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OB1-Reader: A Model of Word Recognition and Eye Movements in Text Reading

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Decades of reading research have led to sophisticated accounts of single-word recognition and, in parallel, accounts of eye-movement control in text reading. Although these two endeavors have strongly advanced the field, their relative independence has precluded an integrated account of the reading process. To bridge the gap, we here present a computational model of reading, OB1-reader, which integrates insights from both literatures. Key features of OB1 are as follows: (1) parallel processing of multiple words, modulated by an attentional window of adaptable size; (2) coding of input through a layer of open bigram nodes that represent pairs of letters and their relative position; (3) activation of word representations based on constituent bigram activity, competition with other word representations and contextual predictability; (4) mapping of activated words onto a spatiotopic sentence-level representation to keep track of word order; and (5) saccade planning, with the saccade goal being dependent on the length and activation of surrounding word units, and the saccade onset being influenced by word recognition. A comparison of simulation results with experimental data shows that the model provides a fruitful and parsimonious theoretical framework for understanding reading behavior.

Keywords: text reading, computational model, orthographic processing, lexical processing, parallel word processing

For decades, reading research has advanced along two relatively independent lines. One of these lines has focused on orthographic processing of single words, spurring various accounts of how readers may code for letter identity and position (e.g., Davis, 1999; Grainger & van Heuven, 2003; McClelland & Rumelhart, 1981; Whitney, 2001). The other line, meanwhile, has made key contributions to our knowledge of eye-movement control in text reading (e.g., Engbert, Nuthmann, Richter, & Kliegl, 2005; Reichle, Rayner, & Pollatsek, 1999, 2003; Reilly & Radach, 2006). These two endeavors have led to large advances in our understanding of the reading system. Word recognition research has enabled us to predict fairly accurately how long it takes to recognize a given word and to describe how orthographic information is integrated over time (e.g., Grainger, 2008, 2018, for reviews). Meanwhile, research on eye-movements in text reading has enabled us to predict temporal and spatial eye movement parameters that are based on properties of the text being read (e.g., Rayner, 1998, 2009, for reviews).

At the same time, it is clear that not all pending issues concerning reading can be answered by these domains in isolation. For example, research on word recognition has generally ignored how recognition processes may be influenced by surrounding words and context. Meanwhile, the major focus of research on text reading has been at the lexical level (but see, e.g., Hyönä, 1995; White & Liversedge, 2004), making it difficult to account, for instance, for how and when text reading may go awry.

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Following the recommendations of Grainger (2003) and Grainger, Dufau, and Ziegler (2016), here we integrate the two domains of reading research in a computational model of reading, OB1-reader, developed with the aim to solve aforementioned issues. In the following section, we provide a theoretical background, comprising a short overview of models of word recognition on the one hand and models of eye-movement control on the other, highlighting those elements that are, in our view, key to achieving an integrative account of reading. In subsequent sections, we summarize the main assumptions and implementation of our model. We conclude with a comparison of simulation results to experimental data.

Theoretical Background: Models of Reading

Models of Word Recognition

Although a substantial body of visual word recognition research has been dedicated to phonological, morphological, and semantic processing (e.g., Frost, Grainger, & Rastle, 2005), orthographic processing, that is, the process of coding for the identities and positions of letters, is generally thought to lie at the heart of the word recognition process. In the early 80s, McClelland and Rumelhart (1981; Rumelhart & McClelland, 1982) provided what has likely been the most influential account of the word recognition process to date. According to their interactive-activation model (IAM), letters in the visual input activate position-coded letter nodes. These in turn activate nodes for words with letters at matching positions (e.g., a letter node coding for letter *e* at Position 2 would activate *best*, *leave*, *see*), until one of the word nodes reaches an activity threshold that marks the point of recognition. Importantly however, activated words provide feedback activation to those letter representations that match their respective location in the word (e.g., *best* would activate the letter node coding for *s* at Position 3). This mechanism accounts for the classic word-superiority effect reported by Cattell (1886), whereby recall of individual letters is better when those letters form a word, as compared to a nonword string. The model also correctly predicted that recognition of low-frequency words is hampered when they have at least one high-frequency orthographic neighbor (sharing all but one letter while respecting letter positions; e.g., blur–blue; Grainger, O'Regan, Jacobs, & Segui, 1989; Grainger, 1990).

One of the major drawbacks of McClelland and Rumelhart's (1981) seminal model, however, was that letter processing took place in a rigid slot-based fashion, meaning that a stimulus with a certain letter at a certain position would only activate words that have the same letter at the same position. Since the IAM's first appearance, there has been a wealth of evidence against such absolute letter position coding, and in favor of a more flexible letter-word interface. Using a paradigm where subjects had to identify two words that were briefly presented together (e.g., *sand lane*), McClelland and Mozer (1986) showed that letter migration errors can occur (e.g., *land sane*). Years later, Davis and Bowers (2004) showed that such illusory identifications do not have to respect position: Given a word pair like *step soap,* participants could also respond *stop*, indicating a migration of the letter *o* from position two to Position 3.

Another body of evidence in favor of flexible letter position coding comes from the masked priming paradigm, which tests the influence of briefly presented prime words on the processing of subsequently presented target words. It has been shown that target words are recognized faster after a transposed-letter prime (e.g., *mother–mother*) as compared with a prime with different letters at the same positions (e.g., *monder–mother*; e.g., Andrews, 1996; Perea & Carreiras, 2006; Perea & Lupker, 2004). Further, Peressotti and Grainger (1999) found that the processing of six-letter target words was facilitated by four-letter relative-position primes (e.g., *mthr–mother*) as compared to unrelated primes (e.g., *lndn–mother*; see also Grainger, Granier, Farioli, Van Assche, & van Heuven, 2006; Van Assche & Grainger, 2006).

The need for more flexibility in the word recognition process has led to three major modeling approaches: *noisy slot-based coding*, *spatial coding*, and *relative-position coding*. Noisy slot-based coding refers to the addition of Gaussian noise to the slot-based scheme of the IAM (Davis & Bowers, 2004; Gomez, Ratcliff, & Perea, 2008), meaning that each letter of a stimulus word would not only activate the node representing that letter at its specific slot (s), but also in slots $s - 2$, $s - 1$, $s + 1$, $s + 2$, and so forth, with increasing eccentricity from the letter's true position leading to weaker activation. This Gaussian noise renders the system less efficient, but more flexible, and allows it to account for the transposed-letter priming effect discussed above. Spatial coding, as used in Davis's (1999, 2010a, 2010b) SOLAR model implements flexibility in a fairly similar way, by adding letter position uncertainty to a spatial code of letter representations. Additionally, the SOLAR model adopts flexibility through length-independence, meaning, for example, that *stop* would also activate *stopwatch*.

The third modeling approach, relative-position coding, abandons the IAM's slot-based scheme altogether. Instead, orthographic input is assumed to activate nodes that represent the relative position of within-word letter pairs (e.g., the stimulus *rock* would activate nodes for *ro*, *rc*, *rk*, *oc*, *ok*, and *ck*; see Whitney, 2001; Grainger & van Heuven, 2003). These so-called open-bigram nodes in turn activate all lexical representations that they belong to. The node *ro*, for example, would activate *rock*, but also *rose* and *ribbon*. Accounting for the transposed-letter priming effect (e.g., *rock* is primed more strongly by *rcok* than by *rduk*), the lexical representation of *rock* would be activated by a larger subset of open-bigram nodes with the former prime (*rc*, *ro*, *rk*, *ck*, *ok*) as compared with the latter prime (*rk*).

