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Decoding Word Recognition: How Word Properties and Individual Factors Shape Processing

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ABSTRACT

Reading is one of the most complex abilities that the human mind is capable of, and the process of visual word recognition is the key aspect of it. In order to gain a better understanding of this process, this study investigated the roles of Semantic Neighborhood Density (SND), Orthographic Neighborhood Density (OND), word frequency, word length, and individual differences in reading speed on visual word recognition. Using a lexical decision task and analyzing the data through a linear mixed model, significant effects were found for SND, word frequency, and word length, with a notable interaction between reading speed and word length. Higher SND and word frequency facilitated faster word recognition, while longer word length slowed it down. The interaction revealed that participants with faster reading speeds were less impacted by word length. These findings align with existing computational models of word recognition but also suggest areas for refinement.

Keywords: Word Recognition, Lexical Decision, Semantics, Individual Differences

INTRODUCTION

Reading is both a product of human evolution and a fundamental contributor to the cultural explosion (Dehaene, 2009). Overall, it is considered one of the most sophisticated abilities of humans. In the last three decades, cognitive psychology has focused on examining the mechanisms involved in this unique ability. The objective is to decipher the set of procedures that a skilled reader uses to solve the challenge of word identification (Dehaene, 2009). Identifying words is regarded as the fundamental basis of reading. Reading will be exceedingly ineffective if mechanisms behind the word recognition do not function fluently and efficiently (Perfetti & Helder, 2022). That is why it is crucial to comprehend the mechanisms that regulate the process of visually identifying a string of letters and determining its meaning. The lexical decision task (Meyer & Schvaneveldt, 1971) is a widely used approach in visual word recognition. In this task, participants are asked to determine whether or not a string of letters represents a meaningful word.

A large amount of empirical research has examined how different written word characteristics affect recognition speed based on responses to behavioral tests like lexical decision (Hauk et al., 2006). Few of the most commonly reported effects in these studies are the effects of word frequency (e.g., Balota et al., 2004; Forster & Chambers, 1973; Keuleers et al., 2012; Murray & Forster, 2004), the effect of word length (Hudson & Bergman, 1985; New et al., 2006; O'Regan & Jacobs, 1992), and the effect of orthographic neighborhood density (Andrews, 1989, 1992, 1997; Forster & Shen, 1996; Keuleers et al., 2010; Yarkoni et al., 2008).

While the importance of orthography and phonology in visual word recognition has been extensively studied, the significant role of the semantics in this process has been relatively neglected. An increasing body of research has begun to reveal the importance of semantics in visual word recognition (Buchanan et al., 2001; Evans et al., 2012; Yap et al., 2012). Electrophysiological studies have demonstrated that the brain processes the semantic information related to a written word during the early stages of visual word recognition, as observed in a lexical decision test (Hauk et al., 2006; Sulpizio et al., 2022).

Building on the growing body of empirical evidence highlighting the influence of semantic factors in visual word recognition, the present study seeks to further elucidate the role of semantics, by investigating the role of semantic neighborhood density (SND). In addition to examining the effects of SND, the well-established effects of word length, word frequency, and orthographic neighborhood density (OND) are also being investigated using a lexical decision task.

To identify the semantic neighbors of a word, the present study employs Distributional Semantics Models (DSMs). It has been demonstrated that the DSMs are capable of providing reliable estimations of semantic representations (Günther et al., 2019). Within DSMs, the semantic interpretation of a word can be approximated by analyzing its patterns of occurrence alongside other words in a given lexicon. Word meanings are encoded as vectors using co-occurrence information (Sulpizio et al., 2022). The DSM employed in this work is fastText (Bojanowski et al., 2017), which incorporates sub-word information by generating semantic representations as the sum of the vectors of letter n-grams associated with each word.

Despite the increasing empirical evidence and methodological advancements elucidating the mechanisms underlying visual word recognition, the role of individual differences remains a relatively neglected area of study. The majority of studies on word recognition have primarily examined data at the group level, which involves averaging the results among participants. This approach has resulted in the identification of the "prototypical" reader (Yap et al., 2012). Taking the assumption that every one of skilled readers possess identical mental processes and reading practices can result in erroneous conclusions regarding the fundamental cognitive mechanisms involved (Andrews, 2015).

Nevertheless, a growing amount of research suggests significant differences among readers. Prior studies have shown that variations in vocabulary knowledge (Mitchell & Brady, 2013; Primativo et al., 2013; Weems & Zaidel, 2004; Yap et al., 2012), lexical familiarity (Lewellen et al., 1993), and reading speed (Hossain & White, 2023) have a significant impact on performance in visual word recognition tasks. Yap et al. (2009), demonstrated that the relationship between semantic priming and word frequency, a widely studied phenomenon, is influenced by individual variations in perceptual skill and language knowledge among participants.

These findings underscore the critical importance of considering the role played by individual differences during visual word recognition. Therefore, the present study aims to explain how individual variability, as reflected by reading speed, might interact with key linguistic predictors like SND, OND, word frequency, and word length. Investigating this underexplored aspect of visual word recognition can provide a more nuanced understanding of the cognitive mechanisms underlying this complex process, with implications for both theoretical models and practical applications in education and cognitive assessment.

CHAPTER 1 - VISUAL WORD RECOGNITION

Reading is without a doubt one of the most complicated cognitive operations that humans are capable of performing. It is more of a coordinated set of abilities than an isolated skill. These functions encompass visual, phonological, and semantic decoding, as well as orthographic, syntactic, and contextual analysis. They also involve emotional appraisal, motor and attentional control, and long and short-term memory, among others. Reading requires the efficient and precise coordination of various operations, which operate at a high speed and accuracy, and mutually impact each other in an ideal manner (Lachmann, 2002).

The particular procedures and factors involved in reading include the recognition of visual elements that are important for identifying letters, the recognition of the visual form of a word, and the conversion from written language to spoken language. Therefore, there are several functionally separate subprocesses that must be operating properly in order to ensure normal reading. Thus, the process of reading engages multiple brain regions. The occipital and occipito-temporal lobes are responsible for processing the visual characteristics of letters. Phonological processing has been linked to the left inferior frontal gyrus and the anterior insula (Friederici & Lachmann, 2002). The Visual Word Form Area (VWFA), situated in the occipito-temporal region on the left side, has a specific role of extracting the representation of letter strings. It is noteworthy that we possess a brain region that is very sensitive to the particular requirements of our reading system, despite the absence of sufficient evolutionary time to develop a specialized brain region for reading (Dehaene, 2005).

This chapter will explore the cognitive processes involved in how a skilled reader recognizes and comprehends a word's meaning. Beginning with a brief overview of the history of reading research, the chapter will then examine the orthographic processing, drawing on empirical evidence from various disciplines that have investigated this phenomenon. It will then delve into the phonological processes that influence visual word recognition, before finally analyzing the role of semantics in word identification.

1.1 Research on Reading

While there were earlier accounts of patients with acquired reading difficulties, Cattell's (1886) tests on the duration of reading words and letter strings are considered the starting point of experimental reading research (Perfetti & Helder, 2022). The release of Huey's "The Psychology and Pedagogy of Reading" in 1908 marked a significant milestone in the early studies on reading. The book addressed word identification mechanisms, inner speech, and reading rate. Despite the use of outdated equipment, the majority of the conclusions covered in Huey's book have been proven to be fundamentally accurate. Therefore, they are still worthy of consideration (Kamil et al., 2010). Psychological study in this area significantly declined throughout the years when behaviorism was the dominant approach in psychology, which was roughly between 1920 and 1960. It was around the end of the 1950s, during the period known as the "cognitive revolution," when significant advancements were made in our understanding of the reading process (Pollatsek & Treiman, 2015).

The major idea behind the cognitive revolution was to try to understand behavior not just as an act that one observes but as the result of a chain of hypothetical mental steps or boxes that started with an input stimulus and ended with a response (Pollatsek & Treiman, 2015). The cognitive revolution has resulted in the development of a variety of experimental methods that psychologists have utilized in order to investigate word identification. In contrast to numerous phenomena in the field of natural science, it is not possible to directly study the mental processes involved in recognizing words. A way to overcome this issue is to adjust and scientifically measure the factors that are associated with the various aspects of word recognition (Reichle, 2021).

For instance, cognitive psychologists show a word to the participants for a very short period of time (such as 50 milliseconds) in order to investigate word recognition mechanisms. In such an experiment, a participant may be instructed to articulate the word or decide if the target is a word or a word in a particular category. Participants are usually asked to press one button to indicate a yes (it is a word) response and another button to indicate a no (it is not a word) response. These types of tasks might not replicate the reading process completely. However, participants may be employing the same cognitive processes utilized while reading in order to answer effectively (Rayner, 2012). The time it takes for participants to complete these tasks is measured with millisecond precision. Reaction time (RT) metrics have been crucial in cognitive studies on reading and other subjects (Pollatsek & Treiman, 2015).

There has been a rise in the number of studies focused on employing eye movements to examine the progression of reading skills. The implementation of gaze contingent display paradigms offered novel means for investigating the regulation of eye movements during the process of reading. Subsequently, eye tracking devices have undergone improvements in usability without any trade-offs in data quality, and they have been integrated with state-of-the-art technological tools (Hyönä & Kaakinen, 2019).

Early cognitive research often relied on broad arguments to connect these unknown processes to specific areas of the brain or other regions of the nervous system. However, significant progress is now being made in the field of cognitive neuroscience to precisely identify the locations of these theoretical functions within the nervous system (Pollatsek & Treiman, 2015). Studies using brain-imaging techniques, which have gained significant popularity in the past two decades, involve people engaging in specific tasks while their brain's neural activity is monitored. This discipline also investigates electrophysiological data, which involves measuring electrical activity on the scalp to draw conclusions about brain activity. Additionally, it analyzes data from individuals who have suffered injury to certain regions of their brains (Rayner, 2012). In addition to laboratory instruments, the advancement of computational modeling has enhanced the accuracy of theoretical explanations, while extensive language corpora offers statistical techniques for modeling the process of reading (Perfetti & Helder, 2022). Visual word recognition is a significant illustration of the advancements achieved in modern-day cognitive science and neuroscience (Seidenberg et al., 2022).

Lexical Decision Task

One of the primary methods used to study word recognition processes in experimental settings is the lexical decision task (Roberts et al., 2010), which is of special importance in this study. The lexical decision task involves presenting letter sequences to participants, who are required to determine whether or not the letter string forms a word in their language. The study analyzes the duration of participants' decision-making process and the rate of errors they make in relation to the altered factors (Rayner & Juhasz, 2006).

Rubenstein and colleagues (1970), were pioneers in utilizing a lexical decision task. The researchers employed English words and nonwords to examine the impact of homography, word frequency, and concreteness of meaning. Subsequently, Meyer and Schvaneveldt (1971), introduced the concept of the lexical decision task. Since then, a considerable amount of research has been carried out utilizing this task, encompassing various types (see Berberyan et al., 2021 for a recent review). The visual lexical decision task is popular due to its cost-effectiveness, both in terms of execution and outcome analysis. The necessary experimental setup is likewise quite simple, comprising a computer and a device for recording responses. The gathered data, consisting of RTs and accuracies, may be readily understood without any manipulation and can be analyzed using established and robust statistical techniques (Keuleers & Brysbaert, 2011).

Word recognition abilities can be cognitively tested with lexical decision tasks. The task paradigm makes it possible to evaluate the accuracy and speed of lexical decisions (Berberyan et al., 2021). Nevertheless, similar to other tasks involving word identification, the lexical decision task also has intrinsic limitations (Diependaele et al., 2012). Initially, it was believed that the performance of lexical decision tasks solely reflected the ability to access and activate specific word representations in the mental lexicon. Subsequently, it was acknowledged that the duration it takes to make a choice about a word's meaning is influenced by how similar the word is to other words in the language (Grainger & Jacobs, 1996) as well as the level of similarity between the word and nonword stimuli (Keuleers & Brysbaert, 2011). Additionally, studies have demonstrated that RTs in this task are influenced by a range of variables unrelated to word identification, such as the type of nonwords utilized in the task (Reichle, 2021).

Notwithstanding the constraints of the tasks, cognitive scientists persist in creating novel models and ways to overcome these restrictions. Various models have been created to comprehend the mechanism underlying the lexical decision task (see Yap & Balota, 2015). On the other hand neuropsychological studies continue to explore the neural pathways activated during these tasks (e.g., Berberyan et al., 2021; Murphy et al., 2019; Wong et al., 2020). The advancement in comprehending word identification has been driven by the fundamental approach of constructing models that encompass the essential processes involved in word identification, as well as the processes necessary to clarify human performance in particular word identification tasks. These models are then integrated with empirical data to enhance our understanding (Reichle, 2021).

1.2 Orthographic Processing

To achieve reading competency, it is crucial to understand all the processes that contribute to the development of automatic word recognition. Although phonological processing has been considered as the most important factor of word identification (Adams, 1990; Share, 1995, 1999), it is evident that phonological skills alone are insufficient to explain the process of word recognition (Cunningham et al., 2001; Cunningham et al., 2011; Share, 1995; Stanovich & West, 1989). Research has demonstrated that orthographic skills make a distinct contribution to word recognition, even when phonological skills, (Stanovich & West, 1989; Olson et al., 1989), age, and non-verbal intelligence (Cunningham & Stanovich, 1990) are taken into account. Researchers have shown that orthographic skills uniquely contribute to the process of word recognition (Apel, 2009; Apel et al., 2011; Berninger et al., 1994; Berninger et al., 1991).

This section will start with how people get to recognize letters, which are the smallest units of words, in various shapes and sizes. The discussion will then transition to the processing of whole words, which is the central focus of the present study. Throughout this section, the various factors that influence word processing, such as orthographic complexity, frequency, and letter position, will be examined in detail.

1.2.1 Letter Recognition

Reading is a skill that involves both visual and linguistic factors, and orthographic processing lies at the key interface between vision and language (Grainger, 2018). From this point of view, it is argued that single-word perception is realized by visual object identification and linguistic processing working together. It is the orthographic processing that provides this connection. Through orthographic processing, mechanisms that process visual information integrate with mechanisms that process word-specific linguistic stimuli. Skilled readers use information about letter characteristics, together with information on their position within the word. Information about a letter’s identity and position constitute the orthographic information (Grainger, 2022).

Identifying letters is the starting point for reading and word recognition (Fiset et al., 2009). Understanding how humans recognize letters and access to their corresponding phonology has been an important topic for the scientific field. Pattern recognition studies have been an important part of revealing this process. The pioneering work of Selfridge was the foundation point of a cognitive theory for processing letters. In his “pandemonium” model, the process of identifying a letter goes through hierarchical layers that consist of feature and letter detectors (Grainger, 2022). In the model, the human brain is conceptualized as a pandemonium, assembled by “demons”. Each demon in the system is assigned with a letter and computes the similarity of the presented stimulus with its assigned letter and “shouts out” the result. The system is based on parallel processing and demons compete with each other. The cognitive demons weigh the information coming from sub demons and yell their results and the decision demon selects the loudest (Selfridge, n.d.).

In trying to understand which features are critical for letter recognition, studies use the confusion matrix method. The variable called letter confusability used in this method is computed by the number of features that any pair of letters have in common. With increased similarity, the possibility of readers confusing the two letters will be increased as well. In this case, the similarity between the letters is referred to as letter confusability (Finkbeiner & Coltheart, 2009). A confusion matrix in these studies is computed by measuring the ability of participants to distinguish individual letters in varying conditions. These conditions are created in order to cause frequent errors, typically in half of the trials. Errors made in these confusion matrices are believed to reflect the features necessary for differentiating letters from one another. As for an example, the frequent confusion of the uppercase letter “E” and “F” is assumed to reflect the diagnostic feature of the inferior horizontal line of the uppercase letter “E” in recognizing this letter (Fiset et al., 2009).

Letter confusability has been the subject of more than 70 published research (Mueller & Weidemann, 2012). These have served as the basis for detailed lists of characteristics for the Roman alphabet's letters, which mostly include lines that have various curvatures and orientations (Grainger, 2022). In a Go–No-Go version of the same–different matching task, Courrieu and colleagues (2004), asked participants to answer only when the two letters were different. Twenty-five dimensions were identified by their findings, many of which were interpreted as basic visual characteristics. Certain combinations of basic characteristics, like "vertical line" and "circle" were grouped together (e.g., b, d, g, p, q). The second similarity class, which corresponds to minor curvilinear shapes (e.g., a, c, e, o, s), is also evident, as are combinations of similarity classes, such as 'vertical line' with one little characteristic (e.g., f, t, i, j, l).

Pelli and colleagues (2006), examined the effectiveness of letter recognition under various viewing situations. Efficiency is determined by comparing real-life performance with that of an ideal observer (Grainger et al., 2008). Pelli and colleagues (2006) discovered that while efficiency varied between alphabets and typefaces, it was unaffected by stimulus duration, eccentricity, and size. Therefore, it was concluded that these results represented feature-based letter identification, in which the identification of each component feature influences the identification of the entire. Because of these variations in efficiency between alphabets and fonts, they have found a strong correlation for one specific metric, called the perimetric complexity. Perimetric complexity, which was explained as the square of the lengths of the inside and outside perimeters divided by the ink area (for size invariance), offered a measure of visual complexity believed to be proportionate to the number of characteristics in the absence of independent evidence regarding the nature of the characteristics that extends to identify letters.

Fiset and colleagues (2009) investigated the nature of the key components for letter perception using the bubbles technique. The fundamental concept of Bubbles is that if a certain visual element is essential to perform the work at hand, masking it will negatively impact performance, but revealing it would result in improved performance. After applying band pass filtering to the image at various channel frequencies, a random collection of "bubbles" is taken out of the filtered letters. A "bubbelized" image is produced by summing the sampled images across frequency channels and displaying it to the participants (Grainger et al., 2008). According to Fiset and colleagues' findings, horizontals and line terminations are the most essential letter properties for letter recognition. For example, the letter W was distinguishable from other letters by having two terminations, one located in the upper left corner and another in the upper right corner (Fiset et al., 2009).

