenge to current theory. *Journal of Experimental Psychology: Human Perception and Performance*, *18*(1), 185-197.

Osterhout, L. (1997). On the brain response to syntactic anomalies: Manipulations of word position and word class reveal individual differences. *Brain and Language*, *59*(3), 494-522.

Osterhout, L., Bersick, M., & McKinnon, R. (1997). Brain potentials elicited by words: Word length and frequency predict the latency of an early negativity. *Biological Psychology*, *46*(2), 143-168.

Osterhout, L., & Holcomb, P. J. (1995). Event-related potentials and language comprehension. In M. D. Rugg & M. G. H. Coles (Eds.), *Electrophysiology of mind: Event-related brain potentials and cognition* (p. 171-215). Oxford: Oxford University Press.

Osterhout, L., & Nicol, J. (1999). On the distinctiveness, independence, and time course of the brain responses to syntactic and semantic anomalies. *Language and Cognitive Processes*, *14*(3), 283-317.

Otten, M., Nieuwland, M. S., & Berkum, J. J. A. van. (2007). Great expectations: Specific lexical anticipation influences the processing of spoken language. *BMC Neuroscience*, *8*.

Otten, M., & Van Berkum, J. (2008). Discourse-based word anticipation during language processing: Prediction or priming? *Discourse Processes*, *45*(6), 464-496.

Paap, K. R., Newsome, S. L., McDonald, J. E., & Schvaneveldt, R. W. (1982). An activation-verification model for letter and word recognition: The word-superiority effect. *Psychological Review*, *89*(5), 573-594.

Penolazzi, B., Hauk, O., & Pulvermüller, F. (2007). Early semantic context integration and lexical access as revealed by event-related brain potentials. *Biological Psychology*, *74*(3), 374-388.

Pickering, M. J., & Garrod, S. (2007). Do people use language production to make predictions during comprehension? *Trends in Cognitive Sciences*, *11*(3), 105-110.

Pitts, M. A., Gavin, W. J., & Nerger, J. L. (2008). Early top-down influences on bistable perception revealed by event-related potentials. *Brain and Cognition*, *67*(1), 11-24.

Plaut, D. C., McClelland, J. L., Seidenberg, M. S., & Patterson, K. (1996). Understanding normal and impaired word reading: Computational principles in quasi-regular domains. *Psychological Review*, *103*(1), 56-115.

Poghosyan, V., & Ioannides, A. A. (2007). Precise mapping of early visual responses in space and time. *Neuroimage*, *35*(2), 759-770.

Pollatsek, A., Reichle, E. D., & Rayner, K. (2006). Tests of the E-Z Reader model: Exploring the interface between cognition and eye-movement control. *Cognitive Psychology*, *52*(1), 1-56.

Raney, G. (1993). Monitoring changes in cognitive load during reading: An event-related brain potential and reaction time analysis. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *19*(1), 51-69.

Raney, G., & Rayner, K. (1993). Event-related brain potentials, eye movements, and reading. *Psychological Science*, *4*, 283-286.

Raney, G., & Rayner, K. (1995). Word frequency effects and eye movements during two readings of a text. *Canadian Journal of Experimental*

Psychology, *49*(2), 151-172.

Rao, R. P. N., & Ballard, D. H. (1999). Predictive coding in the visual cortex: A functional interpretation of some extra-classical receptive-field effects. *Nature Neuroscience*, *2*(1), 79-87.

Rayner, K. (1977). Visual attention in reading: Eye movements reflect cognitive processes. *Memory and Cognition*, *4*, 443-448.

Rayner, K. (1978). Eye movements in reading and information processing. *Psychological Bulletin*, *85*, 618-660.

Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. *Psychological Bulletin*, *124*(3), 372-422.

Rayner, K. (2009). Eye movements and attention in reading, scene perception, and visual search. *Quaterly Journal of Experimental Psychology*, *62*(8), 1457-1506.

Rayner, K., Ashby, J., Pollatsek, A., & Reichle, E. D. (2004). The effects of frequency and predictability on eye fixations in reading: Implications for the E-Z Reader model. *Journal of Experimental Psychology: Human Perception and Performance*, *30*(4), 720-732.

Rayner, K., Binder, K. S., Ashby, J., & Pollatsek, A. (2001). Eye movement control in reading: Word predictability has little influence on initial landing positions in words. *Vision Research*, *41*(7), 943-954.

Rayner, K., & Duffy, S. A. (1986). Lexical complexity and fixation times in reading: Effects of word frequency, verb complexity, and lexical ambiguity. *Memory and Cognition*, *14*(3), 191-201.

Rayner, K., & Well, A. D. (1996). Effects of contextual constraint on eye movements in reading: A further examination. *Psychonomic Bulletin and Review*, *3*(4), 504-509.

Rayner, K., White, S., Kambe, G., Miller, B., & Liversedge, S. (2003). On the processing of meaning from parafoveal vision during eye fixations in reading. In J. Hyönä, R. Radach, & H. Deubel (Eds.), *The mind's eye: Cognitive and applied aspects of eye movement research* (p. 213-234). Amsterdam: Elsevier.

R-Development-Core-Team. (2006). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing.

Reichle, E. D., Pollatsek, A., Fisher, D. L., & Rayner, K. (1998). Toward a model of eye movement control in reading. *Psychological Review*, *105*(1), 125-157.

Reichle, E. D., Pollatsek, A., & Rayner, K. (2006). E-Z Reader: A cognitive-control, serial-attention model of eye-movement behavior during reading. *Cognitive Systems Research*, *7*, 4-22.

Reichle, E. D., Rayner, K., & Pollatsek, A. (2003). The E-Z Reader model of eye-movement control in reading: Comparisons to other models. *Behavioral and Brain Sciences*, *26*(4), 445-526.

Reichle, E. D., Warren, T., & McConnell, K. (2009). Using E-Z Reader to model the effects of higher level language processing on eye movements during reading. *Psychonomic Bulletin and Review*, *16*(1), 1-21.

Reilly, R. G., & Radach, R. (2006). Some empirical tests of an interactive activation model of eye movement control in reading. *Cognitive Systems Research*, *7*(1), 34-55.

Robichon, F., Besson, M., & Habib, M. (2002). An electrophysiological study of dyslexic and control adults in a sentence reading task. *Biological Psychology*, *59*(1), 29-53.

Rossell, S. L., Price, C. J., & Nobre, A. C. (2003). The anatomy and time course of semantic priming investigated by fMRI and ERPs. *Neuropsychologia*, *41*(5), 550-564.

Rubenstein, H., Garfield, L., & Millikan, J. A. (1970). Homographic entries in the internal lexicon. *Journal of Verbal Learning and Verbal Behavior*, *9*(5), 487-494.

Rugg, M. D. (1990). Event-related brain potentials dissociate repetition effects of high- and low-frequency words. *Memory and Cognition*, *18*(4), 367-379.

Rumelhart, D. E., & McClelland, J. L. (1982). An interactive activation model of context effects in letter perception: Part 2. The contextual enhancement effect and some tests and extensions of the model. *Psychological Review*, *89*(1), 60-94.

Ruz, M., & Nobre, A. C. (2008). Attention modulates initial stages of visual word processing. *Journal of Cognitive Neuroscience*, *20*(9), 1727-1736.

Sauseng, P., Klimesch, W., Stadler, W., Schabus, M., Doppelmayr, M., Hanslmayr, S., et al. (2005). A shift of visual spatial attention is selectively associated with human EEG alpha activity. *European*

Journal of Neuroscience, *22*(11), 2917-2926.

Schilling, H. E. H., Rayner, K., & Chumbley, J. I. (1998). Comparing naming, lexical decision, and eye fixation times: Word frequency effects and individual differences. *Memory and Cognition*, *26*(6), 1270-1281.

Schlösser, R., Wagner, G., & Sauer, H. (2006). Assessing the working memory network: Studies with functional magnetic resonance imaging and structural equation modeling. *Neuroscience*, *139*, 91-103.

Schoenfeld, M. A., Hopf, J. M., Martinez, A., Mai, H. M., Sattler, C., Gasde, A., et al. (2007). Spatio-temporal analysis of feature-based attention. *Cerebral Cortex*, *17*, 2468-2477.

Schroyens, W., Vitu, F., Brysbaert, M., & d'Ydewalle, G. (1999). Eye movement control during reading: Foveal load and parafoveal processing. *Quarterly Journal of Experimental Psychology*, *52*(4), 1021-1046.

Schuberth, R. E., & Eimas, P. D. (1977). Effects of context on classification of words and nonwords. *Journal of Experimental Psychology: Human Perception and Performance*, *3*(1), 27-36.

Schuberth, R. E., Spoehr, K. T., & Lane, D. M. (1981). Effects of stimulus and contextual information on the lexical decision process. *Memory and Cognition*, *9*(1), 68-77.

Schvaneveldt, R. W., & McDonald, J. E. (1981). Semantic context and the encoding of words: Evidence for two modes of stimulus analysis. *Journal of Experimental Psychology: Human Perception and Performance*, *7*(3), 673-687.

Schvaneveldt, R. W., Meyer, D. E., & Becker, C. A. (1976). Lexical ambiguity, semantic context, and visual word recognition. *Journal of Experimental Psychology: Human Perception and Performance*, *2*(2), 243-256.

Seidenberg, M. S. (2007). Connectionist models of reading. In M. G. Gaskell (Ed.), *The Oxford handbook of psycholinguistics* (p. 235-250). Oxford: Oxford University Press.

Seidenberg, M. S., & McClelland, J. L. (1989). A distributed, developmental model of word recognition and naming. *Psychological Review*, *96*(4), 523-568.