Although these three modeling approaches have all done a good job in explaining the experimental findings discussed above, some recent lines of research may slightly favor relative position coding over the other approaches. Specifically, it has been shown that processing of a foveal word is facilitated by simultaneously presented orthographically similar parafoveal words (e.g., *rock rack*) as compared with unrelated words (e.g., *rock dash*; Angele, Tran, & Rayner, 2013; Dare & Shillcock, 2013; Snell, Vitu, & Grainger, 2017). In a similar vein, using their flanking letters lexical decision (FLLD) paradigm, Dare and Shillcock (2013) found that lexical decisions about foveal target words (i.e., indicating whether the target is a word or nonword) were made faster and more accurately when the target was flanked by two parafoveal related letters on each side (e.g., *ro rock ck*) as compared with unrelated letters (*sp rock it*; see also Grainger, Mathôt, & Vitu, 2014; Snell, Vitu, et al., 2017). Crucially, the order of flanker bigrams did not matter (i.e., *ck rock ro* facilitated processing as strongly as *ro rock ck*), indicating the importance of relative- rather than absolute letter position.[1]

It is difficult to conceive how noisy slot-based coding would account for these findings. Regarding the flanker effects reported by Dare and Shillcock (2013), for example, a noisy slot-based model would have to assume that the letters in each slot of a four-letter target word would receive additional activation from a letter that is five slots away (given that there are five letter spaces between the *r* in *rock* and the *r* in *ro* in the example in the preceding text). Allowing letters to influence one another at such eccentricities would impair the model's performance greatly (indeed, simulations with the SOLAR model with high position uncertainty showed that the model was unable to distinguish extreme anagrams, (e.g., *bnoclay–balcony*; Davis, 2010b). In contrast, open-bigram coding explains these orthographic parafoveal-on-foveal effects quite effectively. Open-bigram units are location-invariant, meaning that both *rock* and *rack* in *rock rack* activate the nodes *rc*, *rk*, and *ck*, thus resulting in faster word recognition.

Considering that the open-bigram model has been applied only in settings where just one or two words were presented as visual input (e.g., Hannagan & Grainger, 2012), it remains to be seen whether the model would fare well processing normal text. A potential problem is that the visual input during text reading would activate a larger amount of bigrams compared with the visual input during single-word reading, subsequently increasing the chance that incorrect words are activated (e.g., *word* and *bonding*, leading to recognition of *wording*).

Models of Eye-Movement Control in Text Reading

Despite the important contribution of the aforementioned work to our understanding of the reading system, it is clear that reading is more than word recognition. Reading comprises a delicate interplay of various cognitive mechanisms, involving not only sublexical orthographic, lexical, and semantic processing, but also memory, visuospatial attention, and oculo-motor control.

Readers make roughly five saccades (i.e., eye movements) per second to bring words into the fovea, where visual acuity is the highest. In between those saccades, fixation durations (the time spent viewing a word) reflect the time-course of the word recognition process, and can be largely predicted by the length, frequency and predictability of the fixated word (Rayner, 1998, 2009; Sereno & Rayner, 2000) as well as surrounding (parafoveal) words (Kennedy & Pynte, 2005), implying an interaction between lexical processing and oculo-motor control.

Various models of eye-movements in text reading have been developed in the last few decades, all aiming to understand and predict reading behavior on the basis of properties of the text being read. The primary goal of these models is to provide accounts of when and where the eyes move during reading (Engbert et al., 2005; Reichle, Pollatsek, Fisher, & Rayner, 1998; Reichle et al., 2006; Reilly & Radach, 2006). With respect to when the eyes move, the models generally agree that lexical processing has some influence on the decision to move the eyes from one word to another. However, there is much less agreement on the factors driving lexical processing itself—in particular with respect to the role of visuospatial attention therein.

There are roughly two schools of theorizing about attention in reading, represented by sequential attention shift (SAS) models on the one hand and parallel graded processing (PG) models on the other. Driven by the general principle that serial word order is important for sentence comprehension, SAS models operate on the assumption that attention is allocated to exactly one word at a time and that attention shifts from one word to the next in strict serial order (Reichle, 2011; Reichle et al., 1998, 2006). The most prominent of these, the E-Z Reader model of Reichle and colleagues (1999, 2006, 2009b) has been able to account for many phenomena in reading behavior, such as the occurrence of word skips (i.e., instances where the eyes move from word n to word $n + 2$) and refixations (i.e., saccades that update the eye's fixation position within the same word), each representing approximately 20% of all eye-movements in reading (Rayner, 1998).

As has been acknowledged by Reichle, Pollatsek, and Rayner (2006) however, not all phenomena were accounted for by their model. In particular, the model does not explain regressive saccades (i.e., backward eye-movements to earlier points in the text), which make up approximately 10% to 20% of all eye-movements (Radach, Reilly, & Inhoff, 2007; Rayner, 1998). As of Version 10 of E-Z Reader, Reichle et al. (2009b) did incorporate a postlexical processing stage, whereby recognized words would have a certain chance of not fitting with the prior context, thereby prompting a regressive saccade. This process of fitting recognized words with the prior context was not actually modeled in E-Z Reader; rather, regressions were triggered by sampling from a random distribution, intended as "[. . .] a placeholder for a deeper theory of post-lexical language processing during reading" (Reichle, Warren, & McConnell, 2009b, p.7). Although such an approach would indeed allow a model to generate any desired number of regressions, the result is a model that mimics, rather than explains, reading behavior.

E-Z Reader determines its next saccade target by aiming for the center of the closest unrecognized word. The final saccade amplitude is subject to random and systematic error, the latter of which is a tendency to err toward a standard amplitude of seven letters, hence accommodating the finding that saccades shorter than the standard amplitude tend to overshoot the target, whereas longer saccades tend to undershoot the target (McConkie, Kerr, Reddix, & Zola, 1988).

[1] Note, however, that there may be additional mechanisms at play that allow readers to have some knowledge of absolute letter position—at least to the extent of knowing whether letters are situated to the right or left of fixation. In a study using six-letter targets and three-letter flankers, Snell, Bertrand, and Grainger (2018) found that the order of flankers had an influence on target recognition speed (e.g., *target* was recognized faster in *tar target get* than in *get target tar*). Accounting for the discrepancy between these results and results reported by Dare and Shillcock (2013) and Grainger et al. (2014) (i.e., *ck rock ro* and *ro rock ck*, yielding equal response times), Snell, Bertrand, et al. (2018) posited that stimuli comprising more letters bear more processing weight, causing increased lateral activation at early visual processing stages and consequently allowing higher processing levels to make stronger distinctions between information stemming from the left and right visual hemifields.

The theoretical alternative to the SAS approach, represented by PG models, abandons the idea that words are processed in strict serial fashion. Instead, this approach assumes simultaneous processing of multiple words, with the amount of processing per word being modulated by a visuospatial attentional gradient (e.g., Engbert & Kliegl, 2011). The most prominent PG framework is the SWIFT model of Engbert et al. (2005). SWIFT is based on dynamic field theory and assumes that each word in the perceptual span (i.e., the span of effective vision) has a level of activity that represents both the extent to which it is recognized as well as the probability that it is targeted by the next saccade (Engbert & Kliegl, 2011). The Gaussian distribution of visuospatial attention causes words near the center of attention to be activated more strongly, making it likely that foveal words are recognized sooner than upcoming words. As soon as a word reaches its recognition threshold (determined by word length and frequency), its activity falls back to zero, so that it will not be targeted by the next saccade. It is possible however, that previously fixated (or skipped) words have not yet been recognizedand that their activation level triggers a backward saccade. As such, SWIFT has implemented an account of regressions whereas the E-Z Reader model of Reichle et al. (1999, 2006, 2009b) has not (even though the latter model does make regressions, as outlined in the preceding text).

In SWIFT, the decision of when to move the eyes is determined by sampling from a random distribution, with an inhibition of random saccade timing by the amount of activation of the currently fixated word (Engbert & Kliegl, 2011). Thus, whereas SWIFT and E-Z Reader differ strongly in the decision of where to move the eyes (dynamic field activation vs. hardcoded selection of the first unrecognized target, respectively), the decision of when to move the eyes is made in a similar fashion.