Furthermore, Fiset and colleagues (2009), demonstrated that distinct letter characteristics in letter recognition follow distinct temporal histories. That is to say, not only are some aspects more crucial for letter recognition than others, but certain features are also extracted before others.

Research on the function of letter features in visual word recognition indicates that certain parts of letters, or the information at their junctions, may play a more significant role than others in recognizing letters or words. The relative significance of the mid-segments, junctions, and terminals of lower-case letters contained in words was investigated by Rosa et al. (2016). On the basis of the fact that the removal of midsegments resulted in a considerable reduction in the facilitation effect that has been observed on the lexical decision task, they came to the conclusion that midsegments are more important than junctions in the early stages of word recognition. However, since the deletion of a terminal results in word recognition durations that are comparable to those of the entire preview condition, it appears that terminals are the least important component during the early processing of words.

Abstract Letter Representation

A letter is recognized immediately, independent from changes in position, size, case and font. The reader neglects the large differences in visual input while identifying the letter from small features (Dehaene, 2005). To identify a letter, the visual system should compute an abstract representation of that letter independent from their visual appearance, and should encode only its identity (Bowers, 2000). At the abstract letter representation level of the reading system, there is just one unit (an abstract letter unit ALU) that represents a given letter of the alphabet, and it is activated regardless of the font, case, or style in which that letter appears visually in the retina. And this representation is present for every letter in the alphabet, each having their own ALU (Finkbeiner & Coltheart, 2009).

A number of studies support this phenomenon. However, most of the studies investigated word or pseudowords, and the results are attributed to abstract letter identities (Polk et al., 2009). In their study, Kinoshita and Kaplan (2008), used a cross-case letter match task combined with a masked priming procedure. During three experiments, participants were shown a reference letter, a prime letter followed by a target letter. Participants were asked to decide if the target letter is the same or different from the reference letter. Eight similar (e.g., c/C), and eight dissimilar (e.g., b/B) letters were used during all experiments. The results showed a robust priming effect in all three experiments, and the size of the effect did not differ between cross-case dissimilar letters and similar letters. They concluded that the observed priming effect was due to the abstract letter identities.

Most research on ALU is focused on English letters. Unlike English, the vast majority of languages written in the Roman alphabet (e.g., Italian, Spanish, German, Finnish) contain accented vowels. This raises an important question about the representation of the accented and non-accented vowels in the letter recognition system. The research of Chetail and Boursain (2019) on this matter, demonstrated that accented and unaccented vowels activated different letter representations in French, while in Perea and colleagues' (2020) study investigating the same question in Spanish language, accented and non-accented vowels shared the same abstract representation.

Apart from Roman alphabet languages, Carreiras and colleagues (2012), investigated if Arabic is among the languages where priming of abstract letter representations takes place, as the letters exhibit a complex array of contextual shapes. The findings revealed that abstract letter priming was also evident in Arabic. In light of these findings, they proposed the possibility of universality for abstract letter identities.

Nonetheless, rather than orthography, it is hypothesized that the priming effect results from the shared letter phonology (Kinoshita & Kaplan, 2008). To put this to the test, Kinoshita and colleagues (2019) looked at the influence of shared letter names in Japanese. The two writing methods used to write Japanese are syllabic kana and logographic kanji, making it a unique writing language. The Roman alphabet's capital and lowercase versions are comparable to kana syllabaries, hiragana, and katakana. There are two parallel forms with the same identity and letter name, but they may vary in how similar they look on the outside (Perea et al., 2017). The logographic kanji writing system, on the other hand, differs from the kana writing system. A kanji character that is pronounced the same as a kana letter is a homophonic heterograph, not an allograph. They investigated the phonological impact to the priming effect using this particular writing system and discovered that allograph priming is different from phonological priming. These findings were also linked to the universal nature of abstract letter identities (Kinoshita et al., 2019).

To explain how humans develop an abstract identity for letters, Polk and colleagues (2009) suggested that the emergence of distinct visual forms of the same letter in comparable distributions of visual contexts could be the mechanism by which humans build an abstract identity for letters. The concept is that various visual forms of a letter (e.g., “a”, “A”, and “*a*”) occur in the same words written in various formats (“cap”, “CAP”, and “*cap*”). According to their argument, correlation-based learning mechanisms of the human brain (also known as Hebbian learning) would produce similar representations of the letter's various visual forms because these visual contexts are similar. Stated otherwise, the system would create a representation that abstracts from the letter's visual appearance while still reflecting the identity of the letter (i.e., an ALU). They showed that representations of distinct stimuli become more similar when they are repeatedly presented in similar contexts.

Letter Strings

So far, the focus was mostly on identification of individual letters. Reciting the letters is a common starting point for learning to read. Yet, in daily life we usually encounter letters in words, in which the majority contains more than one letter. The initial focus is on the factors that affect letter identification in letter strings. According to Grainger et al. (2016), visual acuity, crowding, and spatial attention are the three characteristics that affect a letter's visibility and, consequently, its capacity to be recognized when given in a letter string. As previously stated, the density of retinal receptors determines acuity, which diminishes significantly and in a linear fashion from the point of fixation of the eyes within foveal vision (Grainger, 2022). Crowding happens when the features that are useful to identify an object (a letter in this case) are combined and interfere with object recognition. While it does not hinder detection, crowding makes it more difficult to recognize, count, and locate objects (Pelli & Tillman, 2008). Pelli et al. (2007), goes further to define the visual span as "...simply the number of characters that are not crowded".

According to Yu et al. (2012), interactions between low-level letter characteristics lead to word crowding. Rather than viewing crowding as purely spatial, Chung (2016) describes it as a spatio-temporal effect. Serial location functions for letter-in-string visibility provide evidence in favor of the roles that crowding, and acuity play in letter identification. These tests usually show a W-shaped visibility function, with the starting, middle, and end positions having the highest letter recognition accuracy. It is believed that this W-function reflects both the reduced crowding for the outer letters and the decline in acuity from the middle letter to the outer letters (Grainger, 2022). While digits follow a similar pattern, other basic visual stimuli such as symbols and forms do not (Tydgat & Grainger, 2009).

1.2.2 Processing of a Word

Proficient reading requires the ability to identify individual words, as it is a remarkably complex and multifaceted process. Words serve to encode and communicate various types of information, including phonology, morphology, spelling, and eventually meaning (Yap & Balota, 2015). Extensive research has been undertaken on the topic of visual word recognition due to its significant importance and complexity. Subsequently, a substantial amount of information has been uncovered. Visual word recognition is widely regarded as a significant accomplishment in modern cognitive science and neuroscience (Seidenberg et al., 2022).

1.2.2.1 Eye Movement During Reading

During reading, eyes are thought to move smoothly from one text to another. In reality, eyes are making rapid jumps that are called saccades and pauses that are called fixations on individual words in the text. It is the brain that creates a smooth perception of the visual experience (Pierce et al., 2019). The text that is being read is not available with the same acuity to the eye as well. A line of written words on the retina is divided into three regions based on the acuity; foveal, parafoveal, and peripheral vision. Fovea is where the acuity is the highest, and it drops off distinctly in the parafoveal area, and it is the lowest in peripheral vision (Rayner, 2012). The two types of photoreceptors, namely cones and rods, are unevenly distributed in the retina. The rods are extremely sensitive to light while the cones map light of different wavelengths in different ways. At the level of fovea, there is a high concentration of cones which enables the acuity, and their density diminishes significantly 10 degrees outside of the visual angle (Pouget, 2019). It is the high density of cones in the fovea that makes it the most useful part of the retina for reading (Dehaene, 2009).

In order to have a precise vision, eyes make saccadic movements to bring the stimulus onto the fovea for a short fixation period. A single fixation period while reading lasts for 200-250-ms for a skilled reader (Hyönä & Kaakinen, 2019). During a fixation period, 10-12 letters are identified on average, 3-4 of letters on the left side of the fixation, and 7-8 on the right side. The rest of the visual field is merely encoded (Dehaene, 2009). McConkie & Rayner (1975), in their moving window paradigm, presented a device that displayed a specified number of letters to the fixation point and replaced the remaining letters with x's. The window moved in synchrony with the gaze during reading. The paradigm showed that the perceptual span was asymmetric, and participants were not able to detect specific letter information nor general word shape information beyond 10–11-character position.

Throughout the years, many studies have replicated the results while revealing more information about the interaction between vision and cognition during reading. Rayner and colleagues (1982), further investigated the perceptual span, and demonstrated that the effect of the paradigm did not differ between letter-based windows and word-based windows. In other words, when the readers are presented with only a few letters of to-be-processed word, they read with the same efficiency as if they were presented with the whole to-be-processed word. On the other hand, readers were slower when the information outside of the visual area was dissimilar to the target letters rather than x's. Miellet and colleagues (2009), demonstrated that the size of the perceptual span was affected by the attention factors rather than acuity factors. By systematically increasing the letter size from fixation point to the limit point, they showed that perceptual span stayed within the 14-15 letter spaces. The perceptual span is affected by language ability (Choi et al., 2015), the writing system (Rayner, 2014), cognitive processing load (Meixner et al., 2022; Schroyens et al., 1999; Henderson & Ferreira, 1990), reading ability (Veldre & Andrews, 2014; Sperlich et al., 2016; Meixner et al., 2022), and typography (Paterson & Tinker, 1947). Meixner and Laubrock (2024), in their longitudinal study, showed that early executive functions contribute to the development of perceptual span, which in turn is crucial for successful reading.

1.2.2.2 Factors Affecting the Eye Movement During Reading

Information about the target word is acquired mainly during the fixation. After almost a quarter of a second, eyes make saccadic movement, landing on the next target word (Taylor & Taylor, 1983). This fixation time might vary, depending on multiple factors. This variation reflects cognitive processes underlying the ability to recognize words. The duration from the first encounter with a target word until the initiation of a new saccade, called gaze duration, is one of the most frequently used measures to understand these processes. What Rayner called “The Big Three” factors that influence word processing are frequency, length, and predictability in context (Clifton et al., 2016). Words that occur more frequently in a language are being processed faster by readers of that language. On the contrary, infrequent words are read with longer gaze duration (Hyönä & Kaakinen, 2019). Kuperman and colleagues (2024), demonstrated that the word frequency effect is present in 12 alphabetic languages from English to Turkish. Words that are encountered more frequently were read faster and were skipped more often than words that are encountered less frequently. The frequency effect has also been demonstrated in non-alphabetic languages like Chinese (Hyönä et al., 2024; Yan et al., 2006).

The second on the list, word length, has also been proven to influence the processing of a word. Longer words contain more constituent letters, which provide more orthographic information to process (Clifton et al., 2016). Consequently, longer words take more time to process (White et al., 2005; Juhasz et al., 2005; Juhasz et al., 2008; Rayner et al., 2011). The effect of word length in eye control is shown also by refixation and skipping in different studies (Clifton et al., 2016; Brysbaert et al., 2005; Rayner et al., 2011). Paterson and colleagues (2015) also replicated these findings in Arabic language where the eye moves from right to left. In their study, longer words resulted in higher refixation probabilities and were fixated for a longer time compared to short words.

The last key aspect of The Big Three is the predictability effect. Words that are predictable from the context of the previous text are fixated for a shorter period of time (Vainio et al., 2009), are fixated less, and skipped more often than words that are contextually unpredictable (Hyönä & Kaakinen, 2019; Clifton et al., 2016; Kliegl et al., 2004; Rayner et al., 2011). These effects were replicated for numerous alphabetic languages (Kuperman et al., 2024) as well as for non-alphabetic languages (Cui et al., 2022; Rayner et al., 2005). Individual differences that affect this phenomenon have also been investigated (Ashby et al., 2005).

Another phenomenon that Rayner focused on was the effect of lexical ambiguity. In their initial work, Duffy and colleagues (1988), showed that ambiguous words had longer gaze duration. They have stated that when presented with words that have more than one ambiguous meaning, all are automatically activated, while the frequency of the possible meanings interferes in the processing. In addition, the context of the sentence affects the processing by influencing the availability of possible meanings of ambiguous words. These results were replicated in recent years (Folk & Morris, 2003; Kambe et al., 2001; Wiley & Rayner, 2000).

Although there are different views on how a word is recognized, one way is by identifying individual words. Characteristics of individual letters or letter clusters in a given word have been found effective in word recognition (Hyönä & Kaakinen, 2019). White and colleagues (2008), used two types of transposed-letter conditions; word-internally (by changing internal letters in a word, e.g., problem-prolbem), and word-externally (by changing the external letters in a word, e.g., problem-rpoblem). The transposed letter effect was greater for the trials where the external letters were changed. These results indicate that letters in the beginning and end of the word are more important for word perception than letters that are in the middle of the word. Other studies replicated these results (Johnson et al., 2007; Gomez et al., 2008). However, this effect was not replicated for languages like Thai, where ordering of the letters does not necessarily match with the ordering of the target word's phoneme (Winskel et al., 2012).

In alphabetic languages, letters correspond to speech sounds called phonemes. Research findings show that phonological coding is crucial for fluent reading (Caravolas, 2022). Languages like English and Dutch are less orthographically transparent. The pronunciation of letters or letter combinations can differ between different words, like in the example of "tough

– though – through" (Brysbaert, 2022). The phonological recoding phase is found to be effective in fixation duration (Hyönä & Kaakinen, 2019). For example, in Inhoff and Topolski's study (1994), words with irregular spelling (e.g., "weird") had longer fixation times than words with regular spelling (e.g., "mood").

Apart from factors that are driven by the stimuli, one other factor that affects the fixation duration is where the readers lay their eyes on. It has been argued that near the center of a word, more specifically the left side of the center, is where the reading performance is more efficient (O'Regan, 1981). In this fixation point, what is called "optimal viewing position", the probability of correctly reporting the target word is higher, reaction times on lexical decision and naming tasks are shorter, and gaze duration is shorter compared to the fixations at the beginning or at the end of a word. In addition to single fixations, participants are less likely to stare at the target word if they make the initial fixation near the center of the word. (Yao-N'Dré et al., 2013). The effect of the optimal viewing position was found in numerous studies (Farid & Grainger, 1996; Hyönä & Bertram, 2011; Jordan et al., 2010; Li et al., 2017; O'Regan & Jacobs, 1992; O'Regan, 1981; Yao-N'Dré et al., 2013)

When readers just make one fixation on a word, this fixation is at its longest when it is placed in the middle of the word, and it stands at its shortest when it is located near the beginning or the end of the word. Put another way, word center is not the best viewing location if one is exclusively fixated on a word. The inverted ideal viewing position (IOVP) is the term used to describe this recent finding (Hyönä & Kaakinen, 2019).

1.2.2.3 Parallel Processing

It is obvious that understanding reading depends on knowing how words are identified. It is likely that children in their preschool years have a more or less developed system for comprehending spoken language; the main skill to be acquired is how to integrate the symbols on the page with that system (Rayner, 2012). The earlier chapters covered how the eyes move when reading, what this movement indicates about the reading process, and how to recognize individual letters. Usually, letters are incorporated into words rather than being displayed alone (Yap & Balota, 2015). It may also seem apparent that letters should be perceived as natural components of words, but this isn't always the case, particularly for skilled readers. That is, experienced readers may be able to skip the letter identification step since word recognition is performed so quickly and automatically (Rayner, 2012). For example, Smith (1971) asserted that skilled readers perceive English words in a manner similar to how they perceive pictures: they perceive the word as a visual pattern based on its visual characteristics, and they do not take into account the word's letter composition. Perea and Rosa (2002) demonstrated that while word shape information does not appear to be necessary for the recognition of common words, visual familiarity does eventually contribute to the process of making lexical decisions.

Gough (1972), on the other hand, presented the argument that letters are utilized in the process of word recognition. He asserts that the reader scans a word in a sequential manner, beginning with the leftmost letter and moving to the rightmost letter, and then encodes the word as a series of letters (Rayner, 2012). Cattell (1886) put this hypothesis to the test by having participants describe what they saw after being shown a word or a letter for a short period of time. He stated that the presentation of letters (such as “n”) in the context of words (born) rather than nonwords (gorn) made it easier for people to record them. As a matter of fact, individuals were more capable of reporting the word than the letter. This resulted in the construction of an experimental paradigm that included a forced choice test for letters that were embedded in words, in nonwords, and letters that were isolated (Reicher, 1969; Wheeler, 1970). Reicher (1969) discovered that reporting accuracy for the target letter that is embedded in a word was higher than that of the same letter alone. Additionally, he discovered that the accuracy when participants were asked to report the letter in isolation was comparable to that of the letter in the nonword. The results of this phenomenon, which came to be known as *the Reicher-Wheeler effect* or *the word superiority effect* (Yap & Balota, 2015), have been replicated by a number of different studies (Cosky, 1976).

The experiment conducted by Reicher disproves the concept that the letters in a word are processed in a sequential manner. In light of Yap and Balota's (2015) findings, it also doesn't seem likely that a visual template or the characteristics of individual words contribute to the fast recognition of words. The theory that words' letters are processed simultaneously and that a word's encoding passes through its constituent abstract letters thus seems to be the sole competing theory left (Rayner, 2012).

There is widespread acceptance that words are perceived by processing letters in parallel. Adelman et al. (2010) provided a particularly convincing example of simultaneous letter processing. According to their findings, all letter information becomes accessible concurrently between 18 and 24-ms after the start of the stimulus.