Sereno, S. C., Brewer, C. C., & O'Donnell, P. J. (2003). Context effects in word recognition: Evidence for early interactive processing. *Psychological Science*, *14*(4), 328-333.

Sereno, S. C., & Rayner, K. (2003). Measuring word recognition in reading: Eye movements and event-related potentials. *Trends in Cognitive Sciences*, *7*(11), 489-493.

Sereno, S. C., Rayner, K., & Posner, M. I. (1998). Establishing a time-line of word recognition: Evidence from eye movements and event-related potentials. *Neuroreport*, *9*(10), 2195-2200.

Shillcock, R., Ellison, T. M., & Monaghan, P. (2000). Eye-fixation behavior, lexical storage, and visual word recognition in a split processing model. *Psychological Review*, *107*(4), 824-851.

Sigman, M., Pan, H., Yang, Y. H., Stern, E., Silbersweig, D., & Gilbert, C. D. (2005). Top-down reorganization of activity in the visual pathway after learning a shape identification task. *Neuron*, *46*(5), 823-835.

Simmons, W. K., Martin, A., & Barsalou, L. W. (2005). Pictures of appetizing foods activate gustatory cortices for taste and reward. *Cerebral Cortex*, *15*(10), 1602-1608.

Simpson, G. B. (1981). Meaning dominance and semantic context in the processing of lexical ambiguity. *Journal of Verbal Learning and Verbal Behavior*, *20*(1), 120-136.

Simpson, G. B. (1994). Context and the processing of ambiguous words. In M. Gernsbacher (Ed.), *Handbook of psycholinguistics* (p. 359-374). San Diego: Academic Press.

Somers, D. C., Dale, A. M., Seiffert, A. E., & Tootell, R. B. H. (1999). Functional MRI reveals spatially specific attentional modulation in human primary visual cortex. *Proceedings of the National Academy of Sciences of the United States of America*, *96*(4), 1663-1668.

Stanovich, K. E., & West, R. F. (1983). On priming by a sentence context. *Journal of Experimental Psychology: General*, *112*(1), 1-36.

Swinney, D. A. (1979). Lexical access during sentence comprehension: (Re)consideration of context effects. *Journal of Verbal Learning and Verbal Behavior*, *18*(6), 645-659.

Tabossi, P. (1988). Effects of context on the immediate interpretation of unambiguous nouns. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*(1), 153-162.

Taft, M. (1979). Recognition of affixed words and the word frequency effect. *Memory and Cognition*, *7*(4), 263-272.

Ullman, S. (1995). Sequence seeking and counter streams: A computational model for bidirectional information flow in the visual cortex. *Cerebral Cortex*, *5*(1), 1-11.

Ulrich, R., & Miller, J. (2001). Using the jackknife-based scoring method for measuring LRP onset effects in factorial designs. *Psychophysiology*, *38*(5), 816-827.

Valdes-Sosa, M., Bobes, M. A., Rodriguez, V., & Pinilla, T. (1998). Switching attention without shifting the spotlight: Object-based attentional modulation of brain potentials. *Journal of Cognitive Neuroscience*, *10*(1), 137-151.

Van Berkum, J. J. A. (2004). Sentence comprehension in a wider discourse: Can we use ERPs to keep track of things? In M. Carreiras & C. Clifton Jr. (Eds.), *The on-line study of sentence comprehension: Eyetracking, ERPs and beyond* (p. 229-270). New York: Psychology Press.

Van Berkum, J. J. A., Brown, C. M., Zwitserlood, P., Kooijman, V., & Hagoort, P. (2005). Anticipating upcoming words in discourse: Evidence from ERPs and reading times. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*(3), 443-467.

Van Petten, C. (1993). A comparison of lexical and sentence-level context effects in event-related potentials. *Language and Cognitive Processes*, *8*(4), 485-531.

Van Petten, C. (1995). Words and sentences: Event-related brain potential measures. *Psychophysiology*, *32*(6), 511-525.

Van Petten, C., & Kutas, M. (1987). Ambiguous words in context: An event-related potential analysis of the time course of meaning activation. *Journal of Memory and Language*, *26*, 188-208.

Van Petten, C., & Kutas, M. (1990). Interactions between sentence context and word frequency in event-related brain potentials. *Memory and Cognition*, *18*(4), 380-393.

Van Petten, C., & Kutas, M. (1991). Influences of semantic and syntactic context on open-class and closed-class words. *Memory and Cognition*, *19*(1), 95-112.

VanRullen, R., & Thorpe, S. J. (2002). Surfing a spike wave down the ventral stream. *Vision Research*, *42*(23), 2593-2615.

Vinckier, F., Dehaene, S., Jobert, A., Dubus, J. P., Sigman, M., & Cohen, L. (2007). Hierarchical coding of letter strings in the ventral stream: Dissecting the inner organization of the visual word-form system. *Neuron*, *55*(1), 143-156.

Vitu, F., Brysbaert, M., & Lancelin, D. (2004). A test of parafoveal-on-foveal effects with pairs of orthographically related words. *European Journal of Cognitive Psychology*, *16*, 154-177.

Wang, Q. H., & Yuan, J. J. (2008). N400 lexicality effect in highly blurred Chinese words: Evidence for automatic processing. *Neuroreport*, *19*(2), 173-178.

West, R. F., & Stanovich, K. E. (1982). Source of inhibition in experiments on the effect of sentence context on word recognition. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *8*(5), 385-399.

Whitney, C. (2001). How the brain encodes the order of letters in a printed word: The SERIOL model and selective literature review. *Psychonomic Bulletin and Review*, *8*(2), 221-243.

Whitney, C. (2008). Supporting the serial in the SERIOL model. *Language and Cognitive Processes*, *23*(6), 824-865.

Whitney, C., & Cornelissen, P. (2008). SERIOL reading. *Language and Cognitive Processes*, *23*(1), 143-164.

Wicha, N. Y., Bates, E. A., Moreno, E. M., & Kutas, M. (2003). Potato not pope: Human brain potentials to gender expectation and agreement in Spanish spoken sentences. *Neuroscience Letters*, *346*(3), 165-168.

Wicha, N. Y., Moreno, E. M., & Kutas, M. (2003). Expecting gender: An event related brain potential study on the role of grammatical gender in comprehending a line drawing within a written sentence in Spanish. *Cortex*, *39*(3), 483-508.

Wicha, N. Y., Moreno, E. M., & Kutas, M. (2004). Anticipating words and their gender: An event-related brain potential study of semantic integration, gender expectancy, and gender agreement in Spanish sentence reading. *Journal of Cognitive Neuroscience*, *16*(7), 1272-1288.

Williams, M. A., Baker, C. I., Op de Beeck, H. P., Mok Shim, W., Dang, S., Triantafyllou, C., et al. (2008). Feedback of visual object information to foveal retinotopic cortex. *Nature Neuroscience*, *11*(12), 1439-1445.

Worden, M. S., Foxe, J. J., Wang, N., & Simpson, G. V. (2000). Anticipatory biasing of visuospatial attention indexed by retinotopically specific alpha-band electroencephalography increases over occipital cortex. *Journal of Neuroscience*, *20*(6), RC63.

Young, M. P., & Rugg, M. D. (1992). Word frequency and multiple repetition as determinants of the modulation of event-related potentials in a semantic classification task. *Psychophysiology*, *29*(6), 664-676.

Ziegler, J. C., Rey, A., & Jacobs, A. M. (1998). Simulating individual word identification thresholds and errors in the fragmentation task. *Memory and Cognition*, *26*(3), 490-501.

Zorzi, M., Houghton, G., & Butterworth, B. (1998). Two routes or one in reading aloud? A connectionist dual-process model. *Journal of Experimental Psychology: Human Perception and Performance*, *24*(4), 1131-1161.

Appendix

A. Potsdam Sentence Corpus 1 (PSC1)

144 sentences of the Potsdam Corpus 1 (PSC1) served as stimuli in Chapters 2 and 3. Frequency and length are uncorrelated on target words (bold).

1. Den **Ton** gab der Künstler seinem Gehilfen.
2. Der **Hof** lag weit außerhalb des eigentlichen Dorfes.
3. Die Wanderer sahen Rehe auf einer Lichtung im **Wald** äsen.
4. Den **Kopf** hieb man früher nur Mördern und Verrätern ab.
5. Vorne am **Bug** sah man eine prächtige Galionsfigur.
6. Sogar aus **Raps** läßt sich Kraftstoff herstellen.
7. Torsten beobachtete gestern eine Maus, die **Efeu** fraß.
8. Der schüchterne kleine **Gnom** mied die Nähe der Elfen.
9. Claudia hatte ihr Fahrrad auf der **Straße** stehen lassen.
10. Wir hätten schon vor einer **Stunde** wissen sollen, ob ihr kommt.
11. Die Eltern konnten ihre Kinder im **Garten** raufen hören.
12. Er hätte nicht auch noch am **Telefon** nörgeln sollen.
13. Wegen ihrer Diät hatte die Gräfin leider keine **Auster** nehmen dürfen.
14. Die meisten **Hamster** bleiben bei Tag in ihrem Häuschen.
15. Man sollte nie Geschirr mit einem dreckigen **Lappen** spülen müssen.
16. Man kann **Spargel** dämpfen oder in viel Wasser kochen.
17. Manchmal sagen **Opfer** vor Gericht nicht die volle Wahrheit.
18. Die meisten Befragten hören **Musik** zur Entspannung.
19. Kinder essen **Quark** am liebsten mit Früchten.