With their Glenmore model, Reilly and Radach (2006) provided a PG framework that is fairly similar to SWIFT, in that saccade targets are determined by dynamic field activation. The main difference between the two models is that Glenmore starts operating at the letter-level, whereas SWIFT (like E-Z Reader) operates at the word level only. In Glenmore, the combined activities of a word's constituent letters determine the activity of the word, and the word with the highest activity becomes the next saccade target (this is fairly similar to SWIFT, in which the most salient word has the highest probability of being fixated). Despite operating at the letter level, Glenmore is not a model of orthographic processing in text reading: each letter unit in the visual field is connected to the appropriate word a priori, meaning that orthographic processing and subsequent lexical selection is assumed rather than modeled. As was acknowledged by Reilly and Radach (2006), the primary focus of their model was on saccade target selection rather than to implement a realistic word recognition module.

Glenmore differs from SWIFT and E-Z Reader in the decision of when to move the eyes. Whereas saccade program initiation in SWIFT and E-Z Reader operates on a random timer, in Glenmore saccades are initiated when the summed activation of all letters in the visual field reaches a certain threshold.

Whether words are processed serially or in parallel is still disputed. Yet, recent research has provided various types of evidence in favor of parallel processing. The first type of evidence is provided by corpus data, which has shown that the time spent viewing word *n* is influenced by the frequency and length of word *n* + 1 (Kennedy, 2008; Kennedy & Pynte, 2005), which is a natural consequence of parallel but not serial processing. The second type of evidence comes from experiments using the gaze-contingent boundary paradigm (Rayner, 1975) to manipulate word *n* + 1 during the fixation on word *n*. Such experiments have shown not only that (upcoming) parafoveal words can be lexically processed prior to being fixated (Hohenstein & Kliegl, 2014; Hohenstein, Laubrock, & Kliegl, 2010; Schotter, 2013; Snell, Meeter, & Grainger, 2017; Veldre & Andrews, 2015, 2016), but also that processing of the upcoming word can occur simultaneously with processing of the fixated word (Angele et al., 2013; Dare & Shillcock, 2013; Inhoff, Radach, Starr, & Greenberg, 2000; Snell, Vitu, et al., 2017). Finally, a third body of evidence is provided by the FLLD studies discussed in the Models of Word Recognition section. In these studies, foveal target word processing was shown to be influenced by parafoveal flanking stimuli (Dare & Shillcock, 2013; Grainger et al., 2014; Snell, Bertrand, et al., 2018; Snell, Vitu, et al., 2017), despite the short stimulus on time (150 ms).

Proponents of serial word processing have taken these findings to argue that parallel processing may occur on a sublexical (letter) level, but that actual lexical access would still occur on a serial basis. Yet, using higher-order (syntactic, semantic) variants of the FLLD paradigm, it has been shown that syntactic decisions (e.g., classifying targets as *noun/verb*) and semantic decisions (e.g., classifying targets as *natural/artifactual object*) were made faster with respectively syntactically and semantically congruent flankers, as compared to incongruent flankers (Snell, Meeter, et al., 2017).

On the other hand, similar higher order parafoveal-on-foveal effects have been elusive in sentence reading (e.g., Angele et al., 2013; Snell, Meeter, et al., 2017; Snell, Declerck, et al., 2018). This absence of higher order parafoveal-on-foveal effects in sentence reading being largely regarded as evidence in favor of serial processing, relatively little attention has been paid to the possibility that higher order information is simply not integrated across words during sentence reading, even if parallel processing were true. As argued by Snell, Meeter, et al. (2017; Snell, Declerck, et al., 2018), a successful parallel processing model would have to keep track of which information belongs to which word, rather than to integrate everything into a single mixture, given that each word has a unique role in contributing to sentence comprehension. The solution to this parallel processing problem, as proposed by Snell, Meeter, et al. (2017; Snell, Declerck, et al., 2018), is that activated words would be mapped onto a spatiotopic sentence-level representation, guided by expectations about word length and syntactic structure. Such a mechanism would prevent parafoveal-foveal integration of higher order information during sentence-reading, whereas integration of parafoveal and foveal information can still be shown outside a sentence-reading setting—postlexically—for instance at the level of making decisions as has been shown in the flanker paradigm.

Interestingly, a key argument against parallel processing has been that a parallel processing system would not be able to recognize words in the correct order (e.g., Reichle, Liversedge, Pollatsek, & Rayner, 2009a). The sentence-level representation effectively overcomes this challenge, by positing that activated words are associated with plausible locations. For instance, in "The scientist is here," *is* may be recognized before *scientist*, but the former is much more likely to be associated with Position 3 than with Position 2 because of low-level visual cues (a two-letter word is expected at Position 3 but not at Position 2) and syntactic constraints (given the article at Position 1, a verb is not expected at Position 2).

In line with the idea of a spatiotopic sentence-level representation is the finding that readers can make very accurate regressions to earlier points in the text to resolve syntactic ambiguity (e.g., MacDonald, Pearlmutter, & Seidenberg, 1994; Inhoff, Weger, & Radach, 2005), which suggests that readers must retain some representation of the syntactic structure of the sentence in working memory. Further evidence for the role of a sentence-level representation in parallel processing was provided by Snell and Grainger (2017). In line with Snell, Meeter, et al. (2017; Snell, Declerck, et al., 2018), they theorized that feedback from the sentence level to the level of lexical representations would constrain the recognition process for individual words. A simple prediction that follows from this theory is that word recognition should be better in a syntactically sound context versus a syntactically incorrect context. In line with this prediction, using the novel rapid parallel visual presentation paradigm, Snell and Grainger (2017) found that the recognition of target words in briefly presented (200 ms) four-word arrays was better when those words formed a correct sentence, compared with when the same words were presented in a scrambled, ungrammatical order (with the target being presented at the same location in both conditions). This sentence superiority effect did not vary as a function of the target's position in the sequence, indicating that syntactic information was indeed retrieved from all four words during their 200-ms presentation time.

OB1-Reader: Key Features and Architecture

Summarizing the previous section, the single-word recognition literature has spawned several modeling approaches, with recent evidence favoring relative position coding. Similarly, although two competing sets of models exist in the domain of eye-movement control in text reading, parallel graded processing models have received somewhat more support recently. These two approaches, relative position coding for word recognition on the one hand and PG-modeling for text reading on the other, make quite a natural fit. Both approaches assume parallel processing, with relative position coding assuming parallel letter identification in multiletter strings, and PG-models assuming parallel processing of multiple words.

The question that remains is whether information from multiple words in a text could be successfully processed by a model that integrates these two approaches. Indeed, relative position coding models have only been tested in situations where the visual input was comprised of one or two words, while PG-models have abstracted away from the level of sublexical orthographic processing where confusion may occur. Hence, OB1-reader was developed to test whether a combination of relative letter-position coding and parallel graded word processing could yield behavioral patterns that are in accordance both with the literature on word recognition and the literature on eye-movements in text reading.

In the present section, we turn to a detailed description of OB1-reader. OB1 has five key components, which are shown in Figure 1 and which are discussed in the following subsections. An overview of the model's parameters is presented in Table 1.

Spatially Distributed Processing

During each fixation, the visual input is comprised of the fixated word (n), along with words $n-2$, $n-1$, $n+1$, and $n+2$.[2] Letters are perceived with variable strength depending on the visual acuity at those letters' respective eccentricities and how attention is distributed across the visual field.