1.2.2.4 Letter Position

In visual word recognition, determining a letter's identity and placement within a word is essential. It is necessary for this computation to take place quickly and precisely within a perceptual environment that is extremely congested. There has been a lot of discussion in the scientific community on issues related to the processes used for these computations (Aschenbrenner et al., 2017). Based on the varied positions of the letters in the string, we may differentiate words that have the same letters (like bale-able) from one another (Peressotti & Grainger, 1999).With regard to the debate of how a word's letter ordering is encoded within its orthographic representation, the majority of existing computational models for word recognition essentially make the assumption that letter positions are determined very early in processing—that is, prior to the letters' identities are recognized. These coding techniques are referred to as "position-specific" coding (Perea & Lupker, 2004).

The significance of letter position in relation to eye movement was previously discussed. For example, the findings of White et al. (2008) demonstrated that the letters at the beginning and end of a word are more significant for word perception than those in the middle. Experiments using masked priming were also used to get a better understanding of the significance of external letters. Humphreys et al. (1990) discovered that significant priming was created by letters that remained in the same relative positions in both the target and prime strings (e.g., wpre-WHITE). Conversely, letters that didn't follow relative position, like pwer-WHITE, failed to do so. Additionally, it was found that external letters, such as the W and E in the word "WHITE," had a tendency to elicit stronger priming than internal letters.

Additional research was conducted by Peressotti and Grainger (1999), to study the effect that letter identity and letter position play in orthographic priming. They employed both the standard masked priming approach as well as a novel incremental priming method. The acquired data revealed that the "relative position" primes (prime: BLCN, target: BALCON) and the absolute position primes (prime: B-LC-N, target: BALCON) exhibited nearly the same pattern of effects. The relative positions of each letter that primes and target words shared were critical in determining the priming effect. There were no discernible priming effects when the target and prime stimuli had the same letters in a slightly jumbled order (e.g., BCLN-BALCON). In addition, the existence of two letters that are not connected to one another in one of the priming circumstances (e.g.,, BSLCRN-BALCON) led to priming that proved to be insignificant.

Aschenbrenner et al. (2017), investigated the location of the first letter advantage within the context of a masked, two-alternative forced choice, entire word paradigm. In the first experiment, they employed word pairings consisting of three to six letters, with each pair being distinct from the other by one letter in a different location (e.g., have-cave). A target word was initially displayed to the participants in the middle of the screen. After 17-ms of a blank screen, they were shown the pair of words on the right and left and told to pick the target word. The reaction time results revealed a clear first-position advantage for all word lengths, whereas the accuracy results revealed a considerable first-position advantage for four- and six-letter words but not for three- or five-letter words. In the last two trials, masked stimuli were displayed in two different orientations: entirely vertically (in experiment 3) or randomly mixed between vertical and horizontal (in experiment 4). A strong first position advantage was nevertheless attained in both situations.

Transposed letter (TL) priming is an additional method for examining the significance of letter location. The most convincing evidence came from studies that compared performance with matching non-anagram nonwords utilizing non-word anagrams (e.g., mohter-mother), which are created by swapping two letters in a genuine word (Grainger, 2008). TL confusability effects have obvious impact for visual word recognition theories. In particular, they suggest that throughout the coding process, it is necessary to determine the identities of the letters as well as their positions within a letter string (Perea & Lupker, 2003).

In a lexical decision task, it is more difficult to reject a TL nonword (e.g., oeby) as a word than a "replaced-letter" (RL) nonword (e.g., ouhy) that is formed by replacing the transposed letters with other ones (e.g., Frankish & Turner, 2007; Lee & Taft, 2009; Perea & Carreiras, 2006; Perea & Lupker, 2004; Taft & Krebs-Lazendic, 2013; Taft & Nillsen, 2013). In masked priming paradigms, for instance, recognition of OBEY is quicker following the masked presentation of oeby than it is following the masked presentation of ouhy (Lupker et al., 2008; Perea & Lupker, 2004; Schoonbaert & Grainger, 2004).

Schoonbaert and Grainger (2004), conducted a study in which they found that seven-letter words had identical effects from primes that were formed by transposing the first two letters (TL-initial, for example, rdoit as prime for DROIT), the last two letters (L-final, for example, droti-DROIT), and an inner letter pair (TL-inner, for example, dorit-DROIT). In contrast to Perea and Lupker (2003) findings, which indicated a greater priming effect for internal letters as opposed to final letters, Schoonbaert and Grainger's research did not support this distinction for words with seven letters. However, they did find that transposed letter primes were only able to improve performance to five-letter targets when the transposition affected inner letters.

The processing of letters does not always follow the same pattern. According to recent studies, vowels and consonants might be processed differently (Carreiras et al., 2009). Perea and Lupker (2004), established that transposed consonants (for example, caniso, which is derived from the base word casino) exhibited more pronounced effects in terms of both TL priming and TL interference compared to transposed vowels (for example, cisano). They also came to the conclusion that vowels need to be differentiated from consonants at an extremely early stage of orthographic processing (for further reference, see Carreiras et al., 2007, 2009; Vergara-Martínez et al., 2011). Nevertheless, the experimental task or linguistic features may affect the temporal course of vowels/consonants processing. Using masked priming tests in Italian, Colombo et al. (2003), discovered an earlier processing of vowels; however, they were unable to reproduce these findings for lexical decision tasks. Lee et al. (2001), looked at English and discovered that consonants are more crucial than vowels in the early stages of word identification.

These results imply that vowels and consonants have qualitatively distinct functions in printed word structures, but they also differ in a few other respects. The fact that vowels are more common than consonants is one of their fundamental distinctions. According to Lupker et al. (2008), transposed consonants with low frequencies had a higher transposed letter priming advantage than transposed consonants with high frequencies. According to these data, it is possible to make the argument that the coding of letter positions might not be different between vowels and consonants, but rather between high-frequency letters and low-frequency letters (Carreiras et al., 2009).

1.2.2.5 Orthographic Neighborhood

Words having a high degree of orthographic resemblance (e.g., mouse-moose) can nonetheless be recognized by our word recognition system in a matter of hundred milliseconds. When it comes to the investigation of lexical access during visual recognition of words, it is essential to have a solid understanding of the processes that are involved in selecting the suitable candidate from a group of neighbors that are highly inconsistent with one another. Studies on lexical access commonly assume that during visual word identification, orthographically comparable word units, or "neighbors," are partially engaged (Vergara-Martínez & Swaab, 2012). In other words, there exists a set of lexical competitors that bear some resemblance to a particular word throughout the visual word recognition process, and these candidates affect how easily the stimulus word is stored or perceived. In their foundational study on word neighbors, Havens and Foote (1963), described the competitor of a word as being composed of more frequent lexical candidates that shared every letter except one with the target word. This orthographic variation was restricted to the word's internal letters (Perea, 2015).

Coltheart and colleagues provided the most widely used definition of an orthographic neighbor, which is known as Coltheart's N. This is a straightforward count of the number of words that may be derived from a specific word by replacing a single letter with another letter as long as the letter position is maintained (for example, FARM stands for harm, firm, form, and so on) (Grainger, 2022). Typically, the orthographic neighborhood of a word can be made up of several neighbor types, including neighbors that substitute one letter, neighbors that are transposed, neighbors that add letters, neighbors that delete letters, and neighbors that may or may not be syllabic.

The main areas of interest for word neighbor research have been (a) how neighborhood size, defined as the total number of word neighbors, affects identification time as well as accuracy, and (b) how neighborhood frequency, defined as the frequency with which these word neighbors appear, affects the same variables (Rayner, 2012).

The results are not entirely consistent when taking into account the neighborhood size impact, which is also known as the neighborhood density effect. According to Andrews's (1997) literature review on orthographic neighborhood effects, most lexical decision studies involving English words found that words with larger neighborhoods elicited faster responses than words with smaller ones, a phenomenon known as a facilitatory neighborhood size effect. Even when controlling for word length, mean neighborhood frequency, word frequency, and syllable count, Huntsman and Lima (2002), showed that larger neighborhoods clearly had a facilitative influence.

While it is true that the facilitative benefits of orthographic similarity are often shown in lexical choice and naming tasks, it is also true that other tasks frequently exhibit a distinct pattern (Grainger, 2022). More specifically, compared to the control words without high-frequency neighbors, words with high-frequency neighbors tend to have longer fixation times and/or receive another fixation back to the target word (Perea, 2015). This phenomenon has been documented through the utilization of many types of neighbors, including neighbors with one-letter substitution (Perea & Pollatsek, 1998), transposed letter neighbors (Acha & Perea, 2008; Johnson, 2009), neighbors with an additional letter and neighbors with a deleted letter (Davis et al., 2009).

Using orthographically comparable words as the prime stimuli in masked priming paradigms is another way to uncover the inhibitory effects of orthographic relatedness. Word neighbor primes have been shown to have inhibitory effects in a number of studies. This is especially true when the prime word has a higher frequency than the target word (Davis & Lupker, 2006; De Moor & Brysbaert, 2000; Segui & Grainger, 1990). An example of this would be the prime blue for the target blur. Furthermore, when nonwords instead of words are the orthographically-related primes, like the prime blun for the target blur, this trend usually becomes facilitatory (Forster & Davis, 1991; Lupker & Pexman, 2010). Additionally, it appears that participants' spelling proficiency and neighborhood density both influence these inhibitory effects; the biggest effects are shown in target words with a high number of orthographic neighbors and in participants who possess good spelling proficiency (Andrews & Hersch, 2010).

Grainger and Jacobs (1996) claimed that task-specific elements in the lexical judgment task were responsible for the facilitating effect of the number of neighbors, which explains the apparent disparity. The theory goes that rather than needing to specifically identify a stimulus, lexical decisions might be made depending on the global lexical activity it generates. The facilitative impact of orthographic neighborhood on lexical decisions are explained by the fact that greater similarities with different words raises levels of global lexical activity (Grainger, 2022). One prediction from Grainger and Jacobs (1996) is that the same words should have an inhibitory impact when they are used in a context where actual word identification is necessary, like sentence reading, because they provide a facilitative effect of neighborhood size in lexical decision. Subsequent research by Pollatsek et al. (1999) verified the assumption.

In the majority of studies on neighborhood impacts, the differentiation between vowels and consonants is a topic that is not taken into consideration (Perea, 2015). The masked priming lexical decision experiment by New et al. (2008), employed a condition in which they preserved the vowels (e.g., rifa-DIVA; onub-OPUS) and a condition in which they preserved the consonants (e.g., duvo-DIVA; apis-OPUS) with regard to the particular issue of consonants and vowels and orthographic neighborhoods. As compared to vowel-preserving primes, consonant-preserving primes were found to enable target processing to a greater extent for adult readers. In fact, there was no discernible difference between the response times in the vowel-preserving priming condition and those in an unrelated priming condition. Partial primes made up of consonants (e.g., csn-CASINO) have been shown to be more effective than partial primes made up of vowels (e.g., ait-CASINO) by Duñabeitia & Carreiras (2011).

Methodological issues provide yet another—and less compelling—explanation for the inconsistent findings. The conventional method for investigating neighborhood effects has been to choose two sets of words that are similar on other pertinent dimensions, including frequency and word length, but differ in their neighborhood features. Nonetheless, a number of pertinent aspects, such as age of acquisition, imageability, and morphological complexity, have not been adequately addressed by the majority of studies (Bowers et al., 2005)

The frequency of the neighbors has been the second noteworthy neighborhood trait. as reported by Siakaluk et al. (2002), the majority of the previous studies found that low-frequency words with neighboring high-frequency words had shorter lexical decision latencies compared to low-frequency words without such neighbors. This phenomenon is commonly known as the inhibitory neighborhood frequency effect. In particular, Grainger and Segui (1990) discovered that the existence of a more frequent word in an orthographic neighborhood causes a delay in lexical access. This delay is likely due to the need for assessing high-frequency words first or to the inhibition they cause when processing lower frequency neighbors.

Rather than being a result of lexical access, pronunciation-specific processes may account for the neighborhood frequency effect's apparent facilitation of the naming task for words with numerous orthographic neighbors (Grainger, 1990; Sears et al., 1995), It has been suggested that this facilitation happens because orthographic neighbors assist the stimulus word's pronunciation by generally having pronunciations that are comparable to the stimulus word. Perea & Rosa (2000), in their review on the impacts of orthographic neighborhood, noted that the overall reading data indicated that the consequences of having a higher frequency neighbor occurred late in the processing of lexical information and were inhibitory.

1.3 Phonological Processing

According to Rayner (2012), one of the most controversial topics in the field of word perception is the connection that exists between the sound of a word and finding out what it means. Within the realm of visual word recognition, one of the questions that needs to be answered is whether or not the phonological recoding is required and/or automatic (Frost, 1998; Pattamadilok et al., 2017). It was often believed that proficient readers could read a text from print to meaning without considering word sounds. However, researchers began to observe that when we read aloud, our minds create the impression that we are "hearing" the words. This subjective internal monologue is a result of phonological coding, the process of translating information from written orthographic forms into spoken phonological forms (Leinenger, 2014).

Phonology is the study of phonetics, or the sound patterns of spoken language. The building blocks of speech that differentiate one word from another are called phonemes. The phonemes for the sounds /r/ and /l/ are distinct. Written representations of phonemes in alphabetic languages are referred to as graphemes, and they can be composed of individual letters or a combination of letters (Brysbaert, 2022). A person's mental operations that utilize the phonological or sound structure of spoken language for decoding written language are known as phonological processing (Torgesen et al., 1994).

There is some debate about whether or not phonological representations are automatically used for visual word recognition, but several psycholinguistic studies have shown that semantic and phonological representations have an impact on visual word recognition, even when they are unrelated to the task at hand or are not readily available (Pattamadilok et al., 2017; Rodd, 2004; Ziegler & Jacobs, 1995). According to Frost (1998), findings across a variety of paradigms generally imply that phonological representations are calculated after printed words are presented, rather than as an exception, even for tasks that do not call for an explicit phonological output or in which phonological recoding improves performance. The potential units that can express semantic notions are limited by phonotactic laws, which are present in every language. Because these phonological units are the means by which syntactic and semantic information are conveyed and because they form the basis of human lexical representations, recovering any language message thus requires gaining access to these units (Frost, 1998).

Written words can trigger phonological activation in two different ways. One is known as addressed phonology; following the recognition of the visual word, the phonological code is only "looked up" at a memory "address" (Rayner, 2012). In the alternative, known as assembled phonology, the phonological code is created or assembled at the moment the visual stimulus is shown. Pronouncing new words and pseudowords is achievable with assembled phonology (Brysbaert, 2022). Because the phonological route requires an additional step to translate visual information to sound before reaching meaning, it is considered slower than the orthographic route in both scenarios. Thus, orthography is considered to be the primary means of meaning activation (Morris & Folk, 2000).

One piece of evidence for the presence of two different channels is that some individuals with brain damage appear to have selective impairment for either the addressed or assembled route to phonology (Rayner, 2012). Individuals classified as surface dyslexic are able to articulate almost all words and nonwords correctly; nonetheless, they frequently pronounce irregular words incorrectly, particularly those with low frequency (Hanley & Gard, 1995). Their issue seems to be that while the direct path has become dysfunctional, the assembled phonology system remains undamaged. The fact that not all irregular words are regularized indicates that the addressed phonology system in these individuals is not entirely compromised. Conversely, most words are correctly pronounced by those with phonological dyslexia, but they nearly never articulate nonwords (Tree & Kay, 2006; Vliet et al., 2004). They seem to be experiencing issues with a nearly entirely damaged assembled phonology system, in contrast to a rather intact addressed phonology system.

There is a significant amount of conflict in the field about (a) the significance of the role that sound coding plays and (b) the formulation of a conceptual framework for the connection that exists between sound coding and orthographic coding (Rayner, 2012). Numerous studies have looked at lexical decisions to pseudo-homophones in order to investigate the possible role of assembled phonology in lexical access. These studies have generally found that pseudo-homophones have longer lexical decision latencies and more errors compared to non-homophonic nonwords (see Leinenger, 2014 for a review). Ziegler et al. (2001), conducted an investigation of this phenomena in German by employing pseudo-homophones (e.g., SAHL) and their spelling controls (e.g., SARL) that are derived from the same base word (e.g., SAAL). They discovered that pseudo-homophones induced more errors and longer "no" latencies compared to spelling controls in the lexical-decision task. Despite having the same level of orthographic closeness and neighborhood size, the effect was still noticeable when comparing spelling controls to pseudo-homophones. Word length has no bearing on this outcome. Additionally, they discovered that rejecting pseudo-homophones originating from low-frequency base words required more time than rejecting pseudo-homophones originating from high-frequency base words.

Since phonology is not required in any way for the lexical decision problem, it would be beneficial for subjects to depend on the supposedly quicker direct route from orthography to semantics. It has been suggested that their continued activation of phonological codes is proof positive that lexical access requires the usage of phonological codes (Leinenger, 2014).

Regarding the function of phonology in lexical access, two major theories have been put forth (Braun et al., 2009). The theory of direct access (Seidenberg, 1985) suggests a straight line of progression from orthography to meaning. This theory states that phonological encoding occurs after meaning is available. As opposed to this, phonological activation is seen to be a prerequisite for semantic access according to the phonological mediation theory (Frost, 1998; Tan and Perfetti, 1999; Van Orden, 1987). As a result, phonology would normally be determined before a word's meaning is revealed. This perspective holds that phonological activation happens spontaneously when reading and that it ought to happen somewhat early in the process of visual word recognition. Another viewpoint holds that phonological coding is a consequence of reading instruction and are primarily epiphenomenal in proficient adult readers (Leinenger, 2014).