20. Bei Wölfen leben **Rudel** nicht verwandter Tiere in getrennten Revieren.
21. Die Frauen in den Andendörfern weben **Stoff** noch auf traditionellen Webstühlen.
22. Die Platzwarte ebnen **Stück** für Stück den Rasen nach dem Spiel.
23. In den Fässern gären **Beize** und Lauge.
24. Die Förster küren **Ahorn** zum Baum des Jahres.
25. Wolfgangs Töchter studieren **Literatur** und Maschinenbau.
26. In der Klosterschule herrschen **Schwester** Agathe und Schwester Maria.
27. Hier scheinen **Klempner** am Werk zu sein.
28. Im Aussehen gleichen **Bratsche** und Geige sich sehr.
29. Angeblich flunkern **Künstler** oft bezüglich ihrer Einnahmen.
30. Manchmal krakeelen **Politiker** genauso wie Demonstranten.
31. Die Armen plündern **Speicher** und Vorratskeller der reichen Bauern.
32. Die Richter der Landwirtschaftsschau prämieren **Rhabarber** und Mangold.
33. Schon immer war der Besitz von **Land** sehr wichtig.
34. Ein berühmter Maler hat sich selbst ein **Ohr** abgeschnitten.
35. Das Pferd ist seinem Reiter auf den **Fuß** getreten.
36. Kein einziges **Tor** fiel im gestrigen Spiel.
37. Der Skandal hat dem **Ruf** des Politikers deutlich geschadet.
38. Als Kapitalanlage ist **Gold** nicht zu empfehlen.
39. Markus klettert gern auf den alten **Baum** im Garten.
40. Sarah hat ihrem Opa ein **Bild** gemalt.
41. Medizinisch gesehen ist das **Herz** ein Hohlmuskel.
42. Jede Sprache der **Welt** besitzt eine Grammatik.
43. Unsere **Küche** müßte dringend neu gestrichen werden.
44. Der Politiker reagierte auf keine **Frage** der Journalisten.
45. Die **Insel** ist nur mit dem Flugzeug zu erreichen.
46. Es sollte mehr **Strom** mit Solarenergie erzeugt werden.
47. Die monotone **Arbeit** machte den Angestellten keinen Spaß.
48. In dem kleinen **Zimmer** standen viel zu viele Möbel.
49. Das **Fenster** im Flur klemmt seit ein paar Tagen.
50. Die Sekretärin informierte den **Kanzler** erst am nächsten Morgen.
51. Vielleicht gibt es bald im **Dezember** Ostereier zu kaufen.

52. Das kleine Unternehmen konnte sich die teure **Maschine** nicht leisten.
53. Der **Franzose** gewann gegen den Belgier.
54. Jan hat sich zum dritten Mal die **Schulter** ausgekugelt.
55. Der Bischof erschien mit seinem neuen **Sekretär** auf der Konferenz.
56. Das **Schicksal** führte die Freunde wieder zusammen.
57. Vor Gericht wurde die **Situation** nachgestellt.
58. Das Wetter im **September** spielte verrückt.
59. Die diesjährige **Konferenz** der Wissenschaftler dauerte vier Tage.
60. Der Hirte wanderte mehrere **Kilometer** durch die Wüste.
61. Yvonne trat unglücklicherweise auf eine **Tube** Klebstoff.
62. Manuela reagiert auf **Senf** allergisch.
63. Martins gebrochener **Zeh** schwoll rasch an.
64. Der alte Kapitän goß stets ein wenig **Rum** in seinen Tee.
65. Die schmale **Öse** ist zu klein für den Faden.
66. Die Tänzer probten ihre **Kür** besonders intensiv.
67. Nach dem Streit schien alles wieder im **Lot** zu sein.
68. Der frisch gekochte **Brei** war noch zu heiß.
69. Die Schneiderin steckte die **Naht** sorgfältig ab.
70. Auf dem höchsten **Mast** hielt der Pirat Wache.
71. Claudia kann Salatsaucen mit viel **Essig** nicht ausstehen.
72. Die **Torte** erwies sich als ein wahrer Leckerbissen.
73. Sie machten einen Spaziergang am **Deich** entlang.
74. Ulf hat schon wieder eine **Niete** gezogen.
75. Der **Giebel** des alten Hauses drohte einzustürzen.
76. Das Karamellbonbon blieb Julia am **Gaumen** kleben.
77. Tamara führte mit der **Hebamme** mehrere Gespräche.
78. Nach der Trauung wartete eine **Kutsche** vor der Kirche.
79. Robert ließ sich den **Schinken** in Scheiben schneiden.
80. Die Kinder hüpften auf der alten **Matratze** herum.
81. Laura stellte eine **Schüssel** Kirschen auf den Tisch.
82. Das entscheidende **Telefonat** verzögerte sich.
83. Mandy aß die **Mandarine** sofort auf.
84. Der Teppich mit dem **Schnörkel** gefiel Bettina nicht.
85. Der majestätische **Gletscher** wurde schon oft bestiegen.
86. Der Großvater fand in seinem **Pantoffel** eine Wäscheklammer.

87. Johannes wollte unbedingt **Karussell** fahren.
88. Die **Olympiade** findet dieses Jahr in Australien statt.
89. Sonja **kam** als Einzige pünktlich.
90. Der alte Mann **zog** einen Karren zum Marktplatz.
91. Keiner wußte, was zu **tun** war.
92. Heute morgen **saß** auf unserer Terrasse ein Frosch.
93. Der Wandersmann **bat** den Wirt um etwas Wasser.
94. Seit gestern **geht** es dem Patienten deutlich besser.
95. Der Waffenstillstand **hält** seit fast vier Monaten.
96. Freundlich zu **sein** kann nie schaden.
97. Die Mutter **gibt** ihren Kindern jeden Montag Taschengeld.
98. Jeder Vorschlag **gilt**, der rechtzeitig eingereicht wird.
99. Ich weiß nicht, ob wir uns noch **sehen** werden.
100. Die meisten Kinder **gehen** gerne zur Schule.
101. Viele Kinder **lesen** nur noch selten.
102. Die Journalisten **fragen** den Bürgermeister nach seiner Meinung.
103. Kevin und Marie **spielen** oft im Garten.
104. Die Geschworenen **glauben** dem Beklagten bestimmt alles.
105. Am besten **stellen** wir das Klavier nicht direkt ans Fenster.
106. Meistens **wünschen** Kinder sich Spielzeug zu Weihnachten.
107. Einige Häftlinge **sprechen** nicht gern miteinander.
108. Nur wenige Menschen **brauchen** ein Handy wirklich.
109. Einige der Angestellten **arbeiten** nur vormittags.
110. Die Spieler hoffen, daß sie ihre Gegner **schlagen** werden.
111. Ich bin nicht sicher, ob alle die Prüfung **schaffen** werden.
112. Die meisten Geschäfte **schließen** samstags früher als unter der Woche.
113. Die Astronauten **antworten** seit Tagen nicht mehr.
114. Die Schüler **schreiben** ihrer kranken Lehrerin einen Brief.
115. Die Beschuldigten **schweigen** zu den Vorwürfen.
116. Die beiden Mädchen **schütteln** sich vor lachen.
117. Dorothea **log** oft bei Fragen nach ihrem Alter.
118. Die Großmutter **wog** die Zutaten beim Backen sehr genau.
119. Die Mutter sagte, Nina **übe** gerade Klavier.
120. Der Gehilfe des Gärtners **sät** Kresse und Radieschen.
121. Die zwei Nichten **öden** sich gegenseitig an.

122. Sei so gut und **miß** bitte die Tiefe des Regals.
123. Jetzt **rate** doch mal, wen ich gesehen habe!
124. Sei so lieb und **lies** mir die Angaben vor!
125. Bitte **wirf** den Ball nicht wieder aufs Dach.
126. Bitte **hilf** deiner Schwester beim Aufräumen.
127. Die streikenden Fahrer konnte man kilometerweit **hupen** hören.
128. Die Gärtner **mähen** den Rasen im Park jeden Mittwoch.
129. Gute Beziehungen **ebnen** vielen Unternehmern den Weg zum Erfolg.
130. Mäuse und Ratten **nagen** gerne an Stromkabeln.
131. Tierärzte **impfen** keine Kaninchen gegen Tollwut.
132. Die Hunde der Wächter **bellen** beim geringsten Anlaß.
133. Affen **kraulen** sich oft stundenlang das Fell.
134. Die Forscher **stapfen** durch den Schnee zurück zum Lager.
135. Viele Babys **schielen** nach der Geburt eine Weile lang.
136. Die Bäume in den Wäldern **speichern** sehr viel Wasser.
137. Die meisten Leute **schummeln** beim Spielen gelegentlich.
138. Nach dem Spiel **massieren** die Therapeuten den Spielern die Beine.
139. Die beiden Mädchen **tuscheln** während des Unterrichts.
140. Die Häuser am Horizont **flimmern** in der Sonne.
141. Den ganzen Tag über konnte man die Raben **krächzen** hören.
142. Vor dem Auftritt **schminken** die Schauspieler sich.
143. Die zwei frechen Jungs **heucheln** Unschuld.
144. Manche Menschen **stottern** bei Nervosität.

B. Potsdam Sentence Corpus 3 (PSC3)

Target words in 144 German items of the Potsdam Sentence Corpus 3 (PSC3) realize a two-by-two factorial design of frequency and predictability (see Chapters 4 and 5). Each item consists of two context sentences (c1/c2) and one neutral sentence frame (ns) that is identical across conditions. Target words (bold) are either of high (stimulus before "/") or of low frequency (stimulus after "/"). Context 1 (c1) biases high predictability of the high frequency target, while the low frequency word is of low predictability. Context 2 (c2) triggers high predictability of the low frequency target, while the high frequency word is of low predictability.