As acuity diminishes with eccentricity, visual input v_i generated by a letter i is assumed to be a decreasing function of eccentricity e_i, computed by assuming a letter size of .33 letters per degree of visual angle. Moreover, visual input is a function of the attentional weight a_i (see Equation 2) and a masking factor m_i. The masking factor reflects crowding, which causes letters to be less visible in the word's center than at its edges or in isolation (Grainger, Tydgat, & Isselé, 2010; Marzouki & Grainger, 2014; Perea & Gomez, 2012). Following Marzouki and Grainger (2014) who found that the recognition of briefly presented (91 ms) letters at Position 2 was approximately half as good as that of letters at Position 1, m_i is set to 1 when i is an outer positioned (edge) letter, and it is set to 0.5 when it is an inner positioned letter. Together, these three factors determine visual input v_i in the following way:

$$v_i = a_i \times m_i\left[1 \Big/ c_e\left(0.018 * e_i + \frac{1}{0.64}\right)\right]. \tag{1}$$

The factor within brackets represents eccentricity's influence on the input and is assumed to be proportional to cortical magnification in V1 (the increase in cortical space devoted to locations closer to fixation). The term within parentheses was taken from Harvey and Dumoulin's (2011) estimate of cortical magnification in humans. Because this formula computes millimeters of cortex, constant c_e rescales magnification so that its maximum value, obtained for letters at the fixation location, equals 1 ($c_e = 35.56$).

Attention (i.e., a_i in Equation 1) modulates the input according to a Gaussian distribution centered on the focus of attention. This approach to implementing attention is similar to that used in other parallel graded models of reading, such as SWIFT (Engbert et al., 2005) and Glenmore (Reilly & Radach, 2006). The attentional weight a_i that a letter i receives is a function of f_i—its distance in letters to the focus of attention and attentional width.

$$a_i = \frac{1}{width} \times e^{-\frac{(f_i)^2}{2*(width*asym)^2}} + c_a. \tag{2}$$

This function describes a Gaussian centered around an attentional focus, with the standard deviation of the Gaussian functioning as a changeable width and a hemispheric asymmetry (*asym*). *Asym* is equal to 1 toward the right and 0.25 toward the left, in line with literature suggesting that the span of effective processing is approximately four times greater to the right (14 to 15 letters) than to the left (3 to 4 letters; e.g., Rayner, 1986, 1998). Outside the Gaussian, the attentional weight is set to constant c_a (fixed at 0.25). The width of the attentional distribution is variable, and is determined by recent success and failure in word recognition: it increases after successful recognition, and decreases again after failure so as to produce more precise reading. As such, the atten-

[2] Clearly, the visual input during text reading normally comprises more than five words. However, we assumed that the influence of words beyond two positions from fixation would be negligible. We therefore limited the number of visible words to five for computational efficiency.

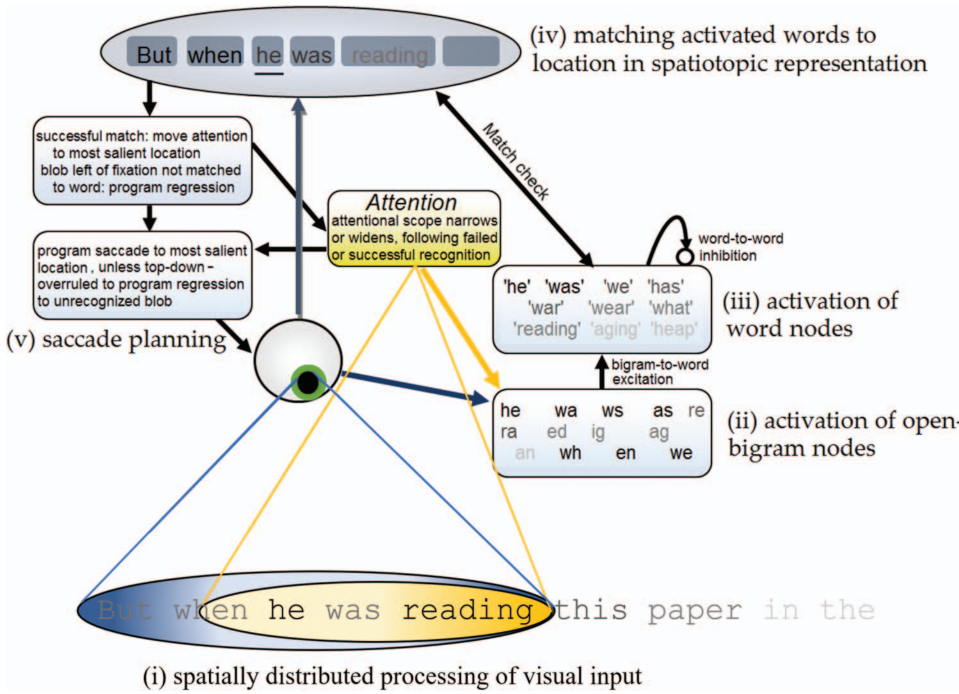

Figure 1. Schematic diagram of OB1-reader. (i) OB1 sees multiple words at a time (two words on either side of the fixated word; i.e., he in this figure). Letters occupy 0.33 degrees of visual angle. Within the visual input, letter processing is modulated by visual acuity and visuo-spatial attention. The attentional distribution is skewed towards the right. The focus of attention can be shifted independently of the eye's fixation. (ii) Open-bigram nodes are activated by the visual input, with stronger activation of letters that are close to the centers of fixation and attention, but weaker activation of crowded letters. (iii) Word nodes are activated by nodes coding for open-bigrams that occur in the word. Word nodes are inhibited by word nodes that share the same bigrams. (iv) Upon fixating a text, OB1 generates a spatiotopic sentence-level representation that represents expectations about the length of individual words. Word nodes that reach a recognition threshold are matched to locations (i.e., "blobs") in the spatiotopic representation based on length. OB1 recognizes a word only when it can be mapped onto a plausible location. Recognized words generate expectations about upcoming words, through feedback activation of word nodes based on cloze-probability. When a word is successfully recognized, attention moves ahead of the eyes to the most salient location. Each word's saliency is determined by the proximity of its letters to the centers of fixation and attention. (v) Whether a saccade program is initiated is stochastically determined in each 25-ms processing cycle, with successful word recognition increasing the chance of initiation. The center of the most salient word form in the visual input becomes the saccade target. Saliency-based saccade targeting is overruled when a word location to the left of fixation has not yet been marked as recognized. Instead, a regression to that location will be executed. The attentional gradient is widened after each fixation during which a word is successfully recognized, although it is narrowed after each fixation without successful recognition. See the online article for the color version of this figure.

tional distribution adapts to the skill of the reader and the difficulty of the text that is being read (see Ans, Carbonnel, & Valdois, 1998, for a similar proposal). Width can vary between three and five letters. It is increased 0.5 with every forward saccade and reset to 3 with every regression. This flexible control of attention was not investigated extensively in the current simulations but will be in future work.

Thus, each letter in the visual input is appointed a weight, set by its eccentricity, its distance from the focus of attention and by whether or not it is adjacent to a space. The model is simulated in cycles of 25 ms, with each saccade lasting one cycle. Visual input is constant during each fixation, and is absent during saccades to simulate saccadic suppression (Campbell & Wurtz, 1978; Erdmann & Dodge, 1898).

Activation of Open-Bigrams

All combinations of letters activate open-bigram nodes that respect the relative order of their constituent letters in the visual input. An open-bigram node is only activated when its constituent letters are within the same word (Grainger et al., 2014) and not further apart from one another than three letter positions. As in Grainger and van Heuven (2003), the activation of each open-bigram node is equal to the square root of its constituent letters' multiplied weights (as defined in Equation 1). Hence, output O_{ij} of such a bigram node is computed as follows:

$$O_{ij} = \sqrt{v_i v_j} \text{ if } i, j \text{ within same word and max. 3 letters apart; } 0 \text{ otherwise.} \quad (3)$$

Table 1
OB1 Parameters

Parameter	Description	Equation	Value	Determination
τ	Decay	4	.05	Heuristic fitting
c_1	Bigram-to-word excitation	4	.0044	Heuristic fitting
c_2	Word-to-word inhibition	4	.0018	Heuristic fitting
c_e	Scaling cortical magnification	1	35.56	Cortical magnification derived from Harvey and Dumoulin (2011), scaled so as to have max. 1
m_i	Masking factor describing crowding	1	1 for outer letters, .5 for inner letters	Marzouki and Grainger (2014)
Asym	Asymmetry of attention	2	1 toward the right, .25 toward the left	Four times greater toward the right than toward the left (Rayner, 1998)
c_a	Residual attentional weight outside of focus of attention	2	.25	A priori
Maximum/minimum attention	Maximum and minimum size of attentional window	2	5.0/3.0	A priori
Time step	Duration of 1 time step		25 ms	Average duration of a saccade
c_4	Weight of word frequency in threshold setting	5	5.5	A priori
c_5	Weight of predictability in threshold setting	5	9.0	A priori
c_6	Maximum lowering of threshold for short words	5	.61	A priori
c_7	Scaling of effect	5	.44	A priori

Note. A priori parameters were fixed prior to simulating the Potsdam Sentence Corpus.