Early phonological processing was found to be present in priming and backward masking, according to the findings of a seminal study conducted by Perfetti and Bell (1991). They discovered that target words (e.g. MADE) that were briefly provided and followed by nonword masks that were phonologically similar (e.g. MAYD) were recognized more accurately than when the masks were unrelated (e.g. MARD). These effects were observed for prime-target stimulus onset asynchrony (SOA) durations as brief as 45-ms, suggesting that written words were phonologically processed early on. It was the interpretation of Perfetti and Bell that their phonological priming effects were situated at a prelexical level; nonetheless, they did not rule out the possibility of top-down contributions from the lexical level to phonemic processing. In many studies, Perfetti and his colleagues discovered that nonwords that were phonetically similar to the targets they were masking yielded higher identification rates than controls that were graphically similar (Berent & Perfetti, 1995; Perfetti & Bell, 1991; Perfetti et al., 1988; also see Perfetti et al., 1992 for a review).

Pexman et al. (2001), conducted research on the effects of homophones on lexical judgment tasks. In comparison to control words, they discovered that homophones elicited longer reaction times. The homophone effect, according to the authors, is caused by two opposing orthographic representations being activated by feedback from phonological representations. Additional research (Van Orden, 1987; Van Orden et al., 1988; Braun et al., 2015), repeated the homophone effect for both words and nonwords, demonstrating that phonological coding is not only quick, but also automatically activated (together with orthographic information) and used for identifying word meaning. Nevertheless, it was discovered that lexical frequency (Jared & Seidenberg, 1991) and list composition (Brysbaert, Praet, & d'Ydewalle, 1990) greatly affected this homophone impact. Consequently, it is also proposed that methodological decisions may have an impact on the phonological effects observed in various tasks.

Amenta et al. (2017), sought to address these problems by studying visual word recognition using phonological information. They used a large-scale data-driven approach, taking advantage of new consistency measures derived from distributional semantics methods, which they called Orthography-Semantics Consistency (OSC) and Phonology-Semantics Consistency (PSC). It has been discovered that both effects play a role in word recognition; shorter RTs are associated with higher values on either measure. Additionally, they discovered that PSC mediates a significant portion of the OSC effect, indicating the importance of phonology in gaining access to word meaning.

Alternatively, neurophysiological techniques such as magnetoencephalography (MEG) or electroencephalography (EEG) can offer real-time, sensitive assessments of ongoing cognitive (and perceptual) operation. Therefore, in order to comprehend the visual word recognition process, it is instructive to review the EEG and MEG data. Braun et al., (2009) demonstrate that event-related brain potentials (ERPs) to pseudo-homophones (e.g. ROZE) differed from compatible spelling controls (e.g. ROFE) as early as 150-ms following stimulus onset using EEG during a lexical judgment test. They have come to the conclusion that this data strengthens the argument that phonological activation happens early enough to influence lexical access.

Wheat et al. (2010), used whole-head MEG to study the spatiotemporal patterns of brain responses arising from a masked pseudo-homophone priming task. Three different types of nonword primes have been used: unrelated controls (e.g. lopus–BRAIN), matched orthographic controls (e.g. broin–BRAIN), and pseudo-homophones (e.g. brein–BRAIN). They found that when visually presented words were primed with pseudo-homophones rather than orthographics, participants responded more strongly to the former within 100-ms of the target word beginning, indicating a pattern of prelexical access to phonological data during visual word recognition.

In summary, findings from neurophysiological recordings, in addition to behavioral studies, demonstrate that phonological processing begins early in the visual word recognition and/or silent reading processes, with ERP and MEG records showing differential processing between 80-125-ms (Ashby, 2010; Ashby et al., 2009; Braun et al., 2009; Cornelissen et al., 2009; Wheat et al., 2010).

1.4 Semantic Processing

The ultimate objective of text comprehension is to derive meaning from words and sentences (Rabovsky et al., 2012). A characteristic of human behavior that is essential to language and our ability to use learned information for planning, thinking, and problem-solving is semantic processing (Binder et al., 2009). Researchers in the field of psychology mostly agree on this main purpose of reading. On the other hand, there is a great deal of dispute regarding the specific mechanism by which meaning is acquired during reading (Reimer et al., 2008). It has been determined that there are three sets of processes involved in visual word recognition: orthographic, phonological, and semantic. Semantic processing has not gotten the same level of attention from other scientific domains as phonology and orthography (Buchanan et al., 2001).

A wealth of empirical data has been obtained regarding the ways in which a word's degree of semantic similarity influences how it is processed or retained in the mind's lexicon (Lenci & Littell, 2008). One empirical proof is derived from semantic priming experiments. Research employing similar priming settings revealed that processing the target is more straightforward when two words are related semantically and/or associatively than when they are not (McNamara, 2005; see also Neely, 1991, for a review). Through the use of an ocular lexical decision task, Hoedemaker and Gordon (2017), were able to observe the influence that semantic priming had on target-word reading durations at roughly 260 milliseconds.

The mediated-priming paradigm provides additional data about the function of semantic processing in visual word recognition (e.g., Farrar et al., 2001; O'Seaghdha & Marin, 1997; Reimer, 2006; Reimer et al., 2001). Rather than establishing a direct association between the prime and the target word, the mediated-priming paradigm makes use of a third word. In the word pair "doctor-nurse-purse" for instance, the target word "doctor" has associative relationships with the mediating word "nurse", which has orthographic and phonological relationships with the target word "purse". A group of studies by Reimer et al. (2008), used associatively mediated (e.g., frog–toad), homophonically mediated (e.g., frog–towed), and orthographically mediated (e.g., frog–told) prime-target word sets and demonstrated that once semantic representations are activated, activation automatically feeds back to orthographic representations but not phonological representations in the early stages of word processing.

When it comes to studying how neighborhood size (N) affects word understanding, not many studies have looked into semantic neighborhood size (SN) effects. The limited understanding of the impacts of SN is partly due to the extensive scope of the semantic space. Unlike phonology and orthography, the definition of semantic similarity lacks distinct and universally accepted semantic components. Words can have various semantic relationships with each other (Buchanan et al., 2001).

Semantic representation theories can be broadly divided into two categories: those that represent the meaning of a word in terms of how it relates to other words, and those that represent the meaning of a word in terms of distinct meaning components that, when combined, determine its meaning (Buchanan et al., 2001). The initial theories of a holistic perspective were formulated as semantic networks, where individual words are depicted as nodes, and semantic connections are represented by labeled links between nodes. In this perspective, the meaning of a word is conveyed through its associations with other words, including the nature and sorts of connections between them. These theories rely on determining the most significant relationships or characteristics for representing meaning. This can be done at a broad level, such as network models, or within more specific domains of meaning, like semantic field theory. Once these relationships or characteristics are identified, an implementation method can be chosen based on them (Vigliocco & Vinson, 2007).

Another relational approach, on the other hand, is to find ways to represent words based on their connections to other words, without assuming any certain principles as being more significant (Vigliocco & Vinson, 2007). Approximately two decades ago, the discipline of cognitive science introduced computationally implemented theories that involve human semantic representations. These theories express word meanings as high-dimensional numerical vectors, which are derived from extensive amounts of natural-language data (Günther et al., 2019). Computational models such as latent semantic analysis (LSA; Landauer & Dumais, 1997) and the hyperspace analogue to language (HAL; Lund & Burgess, 1996) utilize large collections of texts to calculate different aspects of a word's meaning by analyzing the words that appear in similar linguistic contexts (Vigliocco & Vinson, 2007). These models can be viewed as particular parameterizations of a single generalized model constructed based on the same theoretical underpinning, namely the distributional hypothesis (Günther et al., 2019).

Over the past twenty years, significant progress has been made in our comprehension of semantic memory through the creation of computational models that rely on the "distributional hypothesis" proposed by Harris (1954). This hypothesis suggests that words that appear in similar contexts are likely to have similar meanings (Turney & Pantel, 2010). Based on this view, the assortment of linguistic situations in which a specific word is used reveals significant aspects of the word's meaning. This means that similarities between meanings of two words can be recognized and measured by examining the overlap between the sets of situations associated with each word. For example, the words "cat" and "dog" often appear together with the words "animal", "pet", "furry", "house", and "vet" in linguistic contexts, indicating that they have similar meanings. On the other hand, the words "vacation" and "longbow" are typically found in different linguistic contexts, suggesting that they have different meanings (Rotaru et al., 2018).

Studies have shown that distributional semantic models (DSMs) may accurately predict human performance across numerous tasks (Anceresi et al., 2024). Günther et al. (2016) conducted a study to determine whether or not LSA can accurately predict priming effects. The researchers employed two lexical judgment tasks, and the LSA cosines were used as an independent variable. In order to determine the similarity of vectors, the researchers calculated the cosine of the angle formed by two-word vectors. This cosine value falls between the range of -1 to 1. A cosine value of 0 signifies vectors that are not linked, whereas a cosine value of 1 signifies vectors that are the same. Their findings demonstrated that the cosine similarity of LSA can be used to predict priming effects, with higher LSA cosines being associated with shorter reaction times. Additional research has demonstrated that DSMs may accurately forecast human behavior in semantic priming tasks (Jones et al., 2015; Lapesa & Evert, 2013; Lund & Burgess, 1996) and false memory paradigms (Gatti et al., 2023).

A number of studies were carried out by Buchanan and colleagues (2001), in order to investigate the impact of semantic neighborhood size by employing lexical decision and naming tasks. The researchers discovered that HAL's semantic distance accurately predicted the time it took for participants to make decisions about words and, to a certain degree, the time it took for them to name words. Words that have denser semantic neighborhoods tend to be recognized more quickly in lexical judgment tasks, compared to words with sparser semantic neighborhoods. Additionally, they demonstrated that the measure of semantic distance explained a distinct portion of the variation in the time it took to make lexical decisions, even after excluding the influence of imageability. This study is the first extensive analysis of the impact of semantic neighborhood on the recognition of visual words.

Siakaluk and colleagues (2003), conducted a study in which they examined the SND effect by employing a task that involved categorizing stimuli as either animal or nonanimal based on their semantic meaning. Initially, a yes/no task was administered in which the participants were told to hit one button if the stimulus presented was an animal name and another key if it was not. The initial trial yielded no apparent effect of SN. In light of the variations in procedure between the yes/no task, the researchers ran a go/no-go task for the second trial, in which they saw a significant impact on semantic distance. Specifically, participants reacted more quickly to terms with low semantic distance compared to words with high semantic distance.

Building upon the findings of Buchanan et al. (2001) and Siakaluk et al. (2003) regarding the enhancing effect of SND in different tasks, Pexman and colleagues (2008), conducted a study to determine whether three measures of semantic richness, specifically the number of semantic neighbors, number of features, and contextual dispersion, can explain variations in response time and error rates in lexical decision and semantic categorization tasks. The findings indicated that the number of semantic neighbors played a significant role in explaining distinct variability in the lexical judgment task. More specifically, a higher number of semantic neighbors led to quicker response times. Nevertheless, they were unable to reproduce the findings of Siakaluk et al. (2003) with regards to the semantic categorization test.

Recent studies have consistently shown that SND has a positive effect on lexical decision latencies. These findings are supported by multiple studies (Buchanan et al., 2001;

Gatti et al., 2023; Hendrix & Sun, 2021; Pexman et al., 2008; Shaoul & Westbury, 2010; Yap et al., 2011; Yap et al., 2012). However, when it comes to semantic decision tasks, the results are inconsistent. Some studies demonstrate a facilitatory effect (Siakaluk et al., 2003), while others show an inhibitory effect (Shaoul & Westbury, 2010), and some studies do not show any significant results (Pexman et al., 2008; Yap et al., 2011, 2012).

Alternately, Danguecan & Buchanan (2016), used four tasks with different levels of explicit semantic demands—the standard lexical decision task, the go/no-go lexical decision task, the progressive demasking task, and the sentence relatedness task—to compare how well SND processed concrete and abstract words. According to the findings of their study, abstract low SND words, which are words that have neighbors that are not closely related and are relatively far apart, were recognized more quickly than abstract high SND words, which are words that have neighbors that are closely related and are tightly collected together. However, the SND effect was not observed for concrete words, with the exception of one trial. The authors contended that the observed facilitatory effect in the studies conducted by Pexman et al. (2008), and Yap et al. (2011, 2012) might be attributed to the fact that the words employed in the tests were related with numerous physical characteristics and that the lack of SND effect in their data is consistent with these results.

Recent developments in the field of distributional semantics have enabled the computation of distributed semantic representations for new words and, consequently, for words that do not exist (Hendrix & Sun, 2021). FastText (Bojanowski et al., 2017) employs sub-lexical representations to encode word semantics. As an illustration, the word "bear" can be demonstrated using the subsequent sequences: “<bear>,” “<be,” “bea,” “ear,” “ar>,” “<bea,” “bear,” “ear>,” “<bear,” and “bear>” (where "<" and ">" symbolize the left and right word boundaries, respectively). Each word and letter n-gram are assigned semantic vectors. Word vectors are calculated by adding up the semantic vectors for the sequences that are connected to words. Hendrix and Sun (2021), conducted a groundbreaking study where they employed fastText to produce distributed semantic representations for both words and nonwords. Their findings from the lexical decision task indicated that, in contrast to the SND effect on words, the response times for nonwords were prolonged when the SND was increased.

In their study, Gatti and colleagues (2023) examined whether the cognitive processing of both real words and pseudowords may be attributed to shared semantic processes. The researchers initially examined a large dataset of lexical decision results obtained from a semantic priming study, which consisted of English words and pseudowords. They calculated a semantic-relatedness index (SRel) for each pair of prime and target. This index was based on the cosine of the angle produced by vectors that represented the meanings of the respective strings. The findings indicated that when the stimulus onset asynchrony (SOA) was brief, the response durations were longer for target pseudowords that had a stronger SRel with the prime stimulus. For the second experiment, they conducted a separate semantic priming study that involved Italian words and pseudowords. The researchers successfully reproduced the findings of the initial experiment through this replication study. Specifically, an increase in SRel led to reduced reaction times for words, but longer reaction times for pseudowords.

Overall, these findings support the idea that a word's meaning can affect how we understand and process that word, and this can be explained by the concept of semantic feedback (Farsi, 2018). Additionally, they demonstrate that the process of extracting meaning from both real words and pseudowords is influenced by general associative mechanisms in our memory system. (Gatti et al., 2023).

CHAPTER 2 - THEORIES OF WORD RECOGNITION

In this chapter, theories of word recognition will be discussed mainly focusing on individual word recognition. These theories have attempted to explain how the visual system interprets a series of marks on a page as an orthographic representation of a word, and how other cognitive systems use this information to retrieve the pronunciation of words and meaning from memory (Reichle, 2021). Research has concentrated on the processes and knowledge that underpin word recognition; the linguistic, cognitive, and perceptual abilities used for the task; the basis of individual differences; and how this skill develops to facilitate the correct answers (Seidenberg et al., 2022). In order to provide a comprehensive explanation for word recognition, theories have also attempted to explain why certain individuals are unable to master this skill, even with years of formal education and practice, along with how specific impairments in brain development or injury affect word identification (Reichle, 2021).

Models require the specification of theories as functioning simulations, enabling them to be evaluated based on their ability to replicate the phenomena they seek to explain. They are incorporated into frameworks that provide novel approaches for conceptualizing behavior, potentially resulting in hypotheses that deviate from previous assumptions (Jacobs, 2000). By comparing the behavior of a model to that of a human, scientists may determine whether to accept, modify, or discard a theory. This feedback process between the model and the theory, which is based on real-world data, is a powerful way to look into complex topics such as reading (Seidenberg et al., 2022).

The computational models that will be explored in this chapter are the Interactive-Activation Model (McClelland & Rumelhart, 1981; 1982), Dual-Route Cascaded Model (Coltheart et al., 2001), The Triangle Model (Seidenberg & McClelland, 1989), and lastly the Connectionist Dual Processing Model (Zorzi et al., 1998). The reason for including these models is that they are the most influential models that became the starting point for models that came after them.

2.1 Interactive Activation Model

As one of the first connectionist or "neural-network" cognitive models, as described by Norris (2013), the interactive activation (IA) model (McClelland & Rumelhart, 1981; 1982) still remains as one of the most influential models of word recognition to this day (Reichle, 2021). Davis (2003), states that together with competitive neural network equations that had previously been examined by Grossberg (1969, 1973) and Wilson and Cowan (1972), the IA model combined concepts from earlier hierarchical models of recognition, including the Pandemonium model of Selfridge and Neisser (1963), Morton's (1970) logogen model, and McClelland's (1979) work on cascaded processing. The model provided an in-depth account of information processing at a micro level and was maybe the first in this field to fully transparently depict all information processing stages between the input and the output (Hofmann & Jacobs, 2014).

McClelland and Rumelhart (1981) described three main assumptions for the IA model. Firstly, the processing of a visual input regarding a word takes place in three different, yet interacting levels that are organized hierarchically; namely a visual feature level, a letter level, and a word level. Each of these layers constitutes a representation of the input at a distinct level of abstraction than the one that came before it. Higher level processing is also assumed to provide top-down input to the word level. Secondly, the processing occurs in parallel, meaning that an input to the system activates all three levels at the same time. Parallel processing also represents the spatial aspect of letter processing, meaning that a four-letter word is processed simultaneously. Lastly, they describe the perception as a highly interactive process. According to the model, top-down processes (e.g., knowledge about words) jointly influence the perception process with bottom-up processes (e.g., sensory input received from the environment).

At each processing level, there are sets of units in every level called nodes. At the feature level there are 16-line segments per letter developed by Rumelhart and Siple (1974). One-unit codes for the presence of the feature and one for the absence. Due to the fact that the model is programmed with four-letter word knowledge that is derived from Kucera and Francis's (1967) word count, there are four sets of letter units applicable to each letter position at the letter level. At the word level, the system has only one unit available for each word (McClelland & Rumelhart, 1988). Similar with the Logogen Model, when a certain word is present, the nodes representing the visual characteristics of that word will be completely active (Reichle, 2021). Each node is connected to its neighbors, other nodes in the system, acting as excitatory or inhibitory on them. Apart from within level connections, there are between level connections in the system as well. The feature level makes connections with the letter level, and the letter level with the word level. Since the levels are hierarchical, there is no connection between feature level and word level. And the connections in the word level are only inhibitory considering only one word can be present in a given time and place (McClelland & Rumelhart, 1981).