1. **c1:** Gustav sah keinen Ausweg mehr aus seiner Lage und ging zu einem Priester.
   c2: Gustav war nun schon seit vier Wochen arbeitslos und ging zum Arbeitsamt.
   ns: Er hoffte, dort endlich einen guten **Rat**/**Job** zu bekommen.
2. **c1:** Uwe war so konzentriert, dass er die Zeit vergaß und überrascht war, als die Pausensirene hupte.
   c2: Uwe hatte keine Ahnung mehr, warum er gerade das große Beil aus der Garage geholt hatte.
   ns: Verwundert blickte er auf die **Uhr**/**Axt** in seiner Hand.
3. **c1:** Ingo erkannte, dass seine Strategie nicht wie geplant aufgehen würde.
   c2: Ingo erkannte, dass er den Baum mit seiner kleinen Feile niemals fällen könnte.
   ns: Er brauchte dringend eine gute **Idee**/**Säge** für sein Unterfangen.

4. **c1:** Die Mutter sah, dass sie viel zu viel Teig für einen kleinen Kuchen gemacht hatte.
   c2: Die Mutter freute sich sehr über den riesigen Blumenstrauß zu ihrem Geburtstag.
   ns: Geschwind holte sie die große **Form**/**Vase** aus dem Schrank.
5. **c1:** Yuri wollte später unbedingt Komponist werden.
   c2: Yuri wollte später unbedingt Zauberer werden.
   ns: Nichts faszinierte ihn mehr als die **Musik**/**Magie** seiner Vorbilder.
6. **c1:** Frauke fand ihre Waden und Schenkel trotz des vielen Laufens zu dick.
   c2: Frauke zog das Pflaster von der Stelle ihres Fußes, wo der Schuh immer drückt.
   ns: Mit finsterer Miene betrachtete sie ihre **Beine**/**Blase** im Spiegel.
7. **c1:** Bis es zum Streit kam, war der Heerführer Flint ein guter Freund des Landes.
   c2: Im ganzen Land kannte man den Seeräuber Flint, der viele Schätze erobert hatte.
   ns: Mittlerweile galt er als der schlimmste **Feind**/**Pirat** aller Zeiten.
8. **c1:** Keinesfalls konnte der Mechaniker die Werkstatt alleine putzen.
   c2: Allein mit Wasser bekam der Mechaniker die Schmiere nicht von den Fingern.
   ns: Er brauchte dringend ein bisschen **Hilfe**/**Seife** und viel Geduld.
9. **c1:** Beim Joggen fiel Simon ein, was er sich zu Weihnachten schenken lassen könnte.
   c2: Beim Joggen schmerzte Simons Wade plötzlich und die Muskeln verspannten sich.
   ns: Tatsächlich hatte er einen ungewöhnlichen **Wunsch**/**Krampf** und er strauchelte.

10. **c1:** Johannes hörte in einiger Entfernung ein riesiges Flugzeug kommen.
    c2: Bevor Johannes durch den Berg ging, wollte er sicher sein, dass ihm kein Zug entgegenkam.
    ns: Er blickte angestrengt in den **Himmel**/**Tunnel** und lauschte aufmerksam.

11. **c1:** Anita hatte den vierten Raum ihrer Wohnung früher nur für Klamotten genutzt.
    c2: In der Abstellkammer fand Anita die Karnevalsverkleidung, die sie früher selber trug.
    ns: Dieses Jahr vermietete sie das **Zimmer**/**Kostüm** zum ersten Mal.

12. **c1:** Sabine hatte eine ausführliche Beschreibung des Tathergangs verfasst.
    c2: Bei der Personenkontrolle fragte der Beamte Sabine nach ihren Papieren.
    ns: Etwas zögerlich überreichte sie nun ihren **Bericht**/**Ausweis** dem Polizisten.

13. **c1:** Pablo hatte das Konzept gut vorbereitet und sein Vorhaben genau durchdacht.
    c2: Pablo konnte das Netz kaum an Bord ziehen, so voller Fische war es.
    ns: Er war sehr zufrieden mit seinem **Plan**/**Fang** und grinste.

14. **c1:** Markus saß in seinem Auto im Halteverbot, als plötzlich ein Polizist an seine Scheibe klopfte.
    c2: Markus fuhr mit seinem geschlossenen Kabrio durch den Regen, als plötzlich die Sonne hervorkam.
    ns: Markus lächelte und öffnete das **Fenster**/**Verdeck** in beachtlicher Geschwindigkeit.

15. **c1:** Besorgt betrachtet Tobi sein blau angelaufenes Handgelenk.
    c2: Besorgt betrachtet Tobi seinen blau angelaufenen Fußnagel.
    ns: Gestern stieß er sich äußerst schmerzhaft seinen **Arm**/**Zeh** am Schrank.

16. **c1:** Manche Industriezweige erzielen wirklich unglaublich hohe Gewinne.
    c2: Manche Industriezweige produzieren wirklich unglaublich viel Abfall.
    ns: Man fragt sich, was sie mit ihrem **Geld**/**Müll** machen wollen.

17. **c1:** Martina wurde von ihrem Freund gefragt, was sie da gerade lese.
    c2: Martina sah, wie ihr Freund ungeschickt versuchte, mit dem Boot am Steg anzulegen.
    ns: Kurzerhand warf sie ihm das dicke **Buch**/**Seil** zu und lachte.

18. **c1:** Florian tat alles dafür, um das Medizinstudium zu schaffen.
    c2: Florian tat alles dafür, um groß raus zu kommen.
    ns: Er wollte später unbedingt ein berühmter **Arzt**/**Star** in Amerika werden.

19. **c1:** In Nordamerika sind Gewalt und Kriminalität ein großes Problem.
    c2: In Nordamerika ist das Fischen ein beliebter Zeitvertreib.
    ns: In jedem Haushalt findet man dort eine **Waffe**/**Angel** im Schrank.

20. **c1:** Bettina mochte den Hausmeister sehr und beschloss, ihm ein paar nette Zeilen zu schreiben.
    c2: Bettina ärgerte den Hausmeister immer, wenn er den Hof kehren wollte.
    ns: Voll heimlicher Freude versteckte sie den **Brief**/**Besen** in der Kammer.

21. **c1:** Gestern waren am Flussufer plötzlich alle Felder mit Jauche gedüngt.
    c2: Gestern waren am Flussufer plötzlich alle Bäume abgenagt.
    ns: Die Verantwortung dafür trägt wohl ein **Bauer**/**Biber** aus der Umgebung.

22. **c1:** Nach der langen Krankheit war Nico sehr schwach.
    c2: Seit der Pause hatte Nico nichts mehr getrunken.
    ns: Langsam aber sicher bekam er wieder **Kraft**/**Durst** und stand auf.

23. **c1:** Heute sollten die Kinder in der Schule geometrische Figuren malen.
   c2: Heute sollten die Kinder in der Schule heimische Insekten malen.
   ns: Als erstes zeichneten viele Schüler einen dicken **Kreis**/**Käfer** mit Bleistift.

24. **c1:** Frederike erzählte oft Geschichten und die anderen umringten sie.
   c2: Frederike kam richtig ins Schwitzen, als der Bademeister den Aufguss machte.
   ns: Sie saß gerne in der **Mitte**/**Sauna** und genoss das Gefühl.

25. **c1:** Schemenhaft erkannte Philipp zwischen den Bäumen eine weiße, leuchtende Gestalt.
   c2: Schemenhaft erkannte Philipp zwischen den Bäumen eine kleine, bärtige Gestalt.
   ns: Bei dem Gedanken, es könnte ein **Geist**/**Zwerg** sein, erschrak Philipp.

26. **c1:** Im Krankenhaus ist Kilian am liebsten allein und will keinen Menschen sehen.
   c2: Im Krankenhaus ist Kilian im Moment der einzige Epileptiker.
   ns: Gerade gestern bekam er einen unerfreulichen **Besuch**/**Anfall** in seinem Zimmer.

27. **c1:** Carsten sah ein, dass er den neuen Schrank nicht ohne Hilfe montieren konnte.
   c2: Carsten sah ein, dass das Loch in der Wand für die dicke Schraube zu klein war.
   ns: Also holte er seinen großen **Bruder**/**Bohrer** aus dem anderen Zimmer.

28. **c1:** Als nach zehn Minuten noch niemand da war, hofften die Schüler, der Unterricht würde ausfallen.
   c2: Die Schüler sahen den hellen Blitz am Himmel und hielten gespannt den Atem an.
   ns: Dann hörten sie draußen den grummelnden **Lehrer**/**Donner** und sie erschraken.

29. **c1:** Seine Haltung war stramm, seine Stiefel glänzten und sein Gewehr hing gerade.
    c2: Sein Iglu war makellos, sein Mantel aus feinstem Robbenfell und seine Jagdkünste beispielhaft.
    ns: Knud war ein vorbildlicher und beliebter **Soldat**/**Eskimo** und wurde bewundert.

30. **c1:** Friedrich übernahm immer schnell das Kommando und die Menschen folgten und vertrauten ihm.
    c2: Friedrich erzählte immer haarsträubende Geschichten, von denen natürlich keine stimmte.
    ns: Er war wirklich ein geborener **Führer**/**Lügner** und wollte Politiker werden.

31. **c1:** Es stellte sich heraus, dass die zwei Mädchen Halbschwestern waren.
    c2: Die zwei Mädchen präsentierten sich ihre neuen Haarschnitte und erschraken.
    ns: Sie hatten beide die gleiche **Mutter**/**Frisur** und sie waren schockiert.