Activity of single-letter bigrams, for example, *#i,* is computed using the same formula, with j substituted for i (resulting in v_i being squared). If an open-bigram occurs multiple times in the visual input (e.g., *ta* in *that task*), its activation is the sum of the output from each individual occurrence.

Activation of Word Nodes

All open-bigram nodes are connected to nodes coding for the words in which they occur, and during reading those word nodes receive input equal to the sum of their constituent bigram activities. Activity of a word w, S_w, is initialized at 0 and is bound to the interval between 0 and 1. It is updated each time step with the following difference equation:

$$\Delta S_w = -\tau S_w + (1 - S_w) \times \left[c_1\left(\sum\nolimits_{i,j \in w} O_{ij}\right) - c_2\left(\sum\nolimits_k d_{w,k} S_k\right)\right]. \quad (4)$$

In this equation, the first right-hand term gives passive decay back to a value of 0 ($\tau = .05$). This implements the idea that words' activities should decline in the absence of visual input (e.g., during saccades). The second term describes the input to the word node, multiplied by a factor $(1 - S_w)$ that induces an asymptotic increase toward the maximum activity (equal to 1).

The input, between brackets, consists of, first, excitatory input from the bigram nodes that are part of the word. This sum is multiplied by a constant c_1 (set to 0.0044). The second part of the input comprises inhibition from other word nodes. During word processing, activated lexical representations that share at least one open-bigram are considered to be lexical competitors (Grainger & van Heuven, 2003). To lower the chance that a word in the visual input leads to recognition of more than one word (i.e., instances where multiple word nodes reach the recognition threshold simultaneously), these lexical competitors exert mutual inhibition. The more active a word node is, the stronger its inhibition on competing word nodes will be. Additionally, inhibition is influenced by the amount of orthographic overlap between each word pair: Words that share many open-bigrams inhibit each other more than words that do not. This can be thought of as a weight on the inhibitory connection between word nodes. Activity from each word node k is therefore weighted by a factor $d_{w,k}$ that is equal to the number of open bigrams shared between the words. This term is multiplied by constant c_2 (equal to 1.4 divided by the size of the lexicon, since word-to-word inhibition increases with larger lexicons). This architecture is equal to that used in the open-bigram model of Grainger and van Heuven (2003).

OB1 recognizes a word when activation of a word node reaches a recognition threshold. This threshold is influenced by the length, frequency and predictability (given preceding words) of each respective word (i.e., longer, less frequent and less predictable words have a higher threshold; e.g., Bicknell & Levy, 2010; Kennedy & Pynte, 2005; Kliegl, Grabner, Rolfs, & Engbert, 2004; Rayner, 1998) with the following formula:

$$T = C\frac{c_4 ln(freq_{max}) - ln(freq_w)}{c_4 ln(freq_{max})} \times \frac{c_5 ln(pred_{max}) - ln(pred_w)}{c_5 ln(pred_{max})} * (1 - {c_6}^{-c_7 l_w}). \quad (5)$$

Here, l_w is the length of word w, $freq_w$ is the frequency with which w occurs within a reference corpus (we used SUBTLEX-DE for German), and $freq_{max}$ is the frequency of the most frequent word within that corpus. $Pred_w$ is the cloze probability of w given the preceding words (values obtained by Kliegl et al., 2004 and Laubrock & Kliegl, 2015), and $pred_{max}$ is the maximum cloze probability within the sentence corpus. Scaling parameters c_4 and c_5 determine the size of the effect of frequency and predictability on the threshold, with lower values indicating stronger effects;

these were set to 5.5 and 9.0, respectively. Scaling parameters c_6 and c_7 (values 0.61 and 0.44, respectively) alter the size of the effect of frequency and predictability as a function of word length, to compensate for the stronger excitation of long words. Overall scaling value C was set to .22 (C was not an independent free parameter, because it can be scaled against the input parameters c_1 and c_2). Similar variable recognition thresholds are used by E-Z Reader and SWIFT (in contrast, in Glenmore, increased frequency and predictability lead to stronger per-cycle activation, rather than a lower recognition threshold).

The Spatiotopic Representation

Because open-bigram information is location-independent, OB1 does not inherently know which activated lexical representation belongs to which spatial location. However, low-level visual information allows OB1 to generate expectations about the number of to-be recognized words in the visual field and their approximate length; (as is illustrated in Figure 1, to-be recognized words are initially perceived as "blobs"). This information operates as a spatiotopic sentence-level representation in working memory, to which word identities may be appended, or on the basis of which activated word candidates may be rejected (e.g., Snell, Meeter, et al., 2017; Snell, Vitu, et al., 2017). As such, word recognition would be a process of matching activated representations to perceived blobs: The length of the activated representation must meet the expected word length for the representation to count as recognized. As an example, the phrase *sit for dinner* may lead to erroneous recognition of the word *sinner* (which would be mapped onto the third word position because it has a matching length) but not *beginner*, because the latter representation does not match any of the word lengths occurring in the phrase. Moreover, if the eyes were fixated on the first word, but the node coding for *for* reaches its threshold earlier than *sit*, *for* would be erroneously linked to the first word position.

The spatiotopic representation is implemented by means of the creation of an array of word lengths (representing length in number of letters for words $n - 2$ to $n + 2$) on each fixation. The array's indices represent word positions, and these are marked either as *recognized* or *not recognized*. Prior to the activation of a given word in the OB1 lexicon (as per the mechanisms described in the Activation of Word Nodes section), a check is performed whereby the word has to match one of the values in the array. When the word's length does not approximate any of the values, the word does not receive activation. Similarly, when a word reaches its recognition threshold, its length has to approximate one of the array's not recognized length values to be count as recognized. It would not be realistic to assume that OB1 is able to count letters in the periphery, so word length is estimated with a 15% error margin, such that a seven-letter representation might also be matched to a six- or eight-letter word form in the spatiotopic representation.

Saccade Planning

Research has indicated that it takes approximately 125 ms to plan and execute a saccade (e.g., Becker & Jürgens, 1979; Meeter & Van der Stigchel, 2013). Thus, given that the average time spent viewing a word is short (around 200 ms to 300 ms; see, e.g., Rayner, 1998), the decision to execute a saccade has to take place in the first 100 ms of a fixation (but do note that longer fixations principally allow for more lenient numbers). This has led researchers to argue that word recognition cannot be the sole factor driving eye-movements in reading (e.g., Reichle, Rayner, & Pollatsek, 2003). In each of the OB1 processing cycles, random sampling from a Gaussian distribution $N(\mu,\sigma)$ determines whether a saccade program is initiated (this approach is similar to that used in SWIFT and E-Z Reader). Lexical processing influences the decision of when to move the eyes in so far that a wider range of values from this distribution is taken as decision to program a saccade when a word is recognized ($\sigma = 125$ ms, $\mu = 50$), as compared with when no word has been recognized yet ($\sigma = 95$ ms, $\mu = 50$ ms). Whenever the time that has elapsed since the last eye movement is larger than this sample, attention is shifted in the direction of the upcoming saccade (e.g., Baldauf & Deubel, 2008). Processing of upcoming words may thus be enhanced during saccade programming. An eye movement rigidly follows 100 ms after each attentional shift. With the 25-ms motor delay, this aligns with the 125-ms estimate for saccade planning.