McClelland and Rumelhart illustrated the operation of the system in their original paper starting from the resting level of the system and presenting an input. Reichle (2021), uses the example of "CATS" to demonstrate the perceptual processing in the model. In the example, the word "CATS" is presented to the system, with enough visual quality for detection. According to the IA Model (McClelland & Rumelhart, 1981), for each letter in the word presented, units corresponding to the features of the letters will be activated in the feature level for the corresponding position of that letter. Therefore, features representing the letter C will be activated in the initial letter position. The nodes in the feature level then will make excitatory or inhibitory connections with the nodes in the letter level.

As stated by Reichle (2021), when there are characteristics that indicate the existence of a specific letter at a specific place, the node dedicated to that letter's position will become active. Regarding letter C, the lower horizontal line segment will establish excitatory connections with the letter nodes C, S, and E in their original positions. The resting levels of specific letter nodes are elevated beyond their activation levels (McClelland & Rumelhart, 1981). On the other hand, characteristics that do not match the existence of a certain letter in a specific location will prevent the position-specific node for that letter from being activated. Therefore, as in the example of Reichle (2021), the horizontal line on the bottom for the letter C will make inhibitory connections with the letter nodes R, X, F where there is no correspondence to the horizontal line in the bottom. The activation levels of these letter nodes will be pushed below their resting levels. Within the letter level, words that are activated will compete with each other and the letter node with most activation from the feature level will have the highest activation (McClelland & Rumelhart, 1981). Since the activation of the characteristics is spread simultaneously to all letter positions, each letter within a word is detected simultaneously (McClelland & Rumelhart, 1982).

Subsequently, these letter nodes will establish excitatory connections with the corresponding word-level nodes and suppress the word nodes that are not compatible with them (McClelland & Rumelhart, 1981). As a result, the word nodes that have letters in the correct places for their respective words will become active to a degree that is directly proportional to the number of active letters. According to the example, while words containing letter C in the initial position or letter A in the second position (e.g., cute, cars, park, mark) will get some activation, the word CATS will get the highest activation amongst them (Reichle, 2021).

Similar to the letter level, in the word level, every single word node that gets activation will compete with other word level nodes and send top-down feedback to the letter level nodes. When the correspondence of feature nodes to the letters and of the letter nodes to the word nodes are high enough, the positive feedback from the word level will speed up the recognition process. When this is not the case, the nodes in the letter and word level will compete with each other while no single node gets enough activation (McClelland & Rumelhart, 1981). Considering the example of CATS, as the word node for CATS gets enough activation, it will send excitatory activation to letter nodes for C, A, T, and S while sending inhibitory activation to letter nodes such as R, X, F (Reichle, 2021).

Considering the complexity of the model, McClelland and Rumelhart (1981) implemented a computer simulation to demonstrate how the model behaves and how consistent the model's behavior is compared to empirical data. Even though the nodes do not correspond to neurons, the system processes information in a neural-like style to an extent. They have also implemented a cascaded activation process between the nodes. In this way, an activation of a node in a given level will activate corresponding nodes in the higher level without needing to exceed a threshold in order to give an output. Thus, the information flow goes in both directions simultaneously in a continuous manner.

Investigating how well the model accounts for empirical data, previous research (McClelland and Rumelhart, 1981; Rumelhart & McClelland, 1982) tried to apply simulations of several experiments and compared the results. Concerning the word superiority effect, the model was successful at replicating the results from Johnston and McClelland (1973) as well as results from McClelland and Johnston (1977) study showing word superiority effect over pseudowords. The model successfully explained data from a number of experimental paradigms (e.g., Davis, 2003; Grainger & Jacobs, 1993). In the 1980s and 90s, IA models showed remarkable ability in predicting behavioral data, including error rates and the means and distributions of reaction times for a variety of tasks. There have been attempts to connect IA Model's simulations with the neuroimaging and brain-electrical data as well (Hofmann & Jacobs, 2014).

The simplicity of the model's underlying ideas, its ability to explain a variety of word-identification events, and the fact that it is developed as a computer program are some of the characteristics that make it an appealing model (Reichle, 2021). Throughout the years, IA Model has been influential upon different computational models such as the multiple readout model (MROM) (Grainger & Jacobs, 1996), the DRC model (Coltheart et al., 2001), and the spatial coding model (SCM) (Davis, 2010). Additionally, it has been included in models of other syntactic processing components of reading, such eye-movement control (Reilly & Radach, 2003). The model was used to simulate data from a variety of tasks, in combination with a number of task-specific models, such as the Reicher-Wheeler task (Grainger & Jacobs, 1994; McClelland & Rumelhart, 1981), perceptual identification task (Grainger & Jacobs, 1996), the lexical decision task (Grainger & Jacobs, 1996; Jacobs & Grainger, 1992), and the fragmentation task (Ziegler et al., 1998).

Despite its popularity and success on the field, and its influence on the development of other models, the IA model itself is considered limited in theory. The model has been criticized for failing to account for letter-transposition effects, repeated priming across intervening word-identification trials (Reichle, 2021), and effects resulting from phonological or semantic impacts. The model's coding technique is limited to stimuli of a set duration. Additionally, the position-specific coding strategy of the model makes it unable to capture some experimentally reported kinds of perceptual similarity (Davis, 2003). Mewhort and Johns (1988), conducted a number of tests to evaluate the IA model and its implications for the word superiority effect. Through a few of their experiments, they demonstrated that unlike the model's assumption, the automatic activation of the word level node influenced by the word superiority effect did not necessarily lead to top-down feedback to the letter level. They have criticized the model by stating that "the model is based on an oversimplification of perceptual processing; it starts too late in the perceptual system, and at a level that is much too abstract".

2.2 Dual-Route Model

Another highly influential word identification approach is the Dual-Route Cascaded (DRC) model (Coltheart et al., 2001). Its name derives from the assumption that reading aloud occurs in two routes: a lexical route and a non-lexical route and that information is passed on in a cascaded manner by processing stages (Coltheart & Rastle, 1994). Coltheart's (1978) original Dual-Route model is the direct precursor of the current model. Initially, a variety of informal information-processing models, commonly referred to as "box and arrow" models, were used to construct the dual-route theory (Seidenberg & Plaut, 2006). The difficulties in reading aloud that were noted in patients after brain injury led Marshall and Newcombe to develop what became known as the "dual-route" model of reading, which Coltheart and colleagues later extended to unimpaired reading and to the development of reading skills. Researchers have gathered significant amounts of data over many years to help answer fundamental questions about how individuals pronounce words aloud and determine if a letter string is a word. Following this, informal models were developed to match the data. Coltheart developed these previous behaviorally-based dual route models and suggested a computational explanation known as the dual route cascaded model (Seidenberg et al., 2022).

Despite the fact that the model emerged from the final version of the logogen model, Coltheart and colleagues (2001) described the DRC model as a generalization of the Interactive Activation model, with its assumptions regarding several levels of representations and the cascaded flow of activation between nodes. The model was developed on the scope of "nested modeling" that refers to cumulative progress of constructing a new model. Alongside the IA model, the DRC model also incorporated insights from earlier spoken word production models, including those developed by Dell (1986) and Levelt and colleagues (1999), which were somewhat successful in explaining several elements of both normal and aphasic speech production, as described by Coltheart and colleagues (2001).

The DRC model's architecture, which takes into consideration both reading aloud and visual word identification, was explained by Coltheart and colleagues (2001). The authors chose to build the model hand-wired rather than using a learning algorithm. Three routes together form the model, which can be applied to carry out activities like naming and lexical decision-making (Reichle, 2021). Firstly, the lexical semantic route enables pronunciations of words to be obtained indirectly from the phonological output lexicon which uses connections that feedback from the semantic system. Although it wasn't implemented in the original paper (Coltheart et al., 2001), the semantic component of the model is employed in reading aloud as a compensatory approach in acquired dyslexia (Coltheart, 2006), and Pritchard et al. (2018) also included semantics in their explanation of how reading is acquired. Secondly, the lexical non-semantic route produces the pronunciation of a word via the phonological lexicon by creating links between the orthographic input lexicon, that corresponds to the spelling of full words, and the phonological output lexicon, that corresponds to the pronunciations of complete words. Finally, the grapheme-phoneme correspondence (GPC) pathway is an indirect route for assembling word pronunciations using a collection of grapheme-phoneme correspondence rules.

Similar to the IA model, the DRC model is built using several processing levels. The smallest single symbolic components of the model, for example words or characters, are represented by individual units in these layers. The communication between the layers is mostly bidirectional and takes place through excitation or inhibition and through lateral inhibition within layers. The feature units, however, do not get feedback from letter units, the communication is only feed-forward. This is the case for the GPC route. The connections from letter units to GPC rule system, and to phoneme units are only excitatory and feed-forward. Apart from these, one other exception is that the communication between the orthographic lexicon and phonological lexicon takes place through excitatory activation only (Coltheart et al., 2001).

The lexical non-semantic route

The first two layers of the model — the letter units and the visual feature units — are shared by both routes, along with the phoneme layer which is later in the process of reading aloud. The visual feature units are made up from eight distinct subsets that correspond to the eight potential input places. The Rumelhart and Siple (1974) 16-feature font served as the basis for the feature sets. The letter level has a structure akin to the feature set and employs eight distinct subsets. Units for all 26 possible English alphabet letters are included in each subset, along with one unit for the blank letter. At this level, there is lateral inhibition within eight subsets.

Following that, the orthographic and phonological lexicon layers make up the lexical pathway. The characteristics of the word's letters activate the word's letter units simultaneously across all letter locations, which subsequently activate the word's entry in the orthographic lexicon. There are 7,981 units in the orthographic lexicon—one for each monosyllabic word in the CELEX database (Baayen et al., 1993). The excitation or inhibition from the letter units to the orthographic lexicon is similar to the IA model. A letter in a specific position sends excitatory activations to all the units for words that contain the same letter in the same position while inhibiting all units for words that do not contain the letter in the same position. For example, for the letter C in the initial position, all words that start with the letter C will get an activation.

The phonological lexicon has corresponding phonological lexical units for every one of these orthographic lexical units. Therefore, the input to the orthographic lexicon then activates the corresponding units in the phonological lexicon. In the orthographic lexicon, heterographic homophones have different units, while in the phonological lexicon, they share the same unit. In the orthographic lexicon, homographic heterophones have a single unit, while in the phonological lexicon, they have distinct units for each pronunciation. The phonological lexicon contains less units than the orthographic lexicon due to the fact that homographic heterophones are less than heterographic homophones.

Ultimately, the phoneme units of a word are engaged when its corresponding item in the phonological lexicon is active. Furthermore, this activation provides feedback at the letter level. Reichle (2021), uses the metaphor of "filling a bucket" to describe the process of generating a pronunciation: "...when filling a bucket with both small- and large-circumference hoses, the contents of the bucket will reflect the contributions of both hoses, although the latter will obviously contribute more than the former." Consequently, the final pronunciation produced by the DRC model also represents the contributions of the non-semantic/lexical and GPC routes.

GPC Route

The GPC pathway, which explains how word and nonword pronunciations are possibly built, is the second significant component of the model that is implemented (Reichle, 2021). Since the feature and letter levels are shared by the two routes, visual features and associated letter units are activated similarly to the lexical non-semantic route. This route's independent components consist of a grapheme decoding mechanism and a knowledge store regulating how graphemes match phonemes. The GPC rules used in the model are based on the earlier work of Coltheart and colleagues (1993).

When presented with the letters of the word, the GPC route starts to function on the first letter. Until the correct rule for converting that letter into a phoneme is found, the model will continue to search for a collection of rules. Once the correct rule is found, the phoneme system then activates the relevant phoneme's unit. The rules will translate this string into a single phoneme if it is a grapheme, like “ph”, and into a set of two phonemes if it is not a grapheme, like pr. Until the letter string is identified or the last spot in the letter units is reached, this process is repeated, adding a letter every 17 cycles. Hence, the GPC route sequentially builds the letters into phonology, letter by letter.

The serial order of the rule list determines how the rules are chosen when translating a string of letters. Two factors influence how much each phoneme is triggered. One parameter is the GPC activation, which has a range of 0 to 1. The route's total strength is controlled by this parameter. The second step is to activate the letters that match the GPC rules. In this instance, each composite phoneme's activation is determined by averaging the activations of the corresponding letters.

Simulation of the DRC

According to Coltheart and colleagues (2001), if a computer model of reading is to be considered adequate, it must be able to replicate a set of fundamental phenomena that were found in reading aloud experiments conducted on adult fluent readers. The capacity of the model to replicate these effects was examined in order to assess its utility as a model of visual word identification and naming. All of the benchmark data that concern phonological processing, that are restricted to monosyllabic words, were successfully explained by the model by various tasks that were most frequently employed in word identification like lexical decision tasks. The model also proved successful in simulating the Stroop effect. Additionally, various effects associated with surface and phonological dyslexia were simulated by the model successfully, which provided an adequate account of these phenomena. Seidenberg and Plaut (2006), highlight the most significant aspect of the study as the utilization of a single model to analyze over 20 real-world occurrences related to reading both words and nonwords.

Criticism of the Model

The success of the model on replicating a wide range of empirical data makes it a “standard” against other computational models (Reichle, 2021). Despite this success, the DRC model has been the subject of some criticism. The model’s hand-wired architecture makes it unable to learn and adapt, which restricts the model's ability to fully represent the subtleties of human reading behavior (Perry et al., 2007; Pritchard et al., 2012; Seidenberg & Plaut, 2006; Seidenberg et al., 2022). According to Coltheart et al. (2001), the DRC model has no bearing on the actual process of learning to read because it was not created using any sort of learning mechanism.

The model has been criticized on its "benchmark" simulations (Seidenberg et al., 2022). The regularity effect that has been reproduced by the model on Coltheart et al. (2001), were for both high-and low-frequency words, which was not the case in the original experiment by Paap and Noel (1991). The consistency effect that has been replicated by the model has been a subject to criticism as well. Seidenberg and Plaut (2006), criticize the model by arguing that it fails to simulate the data apart from the ones presented in the original paper. Jared (2002)'s study, which is testing the DRC model on consistency effect, is shown as an example of this where the model fails to replicate the consistency effect found in the behavioral experiment. Perry et al. (2007), adds that because processing in its non-lexical pathway is determined by all-or-none regularity rather than graded consistency, DRC has trouble replicating the consistency effect for regular words. Seidenberg et al., (2022) claims that the model missimulated human-data from other studies that were not in the original paper, and that these results were not published, which creates a modeling version of a "file-drawer problem".

Seidenberg and Plaut (2006), also argued that changing the parameters of the model to fit a certain data negatively affects the model's performance on explaining other phenomena. They further state that the model's core assumptions are based on intuitions rather than having a principled explanation for the phenomena. Extending the 2001 version of DRC to new phenomena is considered challenging due to its strong reliance on certain parameter values and implementation-specific features.

Pritchard et al., (2012) in their article comparing the DRC model and Connectionist Dual-Process Models, criticize the DRC model because of its rule-based, and static nature, and that it is incapable of learning or adapting. Based on their findings, they state that only regular nonword responses are produced by the DRC model, which does not match the range of responses seen in human participants. The model also fails to generate any lexicalizations in contrast to human readers who pronounce nonwords as real words. Even though the model is capable of producing plausible pronunciations of the nonwords, its nonword performance differs from that of humans when other phenomena such as consistency effects for nonwords, relative difficulty of word and nonword naming, and length effects for words and nonwords are considered (Seidenberg et al., 2022).

2.3 The Triangle Model

Developed originally by Seidenberg and McClelland (1989), the Triangle model is considered as a family of models that have been updated to address problems in the initial version and to test different word identification theories (Reichle, 2021). Seidenberg and McClelland (1989), described the intention of developing the model as to use a basic design where the element of learning takes center stage. Using a hypothesis of what is learned and how it is represented, they aimed at developing a functional simulation model that demonstrated many of the fundamental phenomena of word recognition and naming.

Many of the concepts found in the IA model by McClelland & Rumelhart (1981) were applied to this distributed model of reading. The model applies many of these concepts to the reading task, drawing inspiration from the NETtalk model developed by Sejnowski and Rosenberg (1986). Seidenberg and McClelland (1989), listed a number of earlier visual word recognition models that impacted the development of the model such as the dual-route model of Coltheart (1978), the lexical analogy model of Glushko (1979), and the logogen model of Morton (1969).

In comparison with earlier descriptions, the model employs different knowledge representations and procedures. The model's central tenet is the absence of lexical representations (Reichle, 2021). The model does not include logogen-like lexical nodes that stand for individual words or feedback from neighbors. Instead, lexical information is distributed throughout processing nodes and patterns of connection weights. Unlike the dual-route approach, there are no lexicons listing word pronunciations or rules dictating the normal spelling to sound correspondences. The model uses a unified mechanism to learn to read irregular words and nonwords in the same way that it learns to read regular words, through experience (Seidenberg & McClelland, 1989).

Assumptions of the model

Processing words, according to the model, requires the computation of three forms of processing nodes: orthographic, phonological, and semantic. Each of these levels represents a different type of lexical information. The production of representations at each of the three levels has been considered to both impact and be influenced by the process of generating a representation at each level. Although they have not been included in the first model, other codes, it is also hypothesized that contextual influences resulting from syntactic, semantic, and pragmatic limitations can affect word processing. Children who are learning to recognize words learn to connect the orthographic codes of words to their pronunciations and meanings. The acquisition of such skills causes the activation of numerous forms of information when processing a textual stimulus, regardless of whether only one type of information may be needed to complete a particular reading task.