32. **c1:** Peter hatte ein Ölbild gemalt und wollte es nun gerne einfassen.
    c2: Peter wollte ein Ölbild malen und hatte bereits Farbe und eine Leinwand.
    ns: Ihm fehlte aber noch ein geeigneter **Rahmen**/**Pinsel** und etwas Platz.

33. **c1:** Beim Kochen dachte die Mutter nach und fragte sich, ob ihren Kindern etwas zugestoßen war.
    c2: Der Mutter fiel plötzlich ein, dass seit drei Tagen der Fisch im Kofferraum lag, und sie öffnete ihn.
    ns: Geradezu unerträglich war dieser entsetzliche **Gedanke**/**Gestank** und ihr wurde schlecht.

34. **c1:** Schon als Kind war Lucas immer der beste in Mathe, Deutsch und Biologie.
    c2: Schon als Kind erreichte Lucas im Wasser Tiefen von dreißig Metern.
    ns: Er war ein ganz hervorragender **Schüler/Taucher** und wollte Meeresforscher werden.

35. **c1:** Von den anderen Studenten wurde Chris oft für seine leserlichen Notizen gelobt.
    c2: Mit den anderen Studenten saß Chris gern am Lagerfeuer und zupfte ein paar Akkorde.
    ns: Er hatte eine sehr schöne **Schrift/Gitarre** von seiner Mutter geerbt.

36. **c1:** Als Fotomodel war Marianne sehr beliebt und vor allem ihr Antlitz war oft in Zeitschriften zu sehen.
    c2: Wenn ihre Eltern kamen, deckte Marianne den Tisch immer mit den goldenen Messern und Gabeln.
    ns: Sie hatte wirklich ein schönes **Gesicht/Besteck** und pflegte es gut.

37. **c1:** Obwohl Lukas es eilig hatte, half er der gebrechlichen Dame über die gefährliche Straße.
    c2: Gestern erschien Lukas ein kleines, elfenähnliches Wesen, das ihm drei freie Wünsche anbot.
    ns: Dies war zweifellos eine gute **Tat/Fee** gerade zum rechten Zeitpunkt.

38. **c1:** Herr Betz kann sich drei Äpfel gleichzeitig zwischen die Backen stecken.
    c2: Herr Betz hat noch nie etwas gespendet oder verschenkt.
    ns: Er ist stadtbekannt für seinen enormen **Mund/Geiz** und leidet darunter.

39. **c1:** Nach Feierabend verabschiedete sich der Lehrling höflich beim Bäckermeister.
    c2: Der Lehrling fragte den Bäckermeister nach einem Treibmittel für den Teig.
    ns: Der Meister reichte ihm lächelnd die **Hand/Hefe** und ging hinaus.

40. **c1:** Einige fragten sich, warum der Fremde Toilettenpapier mit sich herumtrug.
    c2: Einige dachten, der schwarz gekleidete Fremde sei der Tod höchstpersönlich.
    ns: In seiner Hand schwenkte er eine **Rolle/Sense** und schaute finster.

41. **c1:** Pedro drehte sich zu der Frau um, die ihn aus feurigen Augen wutentbrannt anstarrte.
    c2: Pedro stand in der Arena, schwenkte lässig sein rotes Tuch und ließ sich als Torero feiern.
    ns: Da erst bemerkte er den zornigen **Blick/Stier** und er erschrak.

42. **c1:** Eigentlich wollte Theo heute am Strand in den Schatten, aber alle Schirme waren besetzt.
    c2: Der einst vornehme und wohlhabende Theo verlor alles und endete schließlich als Penner.
    ns: Nun lag er jammernd in der **Sonne/Gosse** und war verzweifelt.

43. **c1:** Dem Piloten war es nur in seiner Freizeit gestattet Alkohol zu trinken, jedoch nicht jetzt.
    c2: Der Frau des Piloten wurde gesagt, dass ihr Mann in wenigen Minuten landen würde.
    ns: Er befand sich momentan im **Dienst/Anflug** und musste sich konzentrieren.

44. **c1:** Die Polizei war ihnen dicht auf den Fersen, bevor sie das Land verließen.
    c2: Sie konnten die Wasserlache nicht umgehen, deswegen mussten sie springen.
    ns: Sie schafften es gerade noch, über die **Grenze/Pfütze** zu gelangen.

45. **c1:** Der Bankräuber sah, dass es sieben Uhr war, und um acht wollte die Polizei die Bank stürmen.
    c2: Der Bankräuber hatte mittlerweile sieben von den acht Bankangestellten freigelassen.
    ns: Er hatte jetzt nur noch eine **Stunde/Geisel** und beschloss aufzugeben.

46. **c1:** Heidi mochte es, wenn ihr Krankengymnast italienisch mit ihr redete.
c2: Heidi entspannte sich, als ihr italienischer Krankengymnast ihren Rücken durchknetete.
ns: Sie war sehr angetan von seiner **Sprache/Massage** und seufzte leise.

47. **c1:** Michael hatte bereits dreimal geklingelt, doch niemand öffnete ihm.
c2: Während des Rennens schafften es die Mechaniker nicht, Michaels Reifen zu wechseln.
ns: Er stand schon seit Minuten an der **Tür/Box** und wurde ärgerlich.

48. **c1:** Das Ende von Kapitän Ahab war gleichsam traurig und grausam.
c2: Durch alle Weltmeere segelte Kapitän Ahab auf der Suche nach Moby Dick.
ns: Zusammen mit seiner Mannschaft fand er den **Tod/Wal** im indischen Ozean.

49. **c1:** Alle drängten Frank, endlich ein Foto seiner neuen Freundin zu zeigen.
c2: Durch den Wind waren Franks Haare ganz zerzaust, was er gar nicht leiden konnte.
ns: In seiner Tasche kramte er nach einem **Bild/Kamm** und wurde fündig.

50. **c1:** Für ihren Garten hatten die Kunzes einen Lastwagen voller Humus kommen lassen.
c2: Anscheinend hatten alle Obstbäume im Garten der Kunzes gleichzeitig ihre Blätter verloren.
ns: Vor ihrem Haus lag ein riesiger Haufen **Erde/Laub** mitten im Weg.

51. **c1:** Thomas schlenderte gestern ganz langsam und gemütlich durch den Park.
    c2: Gestern im Casino verlor Thomas jedes Spiel und sehr viel Geld.
    ns: An diesem Abend hatte er richtig viel **Zeit**/**Pech** und er grübelte.

52. **c1:** Nach der langen Fahrt war Pascal völlig erschöpft und nicht mehr fähig zu denken.
    c2: Nach der langen Fahrt durch die Wüste hatte Pascal keinen Tropfen Benzin mehr.
    ns: Gähnende Leere herrschte in seinem **Kopf**/**Tank** und er brauchte eine Pause.

53. **c1:** Der Lehrer hatte gesagt, das Prinzip des Bumerangs sei ziemlich einfach.
    c2: Als sie zurückkamen, war das Lagerfeuer heruntergebrannt und schimmerte noch rötlich.
    ns: Marco warf das gebogene Holz in die **Luft**/**Glut** und wartete ab.

54. **c1:** Während der Fahrt hatte sich Dieter geschworen, das Büro seines Chefs heute nicht zu betreten.
    c2: Dieter dachte, er käme pünktlich ins Büro, denn zunächst war wenig Verkehr auf der Autobahn.
    ns: Wenig später stand er aber mitten im **Raum**/**Stau** und er fluchte.

55. **c1:** Caroline liebte es, sich die Zeit mit Schach, Dame oder Mühle zu vertreiben.
    c2: Caroline liebte es, die Fotos aus ihrer Kindheit anzusehen.
    ns: Oft holte sie aus dem Regal ein **Spiel**/**Album** und öffnete es.

56. **c1:** Bei dem Hochwasser war das etwas höher gelegene Rom das einzige trockene Land.
    c2: In der Bibel steht, dass es während der Sintflut vierzig Tage und Nächte lang regnete.
    ns: Viele Tiere flüchteten damals in die **Stadt**/**Arche** und harrten dort aus.

57. **c1:** Schon als kleiner Junge hing Aramis sehr an seinen Eltern.
c2: Schon als kleiner Junge war Aramis ein hervorragender Fechter.
ns: Niemals verließ er das Haus, ohne seinen **Vater**/**Degen** nach draußen mitzunehmen.

58. **c1:** Robert wollte die ganze Wohnung neu streichen.
c2: Zum Renovieren wollte Robert den ganzen Fußboden abdecken.
ns: Er ging in den Baumarkt und kaufte **Farbe**/**Folie** für achtzig Quadratmeter.

59. **c1:** Paula sah, dass ihr Hund mittlerweile schlief, und sie wollte ihn nicht wecken.
c2: Paula sah, dass die Kohlen mittlerweile glühten, und sie bekam Hunger.
ns: Sie legte die Würstchen vorsichtig auf den **Boden**/**Grill** und trat zurück.

60. **c1:** In all den Jahren hat Stefan seinen Eltern noch nie Kummer bereitet.
c2: In all den Jahren, seit Stefan die Ziegenherde hütet, hat er noch kein Tier verloren.
ns: Alle sagten, er sei ein guter **Junge**/**Hirte** mit recht erstaunlichen Fähigkeiten.

61. **c1:** Frau Beyer war begeistert, als sie die neue Lampe im Wohnzimmer anschaltete.
c2: Frau Beyer war begeistert, als sie die Ausstattung des 6-Sterne Hotels sah.
ns: Sie staunte über so viel **Licht**/**Luxus** und klatschte in die Hände.