Under normal conditions, the saccade target location is determined by the visual salience of word forms in the visual field. This salience is the sum of the weights of words' constituent letters, as determined by crowding, eccentricity, and proximity to the focus of attention (see the Spatially Distributed Processing section). Large words close to the focus of attention are usually most salient, and are thus selected as the target. This approach to saccade target selection is equal to that employed in the Glenmore model of Reilly and Radach (2006) and fairly similar the SWIFT model of Engbert et al. (2005) in which a word's activity determines the probability with which it is fixated (in contrast, in the E-Z Reader model of Reichle et al. [2003], word activation does not play a role, as the first nonrecognized word is selected as the saccade target). The center of the target word is taken as the intended landing location. However, because saccades are imprecise, the final location is affected by both systematic and random error. The systematic error reflects the principle that eye movements tend to overshoot nearby targets and undershoot faraway targets (e.g., Kapoula & Robinson, 1986; McConkie et al., 1988) and is modeled as a tendency to err toward a standard distance, D (set to seven letters). Random error is assumed to be Gaussian, with a standard deviation increasing as a function of intended saccade size. The number of letters moved, h, given a target distance d, is therefore equal to, rounded to the nearest integer:

$$h = N(\mu, \sigma) \quad \text{with} \quad \mu = d + .2(d - D), \sigma = .18 + .08d. \tag{6}$$

For the word that is already being fixated, salience is computed only for the portion to the right of the currently fixated letter. This prevents leftward letters from having an influence when the intention is to make a forward (rightward) saccade. Naturally, that is not to say that leftward letters are not visible; rather, we assume that the direction of the saccade (left/right) is determined before the actual goal of the saccade. Given that the two visual hemifields are represented in different hemispheres of the brain, the directional decision entails that saliency is computed for visual input in one hemisphere without interference from the other.

It is possible that saliency-based target selection is overruled by the need to make a regression. This happens when any of the words that the eyes have already gone past has not yet been marked as recognized (i.e., there would still be an unmarked blob to the left of the fixated location in the spatiotopic representation; see the Spatiotopic Representation section). In such a case, the unrecognized word is marked as the target, prompting a regressive saccade. An unrecognized word can trigger only one regression: If this does not result in successful recognition, the word is simply left unidentified (which would reveal a weakness in the OB1 word identification capabilities).

Evaluation of the Model

We expect OB1 to account for a range of low-level reading phenomena, such as refixations, regressions, word skips, preview effects, and spillover effects. Its word recognition mechanisms should be able to account for orthographic parafoveal-on-foveal effects (e.g., Angele et al., 2013; Dare & Shillcock, 2013; Grainger et al., 2014; Snell, Vitu, et al., 2017), neighborhood effects (e.g., Acha & Perea, 2008; Grainger et al., 1989; Perea & Pollatsek, 1998) and possibly lexical parafoveal-on-foveal effects as reported by Kennedy and Pynte (2005). We also expect OB1 to account for the occasional misreading (i.e., instances of erroneous word recognition), which is something no previous model of text reading has been able to simulate. Quantitatively, OB1-reader should depict a distribution of word viewing times similar to that obtained in experimental settings. In particular, we expect OB1 to show word length, frequency, and predictability effects, all of which are well-established in the literature (e.g., Rayner, 1998).

The present section describes how we evaluated these factors. Our assessment consisted of two parts: First, we let OB1 read sentences from the Potsdam sentence corpora (PSC; Kliegl et al., 2004; Laubrock & Kliegl, 2018) and compared simulation results with their experimental data. Second, we simulated the experiment of Dare and Shillcock (2013) that obtained an orthographic parafoveal-on-foveal effect using the gaze-contingent boundary technique to manipulate word $n + 1$ during the fixation on word n. For the sake of consistency, this simulation also made use of the PSC reading materials, rather than the stimuli used by Dare and Shillcock.

The PSC Simulation

Reading materials. We used the 577 sentences (4,921 words) from the EyetrackR package (Laubrock & Kliegl, 2018) as reading materials. This package comprises the PSC (Kliegl et al., 2004), PSC2 (the second Potsdam sentence corpus; Laubrock & Kliegl, 2015), and a sample of the Potsdam Commentary Corpus (Stede & Neumann, 2014). The experimental data obtained with these materials comprises eye-movement data of 180 participants between 15 and 80 years old. The log-frequency of each word in these texts was determined with the SUBTLEX-DE database of Brysbaert et al. (2011) and is based on the occurrence of the word in German subtitles for film and TV. Kliegl et al. (2004) and Laubrock and Kliegl (2015) obtained the predictability value for each word using the incremental-cloze task.[3]

OB1 was given a mental lexicon comprising all the words occurring in one or more of the three PSC, such that the lexicon contained 701 unique word forms. We further made sure that the 200 highest frequency words as indicated by the SUBTLEX-DE database of Brysbaert et al. (2011) were part of the lexicon, leading us to add another 75 words to bring the final lexicon size up to 776 words.[4]

Model parameter fitting. An overview of all parameters is presented in Table 1. We make a distinction between free and fixed parameters. Free parameters are parameters for which we could not make reasonable estimations, and which were thus determined through trial and error. These include decay, bigram-to-word excitation and word-to-word inhibition. Fixed parameters were determined a priori, with values being based on reasonable theoretical assumptions (e.g., values reported in the literature).

The process of fitting the model's free parameters (i.e., bigram-to-word excitation, word-to-word inhibition and per-cycle activity decay) consisted of, first, taking values representing bigram-to-word excitation and word-to-word inhibition from the open-bigram model of Grainger and van Heuven (2003), and second, repeatedly letting the model read short texts and making continuous slight parameter adjustments to approximate realistic model output. Here, we mainly focused on word viewing times and fixation type probabilities. It is possible that a more extensive parameter search would have yielded better quantitative fits (but see, e.g., Roberts and Pashler (2000) for arguments against the importance of quantitative fit). During the heuristic fitting process, we first fitted Dutch and English short texts, before going on to use the PSC2 reading set. Switching text language did not noticeably affect model performance. Note that all final parameter values were fixed during the actual simulation.

Procedure. The 577 sentences were presented to OB1 as one continuous sequence of words. Given that its saccade planning mechanisms make OB1 nondeterministic, we let OB1 read the materials four times, and the simulation results thus represent an average of these four simulations. Because of the size of the stimulus set, each replication yielded similar averages and adding replications did not alter results.

Simulation results. Figure 2 shows the various fixation type probabilities for OB1 compared with the Potsdam experimental data. The simulated fixation type probabilities approach the experimental data quite well, with a slight overestimation of the amount of refixations and regressions and a slight underestimation of the amount of single fixations. Moreover, these probabilities were modulated by word length (see Figure 3), frequency (see Figure 4), and predictability (see Figure 5) in a way very similar to that depicted by the Potsdam experimental data.

Like the experimental data, OB1 shows an effect of word length on word viewing times, with longer words leading to longer viewing times (see Figure 6). In both the simulated and experimental results this effect is expressed in gaze duration (GD) and

[3] In the incremental-cloze task, participants start each trial by guessing the first word of a sentence, after which the actual word is displayed and participants have to guess the next word. This process continues until the end of the sentence is reached (see Kliegl et al., 2004).

[4] We acknowledge that the present lexicon size is relatively small compared with the actual number of words known by skilled readers. It should be noted, however, that the present lexicon size is comparable to that used in single-word recognition models. Moreover, larger lexicons would slow the simulations exponentially.

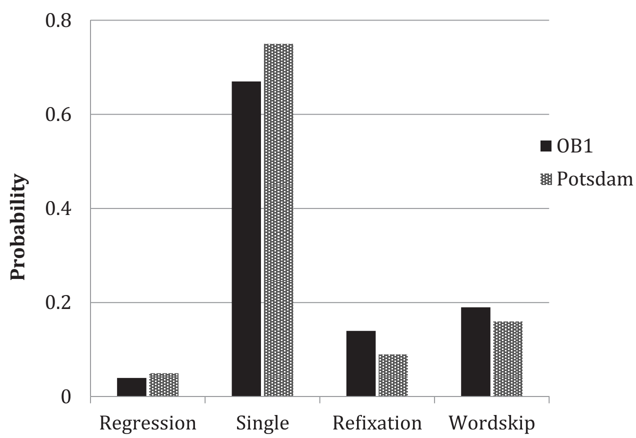

Figure 2. Fixation type probabilities for the simulated data of OB1 and the Potsdam experimental data.