The orthographic level, phonological level, and inter level that contains hidden units between these two are the only levels implemented in the model, and the semantic and contextual levels were eliminated from this simplified version of the larger framework. In the simplified model a variation of Wickelgren's (1969) triples approach was employed to describe the orthographic or phonological content of words. Letters were represented as letter-triples in the Triangle model, with every single letter in a word being represented together with its preceding and following letters. Seidenberg & McClelland (1989), provided the example of the "MAKE" letter string. While the phoneme string /mAk/ is considered as the set of phoneme triples "#mA, mAk, Ak#", the letter string is represented as the set of letter triples "#MA, MAK, AKE, and KE#" (The “#” symbol in the example is signifying the beginning or conclusion of a word).

There are 460 of these units in the phonological level, and the representation employed at the phonological level is the same as that employed by Rumelhart and McClelland (1986). The representation employed for the orthographic level is comparable to that employed at the phonological level, with the exception that 400 units were used in this case. The original Triangle model employed a distributed, coarse-coding approach in place of a single node to represent each potential letter-triple. Ten potential initial, ten potential middle, and ten possible final letters were listed in a table for every orthographic unit.

Each 400 nodes in the orthographic level have reciprocal connections to all 200 hidden nodes. This feedback from the hidden units to the orthographic units represents the top-down word-to-letter connections, similar to the IA model. Each of the hidden units are connected to phonological level as well. However, feedback from phonological level to hidden nodes are not implemented in the original model (Seidenberg & McClelland, 1989). The system's understanding of the relationships between the various sorts of information is encoded by the weighted connections that control unit interactions. An autonomous learning process determines the precise values of the weights based on the system's interaction with spoken and written words as well as their meanings (Reichle, 2021)

Training

In order to learn how to correctly spell and pronounce a word, the model uses the algorithm called back-propagation of Rumelhart and colleagues (1986). Seidenberg and McClelland (1989) describes the learning procedure of the model in the following way. Upon receiving a letter string, the activation first starts at the orthographic units, where the input is represented by letter-triples. The hidden units are activated in response to the activation of the orthographic units. Then based on the activation of hidden units, a feedforward activation pattern is computed to the phonological units as well as a feedback pattern to the orthographic units. When the output patterns are computed for both units, the model is trained via error correction using the generated orthographic and phonological output. For each output node, this initially entails computing the difference between the desired activation and the actual activation. Each connection's weight is then adjusted based on the resulting error.

For the training procedure, Seidenberg & McClelland (1989) used the 2,884 unique monosyllabic words with three or more letters from Francis and Kurcera (1982) as its training corpus. Two components of word identification can be simulated by the model: the production of a word's pronunciation and spelling from complete or partial orthographic input. To perform naming and lexical decision tasks, Seidenberg and McClelland used the phonological and orthographic error scores. Phonological error score is implemented as an indirect measure that is used as a way to predict naming latencies; lower error scores are thought to be associated with quicker and more correct responses under time pressure. Conversely, orthographic error scores are thought to be calculated by human participants when performing a lexical decision task.

Simulations

Considering the naming simulations, 97.3% of the words, including the majority of exception words, were pronounced correctly by the network following the training. Higher frequency words typically resulted in lower error scores, which were interpreted as faster responses. Additionally, the model simulated interactions between frequency and regularity, and the findings from simulation were successful at replicating the experiments. The explanation for both effects was that for frequent and regular words, the connections necessary for correct performance are modified more often in the desired direction than for irregular or uncommon words. Because regular words utilize the same connections as neighboring regular words, this remains true for regular words as well. In addition, the behavioral data from research using regular inconsistent words, unusual words, and unique words were well-represented by the model.

In order to replicate lexical decision-making, the model compares the activation generated by the input across the orthographic units with the activation generated by the hidden units' feedback. Despite the fact that there is no lexicon to access in the model, it successfully replicated many of the major lexical decision phenomena; consequently, Seidenberg and McClelland (1989), argued against the commonly accepted notion that decisions must be made by determining if the target stimulus has meaning.

Seidenberg and McClelland (1989) performed an additional simulation in which the number of hidden units were decreased to 100. This adjustment on the model caused an impairment on overall word-naming performance. Additionally, it led to a more focused deficiency that inhibited the model's ability to acquire the word-specific knowledge required to correctly name words that are inconsistent or low frequency, which is comparable to what is seen with surface dyslexia (e.g., Patterson et al., 1985).

In summary, one of the model's key contributions was showing that naming the exception words and nonwords may be performed by a single process employing weighted connections between units. The model captured some key aspects of the child's acquisition of word naming skills. Additionally, the model offered an explanation for why dyslexic readers show impaired performance on reading and lexical decision tasks (Seidenberg & McClelland, 1989). Moreover, the model addressed a number of strategy-related data that have been found in the literature by implementing the notion that lexical judgments can be made based on orthographic as well as phonological error scores (Reichle, 2021).

Though it is considered very successful in many ways, Plaut (2005) criticized the model, claiming that it failed to disprove conventional claims that distinct processes and localist, word-specific representations are required to account for effective reading. When it came to lexical judgment and the pronunciation of orthographically legal nonwords, the model performed much worse than proficient readers in some situations (Besner et al., 1990).

McCloskey (1991), criticizes Seidenberg and McClelland for failing to explain what kinds of idiosyncrasies and regularities are encoded through word experience, and how learned information is distributed across a set of connection weights. He states that the connectionist models are too complex to analyze the dynamics within the system. According to him, “the Seidenberg and McClelland theory is not sufficiently well-developed to provide specific answers”.

Developments

Plaut et al. (1996), responded to these critiques of the Triangle model by presenting four simulations that included modifications of the fundamental Triangle model. To improve the word as well as nonword reading abilities of the model—including low-frequency exception words—new orthographic and phonological representations were utilized in the first simulation experiment. The model was able to read words in the training corpus with 100% accuracy and showed a similar performance to skilled readers on reading pronounceable nonwords. In response to criticism of McCloskey (1991), they also provided a thorough mathematical analysis that explained how training frequency and consistency between a word's spelling and sound correspondences with other words with similar spellings jointly affect word naming latencies. The second simulation confirmed these observations.

In the third simulation, they have employed the back-propagation through time algorithm, which eliminates the requirement to incorporate error as a stand-in for reaction time by directly reproducing the name latency data in its time to decide on a response. For the final simulation, the implications of the semantic impact on reading were examined in relation to explaining the poor reading performance of acquired surface dyslexic individuals who had suffered brain injury. They implemented this by adding the assumption that semantics often provides some support for word naming.

Plaut et al. (1996), discovered that the normal functioning of a separate phonological route, which formed with help from the semantic pathway, accounted for the surface dyslexic reading pattern. Based on these results, they proposed a division of labor for the model where neither the phonological nor the semantic pathway is capable of supporting proficient word and nonword reading on its own. Instead, the two pathways must cooperate to provide proficient word and nonword reading.

Harm and Seidenberg (2004), have developed an extensive version of the "triangle" approach that targets reading for meaning. This paradigm deals with the computation of meaning in a system that has access to both phonologically-mediated (orthography - phonology - semantics) and visual (orthography to semantics) pathways. In this framework, a word's meaning is calculated by activating semantic units that develop with time through constant input from the triangle's orth-sem and orth-phon-sem components. With this extension, they primarily focused on the computational factors that establish how the model determines an effective labor division across different input sources and whether or not it can mimic the human reader.

The basic assumptions of the network are mostly similar to the previous work. They have implemented attractor basins to the system to replicate the dynamics of the human reading system. They have also implemented the pre-existing knowledge about word's phonological and semantic by pretraining these components before introducing the orthography to the model. Harm and Seidenberg (2004), tries to capture the nature of reading acquisition with these implications. The learning process for the model is described as follows. A pattern of letters is provided to the model, allowing it to produce semantic output. This output is then compared to the expected, correct pattern, and the difference is used to make minor weight modifications. As a result of several such encounters, the weights are expected to take on values that produce correct performance.

Following the training, the model was able to activate the right phonological and semantic characteristics for 99.2% and 97.3% of the words, respectively. When it came to naming words, the trained model replicated the effects of word frequency, spelling-sound consistency, and imageability. It was also just as accurate at naming pseudowords as proficient readers. From their analysis of the division-of-labor, they have shown that, even if the model initially depended strongly on phonological mediation (orthography-phonology-semantics), as the ability to read strengthened, it progressively moved towards a greater dependence on the direct route (orthography-semantics). Nevertheless, both routes continued to significantly improve performance even after training was completed.

In spite of these revisions, the model is unable to account for a large number of additional key word recognition findings (Reichle, 2021). Despite the fact that the model describes how words could be learnt, the back-propagation technique employed to simulate learning fails to relate well to human learning. The number of intervals needed to train the model does not accurately capture the way children learn in single trials (Nation et al., 2007). In a similar vein, the model is criticized for not being able to account for data pertaining to orthography, phonology, or other learning-related findings. Nevertheless, the model has yielded significant experimental evidence demonstrating that learning a "quasi-regular" domain, such spelling-sound mappings in English, does not necessitate the use of different processing pathways. More models have probably been developed with greater computational transparency as a result of the model's explicit implementation.

2.4 Connectionist Dual Process (CDP) Approach

2.4.1 CDP Model

Zorzi et al. (1998) developed the Connectionist Dual Processing model with the aim to build upon the advantages of the dual route and connectionist models while trying to overcome their limitations. The model preserves the consistent computational approach of the Parallel Distributed Processing models, while avoiding a strict commitment to a unified path. Considering that the model does not incorporate an orthographic vocabulary, the phonological representation of the word is activated directly through the use of print. Zorzi et al. (1998) provided three experiments supporting the CDP model. In the first demonstration, they have decided to use a simple two-layer feedforward network, also referred to as two-layer assembly (TLA) (Reichle, 2021).

Similar to the letter detector level of McClelland and Rumelhart (1981), the orthographic representation in the CDP model is structured purely position specific and slot based. There is a full set of letter units that are intended to be activated from a previous feature detector level for every potential letter location. On the other hand, the positions are specified in terms of orthographic rime and orthographic onset. As a result, there are 208 units altogether in eight groups of 26 units that make up the input layer. A collection of 308 output units that represent the phonology of a syllable are connected to the input units. Seven groups totaling 44 units make up the representation of the phonological output: three groups correspond to the onset of syllables and four groups to rime.

Zorzi et al. (1998) used the “delta rule” (Widrow & Hoff, 1960), which is a straightforward gradient descent method, to train the model. Error correction for every given input pattern was achieved by adjusting the weights based on the discrepancy between the output units' activation and the desired activation pattern. The desired output was defined as the accurate pronunciation of the orthographical input. From the Oxford Psycholinguistic Database (Quinlan, 1993), 2,774 monosyllables were taken to be used to train the model. Zorzi et al. (1998), stated that there was no specific instruction provided on isolated GPC rules of any sort.

The results of the first simulations on Zorzi et al. (1998) showed that after 12 training epochs, the model accurately pronounced 81% of the training set's words. To evaluate the model’s performance on nonword naming, they have used the 52 nonwords from Glushko's (1979) Experiment 2. The model performed with 98% accuracy, demonstrating only one real mistake. Additionally, they employed the stimuli from Experiment 1 by Glushko (1979), which had regular-exception and word-nonword aspects. Of the 43 normal words, 41 were named properly. Of the 43 exception terms, 6 were accurately pronounced and the other 37 were regularized. From these results, Zorzi et al. (1998) concluded that the model is able to comprehend regularities in the training set but cannot learn the idiosyncratic cases.

The model's consistency and inconsistent nonword naming performance closely mirrored the human participants in Glushko's (1979) trials. Therefore, Zorzi et al. (1998), stated that without specific training on grapheme phoneme correspondences, the model was able to form this correspondence knowledge. Considering the performance for words, the consistency effect was shown as well, although the results didn’t replicate the lexicality impact.

In the second demonstration, they have investigated how the model would behave when it is provided with direct and mediated connections between spelling and sound and trained on the set of monosyllables used in the previous simulations. In order to provide an alternate route from input to output, they have introduced a hidden layer while maintaining direct connections between the input and output levels. According to Zorzi (2010), the network will remain multilayer even with the addition of hidden units if the direct connections are left in place.

After training, the model accurately pronounced 97% of the training corpus, including both regular and irregular words. The model's performance in naming Glushko's (1979) was considerably more similar to that of human participants this time (Zorzi et al., 1998). Essentially, the model created two distinct "routes" for pronouncing words and nonwords: a single-layered sub-lexical route that can generate pronunciations through grapheme-phoneme correspondences, and a multilayered lexical route that can generate exception word pronunciations through distributed representations of individual words using the hidden units (Reichle, 2021).

According to the results of the first two demonstrations, the authors stated that in order to accomplish the correct pronunciation of irregular words, it is necessary for some kind of word representation to occur in the system through a mediated mapping. They have also noted that since they have not manipulated the frequency of presentation for the input words in the initial training, the model fails to reproduce the Frequency X Regularity interaction observed in experimental studies.

For this reason, in the third demonstration, they implemented a new route similar to the IA model (McClelland & Rumelhart, 1981). The GPC route implemented in the IA model is slower and therefore conflicts between the two pathways only occur for low frequency exception words. Considering the parallel activation assumptions of the CDP model, Zorzi et al. (1998) follows Carr and Pollatsek (1985) on their proposal to implement the outputs from two pathways in a parallel way instead. A competitive response system, referred to as the "phonological decision system" (PDS), is used in order to model reaction time data. In order to offer a temporal dynamic, this system includes elements like lateral inhibition and progressive activation decay. The inputs from both routes gradually flow to the PDS in parallel. The decision-making process in the PDS therefore relies on competitive interactions between the two outputs. Through this architecture, it is expected to measure the naming latency.

The third simulation's findings demonstrated that the model precisely captures the classic effect of the interaction between consistency and frequency, with consistency having a greater impact on reaction times for low-frequency items. Additionally, the model's reaction times demonstrated a strong lexicality impact, with regular words with low frequency producing higher reaction times than nonwords. Lesioning the lexical pathway revealed that the model replicates the frequency-regularity relationship observed in the surface dyslexic patient by McCarthy and Warrington (1986), with significantly poorer performance on low-frequency exception words than on high-frequency ones without affecting the regular word and nonword naming.

Reichle (2021), argues that the fundamental contribution of the CDP model is that it provides an understanding of how the word identification system specializes in two subsystems to map grapheme to phoneme correspondence in one pathway and to pronounce exception words that do not match with these rules in another pathway. Considering the model’s shortcomings, he states that the CDP model's applicability is limited because it ignores a great deal of fundamental effects associated with learning (such as repetition priming), orthography (such as transposition effects), phonology (such as the identification of polysyllabic words), and it disregards the role of semantics. Roberts et al. (2003), tried to replicate the human data that showed an interaction between the effects of regularity and serial position of irregularity using four computational models of reading. The CDP model failed to reproduce this effect while only the DRC (Coltheart & Rastle, 1994) model was able to do so.

2.4.2 CDP+ Model

The CDP+ model was developed by Perry et al. (2007), on the basis of nested modeling. The basic argument of the nested modeling approach is that new models should relate to its own precursors, and it should be tested with the data sets that the old models were built upon before being tested with new data sets. Following this approach, they have analyzed the shortcomings of the previous models (e.g., the IA model, the DRC model, and the CDP model) and built the new model on the strengths of these models.

One of the new features in CDP+ model is a fully implemented localist lexical route that is based on the IA model. Perry et al. (2007), hypothesized that this would allow the model to capture effects related to orthographic processing and lexical access as well as making the evaluation of the non-lexical route simpler. In addition, grapheme representations were used as orthographic input instead of single letters. Therefore, the graphemic buffer of Houghton and Zorzi (2003) was implemented to the model.

The lexical route of the CDP+ model is almost identical to the one of DRC model. The process starts from the feature level then propagates to the letter level based on the overlap between the features of the letters. This activation then triggers the activation of the word units in the orthographic lexicon. All the word units that have the same letter in the same exact position get activation and inhibit the word units that do not. Then the phonological lexicon gets activated. Additionally, the phonological output buffer was modified to have the same format as the CDP phonological decision system. As a result, the phonemes were positioned to preserve the onset-vowel-coda distinction rather than to form a continuous string.

Similar to the earlier CDP model, the sub-lexical route is structured as a simple two-layer network. For the graphemic buffer added to the sub-lexical route, the model uses the complex graphemes presented by Houghton and Zorzi (2003). These include 10 onset graphemes, 41 vowel graphemes, and 19 coda graphemes. For the representation of the input, the graphemic buffer consists of 7 slots; three onset, one vowel, and four coda slots. There are 96 units for each slot, 26 of which are single letters and 70 are complex graphemes. When letters in the input word have one of these graphemes, the graphemes receive activation instead of single letters. As an example, the word "black" is represented as "b-l-*-a-ck-*-*-*" in the grapheme buffer. The phonological output buffer, which consists of 8 slots likewise, uses the same onset-vowel-code structure. For each lot in the output buffer, there are 43 phonological units. The input and the output units are fully connected to each other, without a hidden layer between them. The activation of the output units is based on the activation of input units, similar to the CDP model.

The grapheme buffer is activated by the letter level, which consists of single letters. The graphemic parsing starts when the first letter position is available to the grapheme buffer. The attention span for the parsing is constructed from three letter slots, in order to identify three letter graphemes. The parsing of the graphemes follows a serial processing from left to right. The process continues until the letters for each of the eight slots are identified or the most activated letter for a position is the null letter.

In order to simulate the developmental process of reading, the TLA network was first pretrained with a set of 115 grapheme to phoneme correspondences that was taken from Hutzler et al. (2004). The set was chosen based on the fact that it consists of similar items to those found in children's phonics programs. Following the pretraining, the network was trained on the selected corpus with the same training parameters used for the CDP model, however, Perry et al. (2007), decided to use a longer training period this time in order to improve nonword generalization.