62. **c1:** Als junger Mann entdeckte van Gogh sein Talent für die Malerei.
c2: Als junger Mann war van Gogh schwer alkohol- und drogenabhängig.
ns: Er verfiel ganz und gar der **Kunst**/**Sucht** und vernachlässigte alles andere.

63. **c1:** Manche fangen bei großer Nervosität an zu krächzen.
c2: Manche fangen bei großer Nervosität an zu hyperventilieren.
ns: Das wichtigste ist dann, die Kontrolle der **Stimme/Atmung** wieder zu erlangen.

64. **c1:** Alle Gläubigen hatten fröhliche Gesichter, als sie nach dem Gottesdienst nach Hause gingen.
c2: Alle Spieler hatten fröhliche Gesichter, als sie nach der Halbzeitpause wieder auf den Platz liefen.
ns: Auch Toni kam lachend aus der **Kirche/Kabine** und schnappte nach Luft.

65. **c1:** Das Verkehrsamt hatte bei dem hohen Verkehrsaufkommen bis zuletzt vor Unfällen gewarnt.
c2: Die Bergwacht warnte nach dem starken Schneefall vor Abgängen, bis das Unglück geschah.
ns: Mitten durch den Ort ging die gefährliche **Straße/Lawine** bis ins Tal.

66. **c1:** Der Kunde hatte plötzlich einen ganz trockenen Hals und musste husten.
c2: Der Kunde kaufte auf einen Schlag mehr als hundert Computer.
ns: Der Händler gab ihm deshalb ein bisschen **Wasser/Rabatt** und nickte großmütig.

67. **c1:** Schon Stunden vor dem Wirbelsturm legte der Hund die Ohren an und begann zu knurren.
c2: Dort, wo der Hirsch gelegen hatte, begann der Hund zu schnuppern und zielstrebig der Spur zu folgen.
ns: Offensichtlich witterte er bereits die **Gefahr/Fährte** und wollte darauf aufmerksam machen.

68. **c1:** Marco sah ein, dass er das Problem auf diese Weise nicht in den Griff bekommen würde.
c2: Marcos Rasierer war mittlerweile völlig stumpf geworden.
ns: Also suchte er nach einer neuen **Lösung/Klinge** und rief seine Frau.

69. **c1:** Dieter war anscheinend sehr stolz auf seinen neuen Job.
c2: Dieter war es anscheinend nicht peinlich, dass er kein Haar mehr auf dem Kopf hatte.
ns: Er redete nur noch von seiner **Arbeit**/**Glatze** und nervte die anderen.

70. **c1:** Nils hatte heute eine Mathearbeit, war aber ziemlich spät aufgestanden.
c2: Nils war völlig verschwitzt, als er vom Joggen nach Hause kam.
ns: Seine Mutter schickte ihn sofort in die **Schule**/**Dusche** und schimpfte laut.

71. **c1:** Fred telefonierte schon ewig und um sein Gespräch zu beenden, forderte er eine weitere Stunde.
c2: Fred wollte Spiegeleier für alle machen, fand aber nichts zum Braten.
ns: Matthias gab ihm dafür lediglich eine **Minute**/**Pfanne** und zudem klare Anweisungen.

72. **c1:** In der Prüfung hatte Anna keine Ahnung, was der Professor mit seiner letzten Frage wollte.
c2: Der Professor hatte gefragt, ob Anna mit ihm ins Kino ginge, aber sie hatte überhaupt keine Lust.
ns: Jetzt suchte sie verzweifelt nach einer **Antwort**/**Ausrede** und dachte angestrengt nach.

73. **c1:** Friedrich war nun schon König, aber damit war er immer noch nicht zufrieden.
c2: Friedrich machte schon als Kind leckere Brezeln und für Brot und Brötchen war er Spezialist.
ns: Er wollte später unbedingt einmal **Kaiser**/**Bäcker** werden und dachte täglich daran.

74. **c1:** Der Nomade war sehr einsam und suchte eine Gemahlin.
c2: Der Nomade wanderte durch die Wüste und langsam ging der Wasservorrat zur Neige.
ns: Eher zufällig fand er dann endlich eine **Frau**/**Oase** und er jubelte.

75. **c1:** Bruno half gerne alten und bedürftigen Menschen und brachte sie häufig zum Arzt.
    c2: Fahrgäste fuhren gerne mit Bruno, weil sein gelbes Auto gepflegt und der Fahrpreis günstig war.
    ns: Bruno hatte zweifellos ein gutes **Herz**/**Taxi** und er war deswegen beliebt.

76. **c1:** Adalbert flüsterte sterbend, dass seine Nachbarin seinen Besitz erben sollte.
    c2: Adalbert schenkte der Nachbarin seinen Balsamico, weil ihrer leer war.
    ns: Dies war gleichzeitig auch sein letzter **Wille**/**Essig** und seine letzten Worte.

77. **c1:** Als die Sonne untergegangen war, setzten die Forscher in der Wildnis starken Kaffee auf.
    c2: Die Forscher in der Wildnis ahnten nicht, dass es in den nächsten Monaten nicht regnen würde.
    ns: Vor ihnen lag eine lange **Nacht**/**Dürre** und der Ausgang war ungewiss.

78. **c1:** Keiner traute sich mit dem Auto über die morsche Brücke, nur Hans trat aufs Gas.
    c2: Alle blieben mit Motorschaden oder geplatzten Reifen liegen, nur Hans schaffte es ins Ziel.
    ns: Anders als die anderen hatte Hans keine **Angst**/**Panne** und wurde gefeiert.

79. **c1:** Onkel Albert lächelte auf dem Sterbebett, als er über alles nachdachte.
    c2: Onkel Albert verkaufte auch Süßigkeiten und Zigaretten in seinem kleinen Zeitungsstand.
    ns: Er war sehr zufrieden mit seinem schönen **Leben**/**Kiosk** und dankbar dafür.

80. **c1:** Philipp regierte das Land mit gerechter Hand und er sorgte gut für seine Untertanen.
    c2: Philipp hat bisher jedes Flugzeug selbst unter schwersten Bedingungen sicher gelandet.
    ns: Im Grunde war er ein hervorragender **König/Pilot** mit einem scharfen Verstand.

81. **c1:** Ernst war vom Anstehen an der Kasse so müde, dass er im Bus einschlief.
    c2: Ernst sah gar nicht hin, als die Verkäuferin alles in die beiden Plastikbeutel packte.
    ns: Erst zu Hause öffnete er die **Augen/Tüten** und atmete tief ein.

82. **c1:** Die Sportler prügelten wie wild aufeinander ein und mehrmals ging einer blutend zu Boden.
    c2: Die Sportler schoben ihre Niederlage auf die neue und ungewohnte Beschichtung des Bodens.
    ns: Es war ein sehr harter **Kampf/Belag** und einige schüttelten den Kopf.

83. **c1:** Der Mann auf dem Bild hantierte mit Modellen der Flotte des Columbus.
    c2: Der Mann auf dem Bild trug eine goldene Krone und saß würdevoll auf einem Thron.
    ns: In seiner rechten Hand hielt er ein **Schiff/Zepter** von beachtlicher Länge.

84. **c1:** Timo kroch aus dem Zelt, streckte sich ausgiebig und atmete tief die klare, frische Luft.
    c2: Timo war begeistert, als er das riesige bunte Zelt, die vielen Tiere und die lustigen Clowns sah.
    ns: Es war ein ganz herrlicher **Morgen/Zirkus** und Timo fühlte sich prima.

85. **c1:** Der Entführer liebte Anna sehr und er wollte sie schon lange heiraten.
    c2: Der Entführer wollte Anna eigentlich nur fesseln, aber ihr ständiges Geplapper ging ihm auf die Nerven.
    ns: Jetzt machte er ihr endlich einen **Antrag**/**Knebel** und holte tief Luft.

86. **c1:** Ihre zwei Zimmerchen sind Karin einfach zu klein geworden.
    c2: Karin hat sich während der Schwangerschaft mit ihrer Geburtshelferin verstritten.
    ns: Sie sucht momentan überall nach einer neuen **Wohnung**/**Hebamme** zu günstigen Konditionen.

87. **c1:** Horst hatte erst gestern beim Verlag angerufen und die Frankfurter Allgemeine abonniert.
    c2: Horst hatte letzte Woche vergessen, den Rechnungsbetrag an seine Werkstatt zu überweisen.
    ns: Heute fand er im Briefkasten dann die **Zeitung**/**Mahnung** und war erstaunt.

88. **c1:** Obwohl das Telefon klingelte, hörte Jörg nicht auf, an seiner Seminararbeit zu schreiben.
    c2: Seit ein paar Tagen war Jörg ganz lustlos und deprimiert, und auch die Zukunft machte ihm Angst.
    ns: Er steckte gerade mitten in einem **Satz**/**Tief** und hätte Hilfe brauchen können.

89. **c1:** Williams kleiner Sohn war über und über mit Schlamm beschmiert, als er nach Hause kam.
    c2: Williams Diebstahl aus der Schiffskombüse wurde schnell bemerkt und nun verbüßte er die Strafe.
    ns: Mit aller Sorgfalt schrubbte William das **Kind**/**Deck** und vergaß dabei keine Stelle.

90. **c1:** Für Wolfgang war es das Schönste, als sein kleiner Daniel geboren wurde.
    c2: Wolfgang liebte seine schönen, langen Haare, die meist ein Gummi zusammenhielt.
    ns: Er war sehr stolz auf seinen **Sohn**/**Zopf** und sprach oft über ihn.