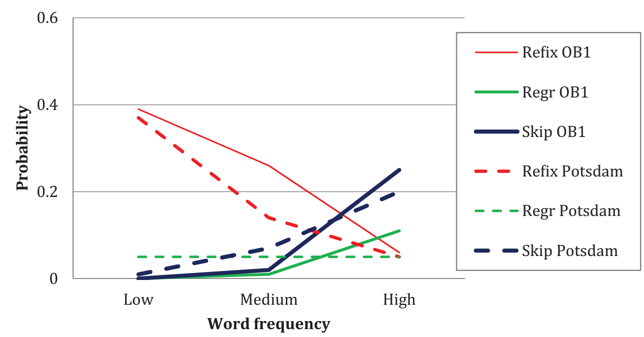

Figure 4. Fixation type probabilities for the simulated data of OB1 (solid lines) and the Potsdam experimental data (dashed lines), as modulated by word frequency (data was split into log-frequency tertiles). Refix = refixation; Regr = regression. See the online article for the color version of this figure.

total viewing time (TVT), but not in the single fixation duration (SFD). Here, SFD refers to cases where words were fixated only once. GD refers to the sum of all first-pass fixations, that is, the sum of first fixations and refixations but not refixations following a regression. TVT refers to the sum of all fixations including regressions. OB1 also depicts an effect of word frequency on word viewing times similar to that of the Potsdam experimental data (see Figure 7).

The saccade amplitude (i.e., the distance between two consecutive fixations) was slightly less variable in the simulation than in the experimental data (see Figure 8). The normal forward saccades (from word n to word $n + 1$) were slightly shorter in OB1, whereas word skipping saccades tended to be longer.

We also tested for lag and successor effects, whereby the time spent viewing word n is influenced by the frequency and predictability of words $n - 1$ and $n + 1$ respectively (Kennedy & Pynte, 2005). Although these effects occurred in the experimental data, they could not be captured in the simulation results (Figures 9 and 10). We address this point in the General Discussion.

The last thing that we tested for in this simulation was the neighborhood size effect, whereby word recognition is slowed as the number of existing high-frequency orthographic neighbors (e.g., *blur–blue*) increases (Acha & Perea, 2008; Grainger et al., 1989; Perea & Pollatsek, 1998). We plotted the GD against the neighborhood size, and indeed found that GD increased with an increasing amount of high-frequency orthographic neighbors (see Figure 11).

Unrecognized words. Approximately 1% of the words were not recognized by OB1. Strikingly, as can be seen in Figure 12, word recognition probability was the lowest for two-letter words. It would be difficult to establish how many words are misread during normal reading, as postlexical processes (which are lacking in OB1) would probably correct many errors. For example, Angele and Rayner (2013) have shown that readers tend to not notice (and skip) the article *the* when it is at an incorrect position (such as in this sentence, right after the reference), indicating that in normal reading, high-frequency function words may go unrecognized as well.

Simulation of the Boundary Paradigm

Procedure. Next, we simulated the gaze-contingent boundary technique as used by Dare and Shillcock (2013), Angele et al.

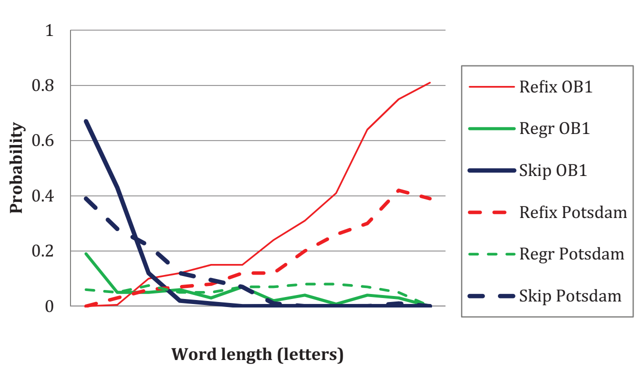

Figure 3. Fixation type probabilities for the simulated data of OB1 (solid lines) and the Potsdam experimental data (dashed lines), as modulated by word length. Refix = refixation; Regr = regression. See the online article for the color version of this figure.

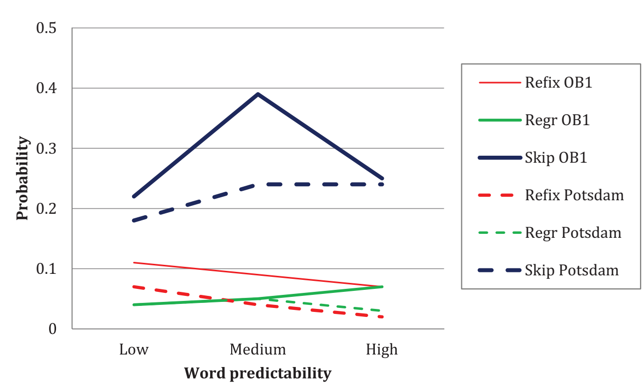

Figure 5. Fixation type probabilities for the simulated data of OB1 (solid lines) and the Potsdam experimental data (dashed lines), as modulated by word predictability (data was split into predictability tertiles. Refix = refixation; Regr = regression. See the online article for the color version of this figure.

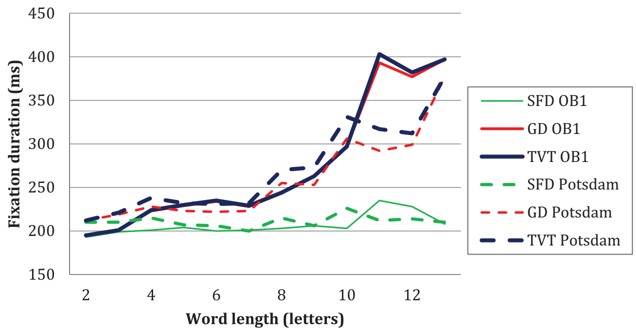

Figure 6. Word viewing times across all word lengths occurring in the corpora, for OB1 (solid lines) and the Potsdam experimental data (dashed lines). SFD = single fixation duration; GD = gaze duration; TVT = total viewing time. See the online article for the color version of this figure.

(2013), and Snell, Vitu, et al. (2017). For this simulation, we filtered all sentences with the occurrence of two adjacent four- or five-letter words from the reading materials of the EyetrackR package (e.g., "The people stay here now"). The first of the two adjacent words was marked as the target in all these sentences, and for each target we retrieved a control word from the SUBTLEX-DE database (Brysbaert et al., 2011) that was equal in length, had no orthographic overlap with the target, and had a log-frequency value that deviated from the target's by 1.0 at most (e.g., *stay–jump*).

Each of these sentences was presented three times to OB1: once with the target word (position n) being repeated at position $n + 1$ during the fixation on n (e.g., "The people stay stay now"; the repetition condition), once with the control word at position $n + 1$ (e.g., "The people stay jump now"; the control condition), and once in the original form (e.g., "The people stay here now"; the baseline condition). During the saccade from word n to word $n + 1$, the latter word was changed into its original form (thus, nothing changed in the baseline condition). The word viewing times on n were compared across these three conditions.