The input word is presented, processed in the feature level and then the letter level. Based on the activation of the letter level, the lexical and the sub-lexical routes start processing the input. At the phonological output level, the activation of the lexical and the sub-lexical routes are combined by adding up the activation from both routes. To pronounce the input word, the CDP+ model uses a different method from that of CDP and DRC. In order for the model to give a decision at the phonological output buffer, Perry et al. (2007), used a settling criterion. According to this criterion, the settling down process starts once there is an activated phoneme in the output buffer. The system settles down when there is no change in activations between two cycles for the phonemes that are below the activation criterion. Once the model settles down and the processing stops, the pronunciation is generated based on the most strongly active phoneme in each position.

When presented with the 7,383 terms in its vocabulary, CDP+ pronounced 98.67% of the word names correctly. Around 70% of the mistakes were either regularization errors or different word interpretations that made advantage of widely known grapheme–phoneme correlations. Perry et al. evaluated the model on a large nonword reading database (Seidenberg et al., 1994) in order to assess CDP+'s overall nonword reading performance. The error rate of the model was quite comparable to the error rate observed in human data (7.3%).

In accordance with the nested modeling, Perry et al. (2007), tested the model on selection of benchmark effects proposed by Coltheart et al (2001), and showed that the model is able to simulate these effects. To test the consistency effect on words, the model was tested to simulate four experiments from Jared's study (2002). The simulations of the CDP+ model yielded highly accurate matches to the human data from Jared (2002), for all four studies and replicated the interaction between frequency, regularity, and consistency and how these effects are modulated by the friend-enemy ratio that a word has. The model was also tested to see if it could simulate the results of Andrews & Scarratt (1998), on consistency effect on nonword naming. The results demonstrated a good match with human performance in two tests assessing how much individuals employ larger-sized spelling to sound connections and grapheme to phoneme correlations while reading aloud nonwords.

CDP+ was also successful at simulating length effects in nonword reading and the interaction between length and lexicality, along with the position-of-irregularity effect. Perry et al. (2007) compared the performance of CDP+ with CDP, DRC, and the Triangle models, on predicting the item-level variance across various large-scale databases (e.g., Balota & Spieler, 1998; Spieler & Balota, 1997; Treiman et al., 1995; Seidenberg & Waters, 1989). As evidenced by its persistent superior performance over the other models, CDP+ explained item-level variance in latencies for word-naming better.

Nonetheless, these achievements are counterbalanced by the CDP+ model's shortcomings. Reichle (2021) argues that CDP+ avoids many of the key discoveries in word identification since it is essentially a word naming model. Additionally, he criticizes the approach for failing to take the semantic impact on reading into account. Perry and colleagues

(2007) point out that because the nodes in the phonological and orthographic lexicons are preset, their model is unable to explain word learning.

2.4.3 CDP++ Model

The latest implementation of the Connectionist Dual Processing Model is a model of reading for disyllabic words that is built based on its direct precursor. In order to expand CDP+ computationally to disyllabic words, Perry et al. (2010) made several changes to the new model and explained these changes as follows. Firstly, there are now sixteen slots instead of eight in the feature level, letter level, grapheme, and phoneme buffers. Secondly, the grapheme set, and the lexicon sizes were expanded in the new model. Thirdly, in order to process a second syllable, the seven slots—three onset, one vowel, and four coda—used in the phonological output buffer and grapheme input buffer were doubled. And finally, two sets of stress nodes—one for sub-lexical stress assignment and the other for stress output—were added to the model to further reflect the position of stress.

There are two sub-lexical stress nodes that are implemented in the TLA sub-lexical pathway. These units are independent from the phoneme units and fully connected to the grapheme units in the network. During the training phase, the network learns the correspondence of stress for every word in the same way that it learns the grapheme to phoneme correspondence. The sub-lexical stress nodes start processing the input once the grapheme buffer processes the last letter of the word. The stress output nodes get activation from both the sub-lexical stress nodes and the phonological lexicon. Thus, the stress output nodes combine these two activation patterns in the same way the phoneme output buffer combines the activation pattern from lexical and sub-lexical pathways. Unless the stress output nodes receive enough activation for a response, the input word will not be named even if the phoneme output is ready.

Perry et al. (2010), noted that assigning graphemes to the different slots in disyllabic words could be a complex process. Therefore, they have decided to follow the “onset maximization” constraint. This is constructed by assigning, when it is possible, the onset positions of the second syllable to the consonant graphemes that occur between the two vowels.

After the training, the CDP++ model was able to provide the correct phoneme for 88% of the words, and it used the correct stress for 82% of the words in the lexicon. The model was also examined with the four datasets that were used in predicting the item-level variance for monosyllabic words previously (e.g.; Balota & Spieler, 1998; Spieler & Balota, 1997; Treiman et al., 1995; Seidenberg & Waters, 1989). The performance of CDP++ was slightly superior to that of CDP+, and naturally that of DRC and the Triangle model. Perry et al. also examined the performance of CDP++ on disyllabic words using the ELP database (Balota et al., 2007) and two large scale item sets from Chateau and Jared (2003), and Yap and Balota (2009). The model accounted for 36.9% of the variance on the ELP database, 45.4% on Yap and Balota (2009), and 33.8% on Chateau and Jared (2003).

Perry et al. (2010), pointed out that because CDP++ can still recreate all significant monosyllabic benchmark effects that drove the development of the prior models, it is entirely backwards compatible with them. The only exception was that, in contrast to CDP+, the model did not demonstrate a significant body neighborhood effect. In addition, Perry et al. (2010), provided a list of benchmark effects for the naming of disyllabic words, including syllable number, stress regularity, consistency and regularity effects, and more. They came to the conclusion that the results were generally satisfactory after testing the model for these effects.

Apart from these results, Perry et al. (2010), acknowledges that the focus was on reading aloud rather than other processes like lexical decision. Gubian et al. (2023), compared the performance of three different reading aloud models, RC00 (Rastle & Coltheart, 2000), CDP++, and a grapheme-to-phoneme algorithm known as Sequitur, on nonword naming. The results showed that the other two models outperformed the CDP++ model on nonword naming.

3. METHODS

3.1 Participants

Fifty-three students participated in the study (20 males, *M* age = 22,28 years, *SD* = 2,16, age range = 19 – 29). All participants were native Italian speakers, had normal or corrected to normal vision and were naïve to the purpose of the study. Informed consent was obtained from all participants before the experiment. The protocol was approved by the psychological ethical committee of the University of Pavia and participants were treated in accordance with the Declaration of Helsinki.

3.2 Materials

Lexical decision task

The words included in the study were selected among the 20,000 most frequent Italian words according to the SUBTLEX-it (http://crr.ugent.be/subtlex-it/), while the pseudowords were selected among a large set of around 100,000 stimuli built using the orthographic Italian module of Wuggy (Keuleers & Brysbaert, 2010) starting from the words included in the Italian ANEW database (Montefinese et al., 2014). The final set included 200 stimuli (100 words and 100 pseudowords).

Words stimuli were selected in order to have a quasi-uniform distribution of our main semantic predictor of interest (see below) and, at the same time, not to have unbalanced distributions of the other predictors included. We included the following predictors: semantic neighborhood density (SND), orthographic neighborhood density (OND), word frequency and length.

Our main predictor was SND, and it was computed following Hendrix & Sun (2021; but see also Anceresi et al., 2024) as the mean semantic similarity between each pseudowords and its *k* closest neighbors (with *k* = 5) within the 20,000 most frequent words in SUBTLEX-it. Higher values thus indicate that a certain stimulus is more embedded in the semantic space. For more information on the computation of the semantic similarity see below the section **Distributional semantic model**.

OND was computed as the average Levenshtein distance (which measures the orthographic distance between two strings of symbols by quantifying the minimum number of single-character edits required to change one element into the other) between the letter string and its 20 closer neighbors (i.e., OLD20; Yarkoni et al., 2008) among the 20,000 most frequent words in SUBTLEX-it. Length was computed as the number of letters in the letter string and word frequency was retrieved from the SUBTLEX-it and log-transformed to account for its skewed distribution (as common in this kind of tasks Hendrix & Sun, 2021).

The task was built using Psychopy (Peirce et al., 2019). Participants were shown one word at the time and were asked to indicate if the stimulus was an Italian word or not as fast and as accurately as possible by pressing the A or L key using the left or right index fingers, respectively. The trials were presented in random order. Each trial started with a central fixation cross (presented for 500-ms) and was followed by a string of letters (presented for maximum 5000-ms). Participants' response ended the trial and moved to a blank screen (presented for 1000-ms), which preceded the fixation cross of the next trial.

Reading measures

In order to assess the reading abilities of the participants, word and nonword reading measures from LSC-SUA (Reading, Writing, and Calculation – University Students and Adults) by Cornoldi & Candela (2022), were used.

Word Reading: This task involves reading aloud four lists of words that vary in length and frequency of use. Each list consists of 28 words (AFC and BFC: 140 graphemes, 64 syllables; AFL and BFL: 260 graphemes, 112 syllables). The examiner, who has a copy of the same protocol, notes the reading errors and the time taken for each list.

Nonword Reading: This task involves reading aloud two lists of nonwords (strings of letters that are pronounceable but do not exist in the Italian language) of different lengths. Each list consists of 28 nonwords. The examiner records both the accuracy and speed of reading in this task as well. For both measures, the participants' performance is evaluated based on speed and accuracy parameters (Cornoldi & Montesano, 2020).

Other measures

Verbal working memory. The assessment of verbal working memory (WM) was conducted using the forward and backward digit span subtests (Wechsler, 1981). The scores have been calculated based on the number of accurate items in each subtest.

Rapid Automatized Naming. The assessment of naming known stimuli was conducted using the Rapid Automatized Naming (RAN) test (Di Filippo et al., 2005). Two subtests, specifically “Colors” and “Figures”, were utilized from the battery. The “Colors” subtest involved the presentation of two matrices, each containing 10 rows of 5 stimuli. The stimuli consisted of colored squares including black, blue, red, yellow, and green colors. The “Figures” subtest involved the presentation of two matrices, each consisting of 10 rows with 5 stimuli. These stimuli were black and white figures, such as a pear, train, dog, star, and hand. During both subtests, the individual was instructed to name each visual stimulus in the matrix in a sequential manner, with the goal of doing so as rapidly and precisely as possible. The study documented the time it took to name items (measured in seconds) and the number of errors made throughout the naming process. In this study, the average raw scores from both subtests (Colors and Figures) were calculated and utilized for the analyses.

Verbal Fluency: To assess the phoneme and the semantic fluency of the participants, the Verbal fluency letter test (COWAT) of Novelli et al. (1986) was used.

a) Phonemic categories: This is a controlled word association test where the participant is asked to say, within one minute, all the words that come to mind that start with a specific letter of the alphabet. The letters presented as stimuli are "F", "P", and "L".

b) Semantic categories: The examiner asks the participant to produce as many words as possible that belong to a specific semantic category. In this version, three semantic categories were considered: car brands, fruits, and animals. The participant has one minute to complete the task

Non-Verbal Intelligence: The Cattell Culture Fair Intelligence Test (CFIT) Form 2A (Cattell & Cattell, 1981), was used to assess the participants' fluid intelligence. This non-verbal test is designed to minimize the influence of language and cultural knowledge, focusing on problem-solving abilities through tasks such as series completion, classification, and matrix reasoning.

Distributional semantic model

The DSM used here was *fastText* (Joulin et al., 2016). Specifically, we trained a *fastText* DSM on itWaC (http://wacky.sslmit.unibo.it): a 2-billion-word corpus constructed from the Web limiting the crawl to the .it domain and using medium-frequency words from the Repubblica Italian journal corpus and basic Italian vocabulary lists as seeds (Baroni et al., 2009).

The model was trained using the Continuous Bag of Words (CBoW) method, an approach originally proposed by Mikolov and colleagues (2013), with 300 dimensions, a co-occurrence window of 5 words. When using CBoW, the obtained vector dimensions capture the extent to which a target element is reliably predicted by the linguistic contexts in which it appears, where "context" is represented as the words contained in a fixed size window around the target word. Specifically, the CBoW model will induce a representation for a given target w_0 based on context words $w_{-n}, ..., w_{-1}, w_1, ..., w_n$.

We employed *fastText* because of its ability to compute semantic representations including also sub-word information. Indeed, *fastText* is based on the idea (originally proposed by Schütze, 1992; and realized computationally by Bojanowski et al., 2017) to take into account sub-word information by inducing semantic representations as the sum of the vectors of the letter n-grams associated with each word. That is, *fastText* computes the semantic representation of each string of letters as the sum of the vectors of the full string plus all the vectors of the n-grams that compose it. The *fastText* DSMs employed here were trained including n-grams ranging from 3 to 6 (Bojanowski et al., 2017).

As an example, consider the word <reading>, composed by different-length character n-grams, as reported in Table 1. The *fastText*-induced representation will be the sum of the <reading> word vector along with the vectors of all the elements reported in Table 1.

Table 1. Example of the sub-word vectors retrieved in order to represent the vector of the word < reading >.

Word	Length(n)	Character n-grams
reading	3	<re rea, ead, adi, din, ing, ng>
reading	4	<rea, read, eadi, adin, ding, ing>
reading	5	<read, readi, eadin, ading, ding>
reading	6	<readi, readin, eading, ading>

Using *fastText*, we therefore obtained semantic representations for the words included in this study as well as for the 20,000 most frequent words included in the SUBTLEX-it. For each pair we computed a semantic similarity index (SRel) based on the cosine of the angle formed by vectors representing the meanings of the corresponding strings. The higher the SRel value, the more semantically related the letter strings are expected to be, as estimated by the model.

3.3 Procedure

Participants were tested individually in the Cognitive Psychology Laboratory of the University of Pavia. Each participant was asked to undergo a battery of tests including word and nonword reading test, backward digit span, RAN, verbal fluency letter test, and the Cattell Culture Fair Intelligence Test Form 2A. Each test was administered by the researcher in a quiet room. Following the administration of the tests, the participants were asked to continue with the lexical decision task.

3.4 Data analysis

All the analyses were performed using *R*-Studio (RStudio Team, 2015). Data was analyzed through a mixed-effects approach, which incorporates both fixed-effects and random-effects (associated to participants and items) and allows for managing non-independency of the observations at both participants and item level (Baayen et al., 2008). A linear mixed model (LMM) was run using the *lme4 R* package (Bates et al., 2015).

The dependent variable was participants' correct response latencies (RTs) for the words included, which were log-transformed to account for their natural positively skewed distribution (see: Gatti et al., 2023). The LMM included reading speed at the individual level as continuous predictor and, at the trial level, SND, OND, frequency and length, as well as the interaction between reading speed and these latter predictors. Participants and stimuli were included as random intercepts. More specifically, the model estimated was:

DV ~ *SND* + *OND* + *Frequency* + *Length* + *(SND* × *ReadingSpeed)* + *(OND* × *ReadingSpeed)* + *(Frequency* × *ReadingSpeed)* + *(Length* × *ReadingSpeed)* + (1 | ParticipantID)

We then performed a model selection using the *MuMIn R* package, with the function *dredge* (Bartoń, 2020). This procedure selects the best fitting model (i.e., the one with the lowest Akaike information criterion, which returns an estimation of the quality of the model, AIC; Akaike, 1973) fitting all the possible combinations of the fixed effects included. In order to check for the consistency of the effects, we also estimated all the models with Δ *AIC* < 2, as models in this AIC range can be considered as equivalent in explaining participants' performance (Hilbe, 2011).

Trials in which participants incorrectly classified the word as a pseudoword or in which RTs were shorter than 300 ms or longer than 3000 ms were removed from the analysis (2.2% of the trials removed).

4. RESULTS

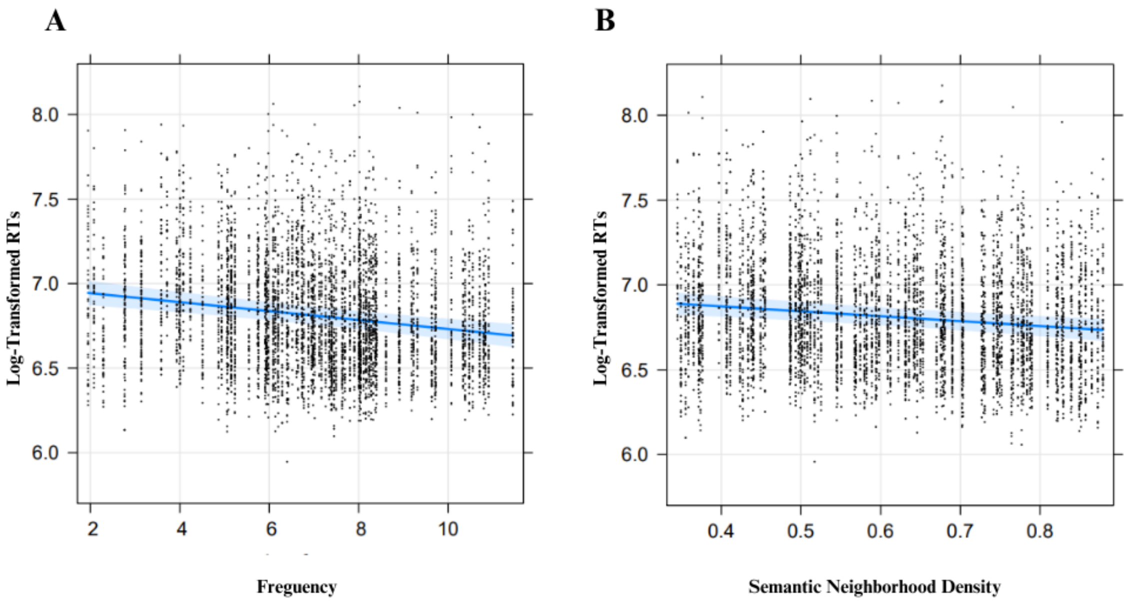
The best model included reading speed, SND, frequency, length and the interaction between reading speed and length (Table 2), *Pseudo-R^2 (marginal)* = .22, *Pseudo-R^2 (total)* = .52. All the other fixed factors were dropped. No model had *Δ AIC* < 2 compared with the best fitting model.