91. **c1:** Die Schlange an der Kasse war zwar etwas länger, aber Udo wartete geduldig.
c2: Udo brach zum Hafen auf, denn er wollte mit seinem Auto zur Insel übersetzen.
ns: Nach zehn Minuten war er an der **Reihe**/**Fähre** und löste ein Ticket.

92. **c1:** Der Züchter hatte sich alles genau erklären lassen und beinahe auch alles verstanden.
c2: Der Züchter hatte soeben neun seiner zehn Pferde verkauft.
ns: Jetzt hatte er nur noch eine **Frage**/**Stute** und kratzte sich am Kinn.

93. **c1:** Gustav wollte, dass Achim mal das Bier in dem riesigen Fass sieht.
c2: Gustav hatte schon alle Zutaten für das Bier besorgt: Hopfen, Malz und Wasser.
ns: Im Keller wollte er es **zeigen**/**brauen** und auch kosten.

94. **c1:** Anna fand keine Möglichkeit, ihren Cocktail kurz abzustellen.
c2: Anna fand nicht die Zeit, sich den Cocktail selbst zuzubereiten.
ns: Sie bat Bert, ihn zu **halten**/**mixen** und regelmäßig umzurühren.

95. **c1:** Lisa hielt einen großen Brotlaib im Arm, aber langsam wurde er ihr zu schwer.
c2: Lisa hatte keine Zeit mehr, den Brotlaib in den Ofen zu schieben.
ns: Ihr Mann bot an, ihn zu **tragen**/**backen** und aufzuschneiden.

96. **c1:** Helmut fiel bei der Führerscheinprüfung positiv auf.
c2: Helmut versuchte, ein Loch in die Wand zu bekommen.
ns: Er konnte schon recht gut **fahren**/**bohren** und erntete Lob.

97. **c1:** Der Lehrer war nicht fähig, komplexe Sachverhalte verständlich darzustellen.
c2: Der Lehrer sollte seiner Tochter einen Zopf machen, was ihm aber nicht gelang.
ns: Er konnte einfach nicht gut **erklären**/**flechten** und verzweifelte daran.

98. **c1:** Julia war taub.
c2: Julia hatte keine kräftigen Hände und besaß auch keinen Schemel.
ns: Sie konnte die muhende Kuh nicht **hören**/**melken** und weinte deswegen.

99. **c1:** Schon seit Wochen dachte Conny daran, sich umzubringen.
c2: Conny ließ sich jede Falte operieren, denn sie war dem Jugendwahn verfallen.
ns: Sie wollte auf keinen Fall mehr **leben**/**altern** und war betrübt.

100. **c1:** Ina schaute Heiners Hände an, aber bloßes Ansehen war ihr zu wenig.
c2: Ina schaute Heiners Hände an und bemerkte, dass sie eiskalt waren.
ns: Sie nahm sie, um sie zu **fühlen**/**wärmen** und zu drücken.

101. **c1:** Kurt benutzte ständig die Sachen seines Bruders, ohne ihn zu fragen.
c2: Kurt hatte schon wegen mehrerer Diebstähle im Gefängnis gesessen.
ns: Auch das Radio wollte er einfach **nehmen**/**klauen** und anschließend verkaufen.

102. **c1:** Knut hatte das Vermögen vor sich liegen, aber er war blind.
c2: Knut gierte schon nach dem großen Vermögen, aber das Testament war ungültig.
ns: Deshalb konnte er das Geld nicht **sehen**/**erben** und er fluchte.

103. **c1:** Die Wanderer hatten nur noch einen einzigen Apfel, aber jeder wollte ein Stück davon.
c2: Die Wanderer waren erschöpft vom steilen Berganstieg und griffen nach dem Proviant.
ns: Sie beschlossen also kurzerhand zu **teilen**/**rasten** und taten dies auch.

104. **c1:** Linda bettelte im Laden um ein bisschen Rabatt für die Hose.
c2: Linda war die Hose viel zu lang.
ns: Sie musste das Kleidungsstück unbedingt **haben**/**kürzen** und zum Geburtstag anziehen.

105. **c1:** Da der Hund viel zu klein war, bekam er eine Hormontherapie.
c2: Der Hund entdeckte einen Eindringling in seinem Revier.
ns: Daraufhin begann das Tier zu **wachsen/bellen** und laut zu knurren.

106. **c1:** Emil hatte sich den Magen verdorben und beförderte nun alles wieder hinaus.
c2: Emil hatte nichts mehr zu essen.
ns: Schon seit Tagen musste er **brechen/hungern** und ihm war elend.

107. **c1:** Annika kam nicht an das Hemd, das weit oben im Schrank lag.
c2: Annikas Hemd war völlig zerknittert.
ns: Sie bat ihre Mutter, es ihr zu **geben/bügeln** und ihr anzuziehen.

108. **c1:** Carola wurde noch mal für einen Moment ins Wartezimmer geschickt.
c2: Carola wollte ihren Schutz gegen Röteln auffrischen lassen.
ns: Der Arzt wollte sie nachher wieder **rufen/impfen** und tat dies auch.

109. **c1:** Hausmeister Tim nahm sich vor, sein Kreuz bei der SPD zu machen.
c2: Hausmeister Tim musste die Flure der Stadtverwaltung mit seinem Besen säubern.
ns: Er ging ins Rathaus, um zu **wählen/fegen** und seiner Pflicht nachzukommen.

110. **c1:** Die Sekretärin wollte, dass der Chef ihr einen Gefallen tut.
c2: Die Sekretärin hätte zu ihrem Chef gern "Konrad" gesagt.
ns: Aber sie traute sich nicht, ihn zu **bitten/duzen** oder zu fragen.

111. **c1:** Susi ruhte sich am Flussufer auf ihrer Decke aus.
c2: Susi lief zum Fluss, um Fische zu fangen.
ns: Sie liebte es sehr, dort zu **liegen/angeln** und sich zu sonnen.

112. **c1:** Die Musiklehrerin probte mit den Schülern ein neues Lied.
c2: Bei der Probe forderte die Musiklehrerin die Schüler auf, es den Bienen gleichzutun.
ns: Sie sollten nun die erste Strophe **singen**/**summen** und im Takt klatschen.

113. **c1:** Elvira erzählte Martin so viele Witze.
c2: Martin war so müde.
ns: Die ganze Zeit musste er laut **lachen**/**gähnen** und dabei grunzte er.

114. **c1:** Der kleine Sohn stieß immer wieder mit seinem Fuß gegen das Schienbein.
c2: Der kleine Sohn stellte immer wieder die gleiche Frage.
ns: Die Mutter schimpfte, er solle aufhören zu **treten**/**nerven** und ruhig sein.

115. **c1:** Peter hat großen Spaß, bei Versteigerungen durch häufiges Handheben den Preis in die Höhe zu treiben.
c2: Peter hat großen Spaß, mit dem Schlitten einen steilen Berg herunter zu fahren.
ns: Am liebsten würde er nie aufhören zu **bieten**/**rodeln** und zu grinsen.

116. **c1:** Anne fand es großartig, ihren Horizont zu erweitern, indem sie anspruchsvolle Bücher las oder in Museen ging.
c2: Anne fand es großartig, am Strand zu liegen und knackig braun zu werden.
ns: Sie liebte es, sich zu **bilden**/**sonnen** und mit Freundinnen zu diskutieren.

117. **c1:** Hannes und Rita hatten verschiedene Bälle zur Auswahl.
c2: Hannes und Rita aßen Kirschen und sammelten die Kerne.
ns: Sie wollten wissen, wer am weitesten **werfen**/**spucken** kann, ohne zu schummeln.

118. **c1:** Erich war an Knochenkrebs erkrankt und kämpfte um sein Leben.
c2: Erich unterließ es, in den Ring zu steigen, denn seine rechte Hand war verletzt.
ns: So wollte er auf keinen Fall **sterben**/**boxen** und er weinte bitterlich.

119. **c1:** Die Lehrerin hatte schon alles besorgt: Mathebücher, Bleistifte und kariertes Papier.
c2: Die Lehrerin hatte schon alles besorgt: Kleber, Schere, Krepppapier und Buntstifte.
ns: Sie wollte mit den Kindern heute **rechnen**/**basteln** und stieß auf Begeisterung.

120. **c1:** Der Vater wollte Linda noch nicht zum Essen rufen, weil sie gerade mit ihren Puppen beschäftigt war.
c2: Während Linda nervös herumhüpfte, ließ sich der Vater viel Zeit, bevor er ihr das Geschenk übergab.
ns: Er ließ sie erst noch ein bisschen **spielen**/**zappeln** und war belustigt.

121. **c1:** Kurt war vom vielen Rad fahren unglaublich müde.
c2: Kurt war vom Camping begeistert und wollte keinen anderen Urlaub mehr machen.
ns: Er wollte von jetzt an nur noch **schlafen**/**zelten** und sich entspannen.

122. **c1:** Hans nimmt sein Lieblingsbuch überall hin mit.
c2: Hans entspannt sich abends gern im warmen Wasser in der Wanne.
ns: Er liebt es, in aller Ruhe zu **lesen**/**baden** und zu träumen.

123. **c1:** Lukas störte es, der Mutter tatenlos beim Arbeiten zuzusehen.
c2: Lukas störte es, dass der Rasen auf dem Hof schon wieder so lang war.
ns: Deshalb wollte er an diesem Nachmittag **helfen**/**mähen** und die Treppe putzen.

124. **c1:** Achim hatte ständig Durst.
c2: Achim rauchte einen Joint nach dem anderen.
ns: Den halben Tag verbrachte er damit zu **trinken/kiffen** und zu schlafen.

125. **c1:** Der Pfarrer hatte Manuela schon oft gedroht, sie zu verprügeln.
c2: Der Pfarrer hatte erklärt, dass er Manuela bei der Zeremonie Wasser über den Kopf schütten würde.
ns: Heute wollte er sie nun anscheinend **schlagen/taufen** und im Anschluss predigen.

126. **c1:** Kevin fand, dass das Klavier mittlerweile ganz furchtbar schief klang.
c2: Kevin wollte den Teppich auch unter dem Klavier verlegen.
ns: Er sagte den Männern, sie sollen es **stimmen/anheben** und anschließend wegtragen.

127. **c1:** Carola wollte nicht, dass Dietrich bei der Kälte nach Hause geht.
c2: Carola rief Dietrich, da es sehr kalt war und sie den Ofen nicht bedienen konnte.
ns: Sie bat ihn ausdrücklich zu **bleiben/heizen** und sich zu ihr zu setzen.

128. **c1:** Man braucht Geduld, um Pilze zu finden, da sie oft versteckt im Unterholz wachsen.
c2: Pilze sind schwer verdaulich, wenn sie im Mund nicht gut genug zerkleinert werden.
ns: In der Regel muss man sie lange **suchen/kauen** und darf nicht aufgeben.

129. **c1:** Die Mutter sagte, dass Äpfel viele Vitamine hätten und sehr gesund seien.
c2: Die Mutter mochte Äpfel so gern, aber sie traute sich nicht auf den hohen Baum im Garten.
ns: Martin musste täglich ein paar Äpfel **essen/pflücken** und langsam reichte es ihm.

130. **c1:** Mein Opa befindet sich schon im hundertsten Lebensjahr.
c2: Mein Opa lässt sich von niemandem etwas sagen und will immer seinen Kopf durchsetzen.
ns: Nicht viele Menschen sind so **alt**/**stur** und so eigensinnig.

131. **c1:** Die beiden geometrischen Figuren unterscheiden sich praktisch gar nicht.
c2: Die beiden geometrischen Figuren sind nicht rund, sondern eiförmig.
ns: Jeder Betrachter bezeichnet sie als **gleich**/**oval** und relativ klein.

132. **c1:** Bäckerin Lisa bekam beim Backen eine Menge Mehl ab, weil es so staubte.
c2: Bäckerin Lisa litt unter einer Ohrenerkrankung, die sich in den letzten Jahren immer mehr verschlimmerte.
ns: Mittlerweile war sie eigentlich völlig **weiß**/**taub** und deswegen recht mürrisch.

133. **c1:** Der Wasserkanister ist bis zum Rand hin gefüllt.
c2: Der Wasserkanister ist nicht rund.
ns: Der Behälter ist wirklich ganz **voll**/**eckig** und aus weißem Plastik.

134. **c1:** Fritz betastete die Eingeweide und war überrascht, denn er hatte sie sich viel lockerer vorgestellt.
c2: Fritz musste sich beim Anblick der Eingeweide übergeben.
ns: Die Gedärme des Schweins waren so **fest**/**eklig** und rochen unangenehm.

135. **c1:** Nach zwei Stunden Kochzeit nahm Johanna die Kartoffeln vom Herd.
c2: Nach dem Kochen der Kartoffeln bemerkte Johanna, dass sie das Salz vergessen hatte.
ns: Sie waren nun bestimmt richtig **gar**/**fad** und hatten eine gelbliche Farbe.

136. **c1:** Christian hatte nicht einen einzigen Freund.
c2: Christian konnte sich in seinem winzigen Zimmer kaum bewegen.
ns: Er fühlte sich hier so **allein**/**beengt** und rief seine Mutter an.

137. **c1:** Inge bemerkte, dass die Tapete noch nicht so alt war.
c2: Inge bemerkte, dass sich die Tapete gar nicht glatt anfühlte.
ns: Tatsächlich war die Tapete recht **neu/rau** und das konnte man sehen.

138. **c1:** Die Blüten dieser Blume gleichen einem vollkommenen Kreis.
c2: Die Blüten dieser Blume hängen schlaff und trocken herunter.
ns: Sie sind in der Tat ganz **rund/welk** und dennoch sehr schön.

139. **c1:** Der Schrank passte nicht an die schmale Wand des Schlafzimmers.
c2: Der Schrank war in einer Farbe gestrichen, die an Flamingos erinnerte.
ns: Er war eindeutig viel zu **breit/rosa** und auch sonst recht hässlich.

140. **c1:** Matti hatte keinerlei Ähnlichkeiten mit seinen Brüdern.
c2: Matti stand oft stundenlang vor dem Spiegel und legte viel Wert auf sein Äußeres.
ns: Alle sagten, er sei total **anders/eitel** und vor allem recht überheblich.

141. **c1:** Andreas trat auf die Hängebrücke und diese brach unter der enormen Last entzwei.
c2: Andreas hatte noch nie eine Freundin, denn er liebte nur Männer.
ns: Er war ohne jeden Zweifel richtig **schwer/schwul** und er stand dazu.

142. **c1:** Arno ist ein Schiedsrichter, der mit ohrenbetäubender Stimme über den Platz brüllen kann.
c2: Arno ist ein Schiedsrichter, der nie ungerechte Entscheidungen fällt oder parteiisch ist.
ns: Kein anderer Schiedsrichter ist so **laut/fair** und zudem ein guter Trainer.

143. **c1:** Kleine Tiere sind für bestimmte Fotoaufnahmen nicht geeignet.
c2: Wilde Tiere sind für bestimmte Fotoaufnahmen nicht geeignet.
ns: Es ist leichter, wenn die Tiere **groß/zahm** sind und ruhig dasitzen.

144. **c1:** Hermann lief vor seinen Verfolgern davon, aber sie holten auf.
c2: Hermann kam schmutzig aus dem Schweinestall und konnte so unmöglich ins saubere Wohnzimmer.
ns: Er bemerkte, dass er einfach zu **langsam**/**dreckig** und auch zu ungeschickt war.

C. ANOVA Table (Chapter 4)

Table C: Global analyses of Experiment 1 (Chapter 4). Three-way ANOVAs (columns 1 to 3) on the factors frequency (2), predictability (2), and electrodes (50) as well as within-predictability class two-way ANOVAs (columns 4 and 5) on the factors frequency (2) and electrodes (50). Analyses were performed in six intervals and included data from the whole subject sample ($N = 32$).

Interval [ms]	Frequency x Electrode	Predictability x Electrode	Frequency x Predictability x Electrode	Frequency x Electrode: Low Pred.	Frequency x Electrode: High Pred.
50-90	$P = .248$ $F(3,120) = 1.373$	$P = .577$ $F(3,123) = .723$	$P = .841$ $F(3,103) = .305$	$P = .542$ $F(3,100) = .737$	$P = .406$ $F(3,109) = .998$
90-140	$P = .209$ $F(2,89) = 1.546$	$P = .425$ $F(5,185) = 1.002$	**P = .006** $F(4,134) = 3.602$	$P = .349$ $F(3,115) = 1.120$	**P = .014** $F(3,97) = 3.637$
140-190	$P = .053$ $F(2,92) = 2.663$	$P = .688$ $F(4,149) = .608$	$P = .148$ $F(3,123) = 1.732$	$P = .480$ $F(3,102) = .849$	**P = .006** $F(3,114) = 3.981$
190-240	$P = .297$ $F(4,144) = 1.234$	$P = .308$ $F(6,191) = 1.198$	$P = .450$ $F(3,115) = .918$	$P = .533$ $F(4,131) = .801$	$P = .256$ $F(3,119) = 1.350$
240-290	**P = .002** $F(5,169) = 3.915$	**P = .008** $F(3,115) = 3.741$	$P = .482$ $F(4,130) = .881$	**P = .023** $F(4,147) = 2.741$	$P = .120$ $F(4,139) = 1.823$
300-500	$P = .195$ $F(4,145) = 1.506$	**P < .001** $F(5,162) = 41.346$	$P = .544$ $F(5,169) = .822$	$P = .451$ $F(4,142) = .942$	$P = .200$ $F(5,155) = 1.477$

In reading, word frequency is commonly regarded as the major bottom-up determinant for the speed of lexical access. Moreover, language processing depends on top-down information, such as the predictability of a word from a previous context. Yet, however, the exact role of top-down predictions in visual word recognition is poorly understood: They may rapidly affect lexical processes, or alternatively, influence only late post-lexical stages. To add evidence about the nature of top-down processes and their relation to bottom-up information in the timeline of word recognition, we examined influences of frequency and predictability on event-related potentials (ERPs) in several sentence reading studies. The results were related to eye movements from natural reading as well as to models of word recognition. As a first and major finding, interactions of frequency and predictability on ERP amplitudes consistently revealed top-down influences on lexical levels of word processing (Chapters 2 and 4). Second, frequency and predictability mediated relations between N400 amplitudes and fixation durations, pointing to their sensitivity to a common stage of word recognition; further, larger N400 amplitudes entailed longer fixation durations on the next word, a result providing evidence for ongoing processing beyond a fixation (Chapter 3). Third, influences of presentation rate on ERP frequency and predictability effects demonstrated that the time available for word processing critically co-determines the course of bottom-up and top-down influences (Chapter 4). Fourth, at a near-normal reading speed, an early predictability effect suggested the rapid comparison of top-down hypotheses with the actual visual input (Chapter 5). The present results are compatible with interactive models of word recognition assuming that early lexical processes depend on the concerted impact of bottom-up and top-down information. We offered a framework that reconciles the findings on a timeline of word recognition taking into account influences of frequency, predictability, and presentation rate (Chapter 4).

ISSN 2190-4545
ISBN 978-3-86956-059-5