Table 2. Fixed effects revealed by the LMM and their *p*-values.

FIXED EFFECT	*F*-value	*NumDF, DenDF*	*p*-value	*b*
SND	15.59	1,93	**< .001**	**-.29**
frequency	28.45	1,93	**< .001**	**-.03**
length	56.19	1,98	**< .001**	**.04**
reading speed	.66	1,77	.42	-.02
reading speed : length	56.30	1,5031	**< .001**	**-.01**

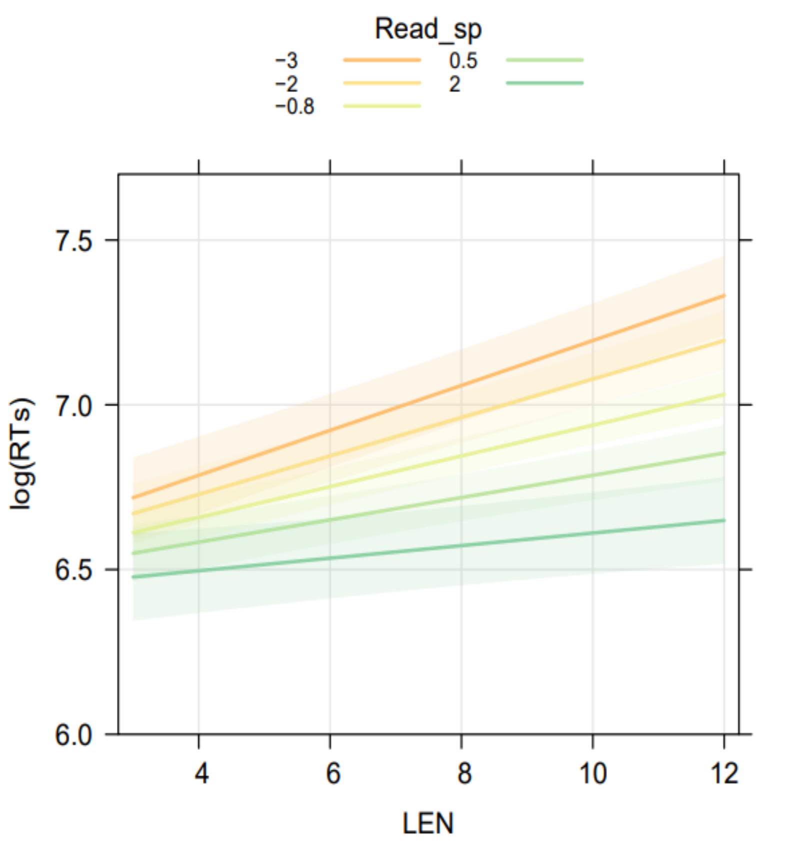
The linear mixed model revealed several significant fixed effects. More directly, the effect of SND was significant, $F(1,93) = 15.59$, $p < .001$, with a regression coefficient $b = -0.29$. As can be seen from Figure 1B, the negative effect of SND indicates that the higher the density of the semantic neighborhood, the faster the participants. The effect of frequency was also significant, $F(1,93) = 28.45$, $p < .001$, with a regression coefficient $b = -0.03$. The negative effect of frequency indicates that the higher the frequency of the word, the faster the participants (Figure 1A). The positive effect of length, $F(1,98) = 56.19$, $p < .001$, with $b = 0.04$, indicates that the longer the word, the slower the participants.

Figure 1. Effects of Frequency (A) and SND (B) on Reaction Times (RTs).



Finally, from a visual inspection of Figure 2 we can infer that the significant interaction reading speed by length $F(1,5031) = 56.30$, $p < .001$, with $b = -0.01$ indicates that the longer the word, the slower the participants, with participants showing faster reading times being less affected by this component.

Figure 2. Reading Speed by Length Interaction



However, the effect of reading speed alone was not significant, F(1,77) = 0.66, p = .42, with b=−0.02, suggesting that reading speed did not have a meaningful impact on reading speed.

5. DISCUSSION

In the present study, the role of SND, OND, word frequency, word length, and individual differences in reading speed on identifying words were investigated, with a focus on how reading speed affects reaction times and interacts with these variables. The results of the lexical decision task, analyzed through a linear mixed model, revealed significant fixed effects for SND, word frequency, and word length. Furthermore, a significant interaction between reading speed and word length was identified. This chapter will discuss these findings in the context of prior research and their implications for computational models of reading.

Semantic neighborhood density effect

The significant negative effect of SND indicates that words with higher semantic neighborhood density were recognized more quickly by participants. This result is in line with the previous findings. Recent studies have consistently shown that words with larger SND are recognized significantly faster than words with small SND in lexical decision tasks (e.g., (Buchanan et al., 2001; Danguecan & Buchanan, 2016; Gatti, Marelli, & Rinaldi, 2023; Hendrix & Sun, 2021; Macdonald, 2013; Pexman et al., 2008; Shaoul & Westbury, 2010; Yap et al., 2011; Yap, Pexman, et al., 2012). Buchanan et al. (2001) proposed one possible explanation for the role of semantics in lexical decision tasks: the interactive activation within the semantic lexicon enhances the activation in the orthographic and phonological lexicons. This suggests that a response in lexical decision tasks is based on the combined activation across all three lexicons, rather than relying on activation in just one.

The current findings can be interpreted through several computational models discussed earlier. Although the original IA model (McClelland & Rumelhart, 1981) did not include a semantic level, Balota et al. (1991) proposed a modification that adds a meaning-level unit. In this modified model, activation spreads from the feature level to the letter level, then to the word level, and finally to the meaning level. After being activated, semantic-level units send feedback to the word-level units via feedback connections. During a lexical decision task, the orthographic level receives feedback from the semantic meaning level, which results in an increase in activation at the orthographic level. Greater semantic similarity results in increased activation at the semantic level, hence enhancing activation at the orthographic level, ultimately facilitating faster word recognition. (Macdonald, 2013).

Models that rely on cascaded processing, such as the DRC model (Coltheart et al., 2001), assume that activation spreads automatically throughout the system, allowing semantic influences on word recognition even before the stimulus is fully recognized. During visual word recognition, activation extends to the semantic units (Macdonald, 2013). When words have richer semantic representations, the activation pattern within the semantic system is stronger and more pronounced. This enhanced activation then feeds back to the orthographic level, enabling the orthographic units to stabilize more quickly, which results in a facilitatory effect during lexical decision (Yates et al., 2003).

In its initial implementation, the Triangle Model (Seidenberg & McClelland, 1989) characterized the lexical decision process as a judgment based primarily on non-semantic properties of both word and nonword stimuli. However, in a later development, Harm and Seidenberg (2004) expanded the model by introducing a mechanism through which a word's meaning is computed via the activation of semantic units. These units develop over time through continuous input from the model's orth-sem and orth-phon-sem components. This enhanced version of the model also introduced a sem-orth feedback pathway, where feedback from semantics to orthography is provided. This feedback mechanism could plausibly account for the significant effect of SND observed in the current study.

The current findings not only align with existing theories but also further substantiate the idea that richer semantic networks can significantly boost the speed of word recognition, underscoring the necessity for models to incorporate more dynamic semantic feedback mechanisms.

Word frequency effect

Beyond the influence of semantic density, this study also emphasizes the strong impact of word frequency on word recognition, a phenomenon that has been widely documented across various languages. Word frequency had a significant negative effect, meaning that frequently encountered words were recognized more rapidly by participants. This effect is one of the most consistently replicated findings in word identification research (e.g., Gardner et al., 1987). The greater the reader's exposure to a word, the less cognitive effort is needed for its recognition. This mechanism has been demonstrated across different alphabetic languages (Kuperman et al., 2024). Recent findings from lexical decision tasks are also in line with the results from the present study, showing faster RTs for high frequency words (Hendrix & Sun, 2021; Juhasz et al., 2019).

The significant word frequency effect observed in this study aligns with predictions from various computational models of word recognition, including the IA Model, DRC Model, Triangle Model, and CDP Model. While all these models highlight the efficiency gained from repeated exposure to high-frequency words, they differ in their details. The IA and Triangle Models attribute the effect to stronger mental representations formed through frequent encounters, whereas the DRC and CDP+ models emphasize faster retrieval via the lexical route, where high-frequency words benefit from more robust connections. For instance, in the DRC model, the orthographic lexicon is sensitive to frequency, leading to quicker activation for high-frequency words (Coltheart et al., 2001). Taken together, the current work reinforces the foundational principles of these models, particularly the role of repeated exposure in strengthening mental representations and enhancing processing efficiency.

Word length effect

In addition to SND and word frequency, the present study also demonstrated a significant positive effect of word length on reading time, suggesting that longer words are inherently more demanding to process. This could be explained by the fact that longer words contain more constituent letters and therefore provide more orthographic information to process (Clifton et al., 2016). In fact, longer words take longer reading times and are skipped less. This is true across different languages (Kuperman et al., 2024).

However, the functional form of the word length effect in lexical decision is not entirely undisputed. Some studies have found that longer words yield longer latencies (Balota et al., 2004; Hudson & Bergman, 1985; O'Regan & Jacobs, 1992), which the current study is in line with, and others found null results (Acha & Perea, 2008; Frederiksen & Kroll, 1976; Richardson, 1976). More recently several studies (Baayen, 2005; Ferrand et al., 2010, 2011, 2018; New et al., 2006) documented a U-shaped effect of word length. Indeed, it appears that the effect of word length is not linear: reaction times are constant for words between 5 to 8 letters, but they increase with length for words shorter than 5 or longer than 8 letters. Hendrix and Sun (2021) reported the inhibitory effect of word length during early stages of word identification, while later in the process this effect became facilitatory. They argued that since long words contain more sub-lexical information, it helps the reader identify the word faster compared to shorter words.

Simulating the length effect in lexical decision tasks poses challenges for all classes of word processing models. While none of the aforementioned models explicitly address the length effect, it is generally attributed to serial processing within the non-lexical route (Juphard et al., 2004). For instance, in the DRC Model, lexical decisions are based solely on the contents of the orthographic lexicon, accessed via the lexical route. This route allows for the retrieval of word knowledge stored in a mental lexicon developed during reading acquisition. As a result, for frequent words processed via the lexical route, word identification latency is generally unaffected by word length. Word length becomes relevant only when a novel word is processed through the grapheme-to-phoneme conversion (GPC) route in a sequential manner. Similarly, the Triangle Model does not predict a direct word length effect but suggests that factors such as word length or the number of syllables can influence word processing. A later version of the model demonstrated a small length effect using a parallel processing approach (Plaut et al., 1996).

On the other hand, the CDP model and its subsequent versions only focuses on naming. However, CDP+ and CDP++ are equipped with a lexical route that is identical to that of DRC up to the level of the phonological lexicon, and as such it could perform lexical decision in exactly the same way as DRC (Perry et al., 2007).

While the linear nature of the length effect observed here aligns with certain studies, the variability in findings across the literature suggests that word length interacts with multiple linguistic factors, requiring a nuanced approach in modeling.

Reading Speed by Length Interaction

Overall, the effect of word length is complex and multifaceted. It not only interacts with higher-order factors such as frequency and imageability, but it is also independent of syllable count and varies according to the reader's skill level and the regularity of the language being processed (see Barton et al., 2014 for a review). The current study adds another layer to this complexity by exploring the interaction between word length and individual reading speed. Specifically, the present findings indicate that participants with higher reading speed were less affected by the length effect compared to those with lower reading speed. Considering that longer words contain better orthographic information, it could be argued that readers with more orthographic knowledge are less hindered by increases in word length (Slattery & Yates, 2018).

Prior research has demonstrated that perceptual span is larger for faster readers (Rayner et al., 2010). Kuperman & Van Dyke (2011) reported that compared to readers with poor word identification skills, the gaze durations of better word identifiers increased to a lesser degree as word length increased. Number of studies using lexical decision or naming tasks also showed that skilled readers are less influenced by word characteristics such as length (Butler & Hains, 1979; Yap et al., 2012), which is interpreted as skilled readers being more reliant on relatively automatic lexical processing mechanisms. These latter studies, however, used vocabulary knowledge as an indicator of skilled reading.

Research on the impact of reading speed on various reading processes remains limited. While some studies have examined its effect on reading comprehension (Cutting & Scarborough, 2006) and transposed word effects (Hossain & White, 2023), the influence of reading speed on word identification processes has not been extensively explored. The present study addresses this gap by offering novel insights into how reading speed interacts with word recognition, contributing new findings to the literature.

This finding can be understood through the lexical and non-lexical routes of the DRC Model. Individuals with high reading speed may have mastered grapheme-to-phoneme correspondence rules, allowing them to shift away from sub-lexical processing strategies. For these readers, most words are recognized through rapid, automatic activation of lexical representations (Kuperman & Van Dyke, 2011). In contrast, those with lower decoding abilities have poorer-quality lexical representations due to a less refined phonological coding system. These readers might rely more on sub-lexical processing, which is inherently noisy due to incomplete grapheme-to-phoneme knowledge and insufficient feedback from phonological and semantic representations (Perfetti, 2007). Consequently, a larger word length effect indicates greater reliance on sub-lexical decoding strategies (Martens & de Jong, 2006).

Ultimately, these findings contribute to a more comprehensive understanding of the word recognition process, emphasizing the need for ongoing refinement of theoretical models to accommodate the diverse factors influencing reading behavior.

5.1 Limitations

Although this study aimed to help understand the processes underlying the visual word recognition as possible, it has certain limitations.

Firstly, the majority of the participants in the lexical decision task were either a university student or have already graduated from university. It is evident that the total years of education has an influence on the processes affecting word recognition (Kosmidis et al., 2006; Tainturier et al., 1992). This factor is also evident in the studies showing the role of vocabulary knowledge on word recognition.

Apart from the education level, the participants in this experiment were mostly in their early adult years (between 19 and 29 years-of-age). Several studies showed an association between age and semantic effects on lexical access (Bowles & Poon, 1988; Robert & Rico Duarte, 2016), however there are also studies showing no influence of age on other factors affecting word recognition (Cohen-Shikora & Balota, 2016; Tainturier et al., 1989). Overall, the homogeneous characteristics of the participants might have an effect on the observed results. Therefore, it is important to consider this limitation when evaluating the current results.

One other possible limitation of this study is the way in which the semantic neighborhood density is detected. In this study, the DSM used fastText includes sub-word information that allows to generate higher quality word vectors even for words with low frequencies. Recent studies showed the benefits of using DSMs (Günther et al., 2019; Hendrix & Sun, 2021), however object-based models of semantic organization differ in the predictions they make regarding SN effects. Consideration of object properties can also provide additional insights for the visual word recognition process (Buchanan et al., 2001). There are also studies showing different effects of SND for various types of words (Danguecan & Buchanan, 2016; Locker et al., 2003). In light of these, the single aspect of semantics investigated in this study could create a limitation for the results.

5.2 Recommendations for future research

The current study offers valuable insights into the roles of Semantic Neighborhood Density (SND), word frequency, word length, and individual differences in reading speed during visual word recognition. To further advance our understanding of these processes, future research should aim to include a more diverse participant pool. Incorporating individuals from varying educational backgrounds and age groups would enable a more nuanced analysis of how demographic factors interact with SND, word frequency, and word length.

This study utilized a standard lexical decision task, which is widely recognized for assessing how individuals identify visually presented words. However, employing different experimental paradigms could provide a more comprehensive understanding of the reading process. For example, comparing results from lexical decision tasks, word naming tasks, and text reading could elucidate how factors such as SND and individual differences influence different aspects of reading. Additionally, incorporating neuroimaging techniques, such as fMRI or EEG, would allow researchers to explore the neural mechanisms underlying these processes, offering insights into how the brain supports word recognition and the influence of individual variability.

Finally, considering the various methods available for measuring semantic neighborhood density, systematically comparing these approaches would enhance the precision of computational models in explaining semantic processes. This could lead to the development of more accurate models that better capture the complexity of semantic representations in the brain. Moreover, future studies could explore how different measures of semantic neighborhood impact word recognition across diverse linguistic contexts, potentially leading to cross-linguistic models of visual word recognition.

5.3 Conclusion

The present study provides important insights into the cognitive mechanisms underlying visual word recognition, particularly focusing on the roles of SND, word frequency, word length, and individual differences in reading speed. The findings revealed significant effects of SND, word frequency, and word length on word recognition, with faster recognition associated with higher SND and word frequency, and slower recognition with increased word length. The interaction between reading speed and word length further highlighted the complexity of these processes, suggesting that individuals with faster reading speeds are less affected by the challenges posed by longer words.

While these findings align with existing computational models of word recognition, they also point to areas where current models may need refinement. The significant effect of SND supports the inclusion of dynamic semantic feedback mechanisms in models like the Interactive Activation Model (IAM) and Triangle Model. Similarly, the word frequency effect reaffirms the importance of robust lexical connections in models such as the Dual Route Cascaded (DRC) Model and Connectionist Dual Processing (CDP) Model. However, the variability in the word length effect suggests that models should more precisely account for the interaction between word length and other linguistic factors, as well as individual differences in reading speed.

Despite its contributions, the study has limitations, including the homogeneity of the participant sample and the specific methods used to measure semantic neighborhood density. Future research should address these limitations by including more diverse participant samples, employing a variety of experimental paradigms, and exploring alternative methods for measuring semantic neighborhood density. Such efforts will not only enhance our understanding of visual word recognition but also contribute to the development of more accurate and generalizable computational models.

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