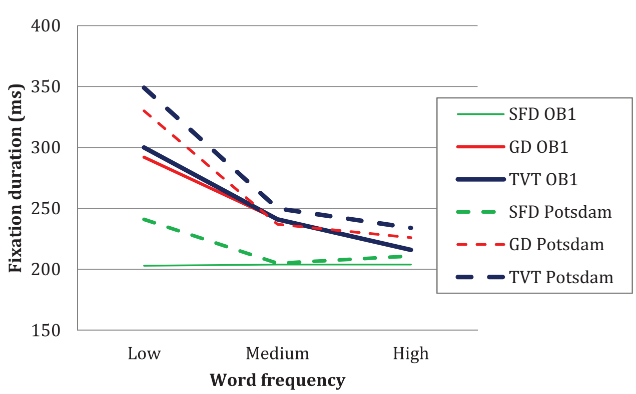

Figure 7. Word viewing times as modulated by word frequency (divided into log-frequency tertiles), for OB1 (solid lines) and the Potsdam experimental data (dashed lines). SFD = single fixation duration; GD = gaze duration; TVT = total viewing time. See the online article for the color version of this figure.

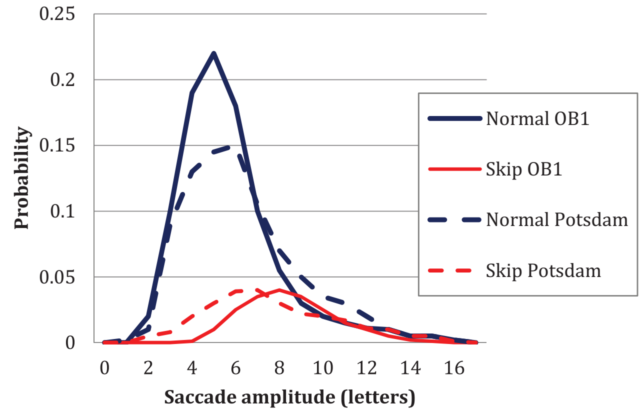

Figure 8. Distribution of saccade amplitudes for normal forward saccades and word skipping saccades. See the online article for the color version of this figure.

Simulation results. In line with results reported by Dare and Shillcock (2013) and Angele et al. (2013), OB1 depicted shorter viewing times on the target (n) when the target was repeated in $n + 1$, compared with when $n + 1$ was an orthographically unrelated control word (see Table 2). The rate of refixations also decreased in the repetition condition.

Further aligning with the studies of Dare and Shillcock (2013) and Angele et al. (2013), differences were observed between the repetition and baseline condition, whereas results in the baseline and control condition were virtually equal.[5] With respect to effect size, the difference in SFD between the repetition and control condition was similar to that reported by Angele et al. ($b \approx 7$ ms in their study vs. 5 ms in our simulations), whereas the difference in GD was more pronounced in OB1 ($b \approx 20$ ms vs. 32 ms, respectively).

Hence, these simulation results underline the theoretical plausibility of the idea that orthographic parafoveal-on-foveal effects are driven by location-invariant activation of sublexical nodes (e.g., bigrams, letters) by letter information across the visual field.

General Discussion

In this article, we describe a set of theoretical ideas about word recognition and eye-movement control in reading, along with a computational model that integrates these ideas. OB1-reader is the first model of eye-movements in text reading that incorporates a word recognition module wherein letter information from the visual field activates lexical candidates. At the same time, OB1-reader distinguishes itself from word recognition models by moving from isolated word recognition to text reading, taking into account evidence that words are processed not only in—but also beyond—the fovea.

Our simulations show that OB1 successfully recognizes most words in the text and that it reproduces orthographic effects such as that of neighborhood size (e.g., Acha & Perea, 2008; Grainger

[5] Do note that Snell, Vitu, et al. (2017) observed longer word viewing times in the control condition compared with in the baseline condition. This difference was ascribed to readers' awareness of the syntactically implausible preview at position $n + 1$ during the fixation on n in the control condition. Naturally, the lack of postlexical processes in OB1 prevents the model from capturing such effects.

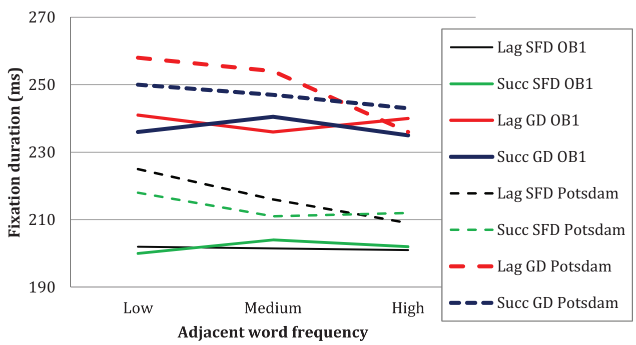

Figure 9. Influence of the frequency words n – 1 (lag) and n + 1 (successor) on word n viewing times in OB1 (solid lines) and the Potsdam experimental data (dashed lines). SFD = single fixation duration; GD = gaze duration; TVT = total viewing time. See the online article for the color version of this figure.

et al., 1989; Perea & Pollatsek, 1998). OB1 also accounts for a range of text reading phenomena, such as refixations, regressions, word skips, and preview effects (e.g., Rayner, 1998). Quantitatively, OB1 produces a distribution of word viewing times, word length, frequency and predictability effects, and landing positions similar to those obtained in experimental settings.

However, the main advance may be theoretical. OB1 is a descendant of the parallel-graded attention line of models of eye-movement control (e.g., SWIFT, Glenmore) on the one handand relative position-coding models of word recognition (e.g., open-bigram model) on the other. Specifically, OB1 adopts the successful approach of SWIFT and Glenmore in addressing the question of where to move the eyes during reading (i.e., saliency-based target selection). By adopting the relative position-coding approach to word recognition, OB1 has a clear means to code for letter position across multiple words in parallel.[6] As is evidenced by our simulations, the integration of these approaches allows OB1 to account not only for the "traditional" phenomena mentioned earlier, but also for sublexical parafoveal-on-foveal effects as reported in more recent research (Angele et al., 2013; Dare & Shillcock, 2013; Grainger et al., 2014; Snell, Vitu, et al., 2017). Moreover, this integration allows us to inspect how and when word identification processes in text reading might go awry—a feature that is not possessed by other models of text reading.

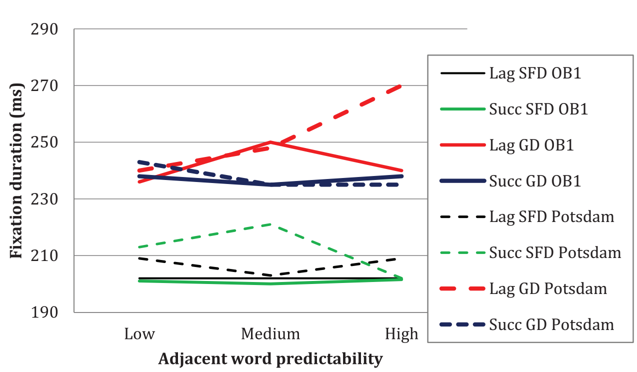

Figure 10. Influence of the predictability of words n – 1 (lag) and n + 1 (successor) on word n viewing times in OB1 (solid lines) and the Potsdam experimental data (dashed lines). SFD = single fixation duration; GD = gaze duration; Succ = successor. See the online article for the color version of this figure.

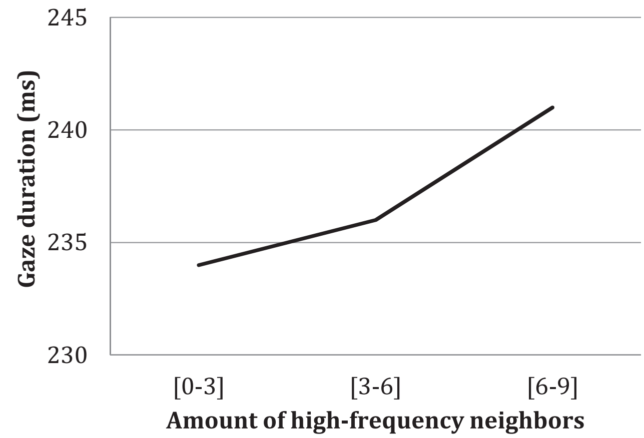

Figure 11. Gaze duration as modulated by the high-frequency orthographic neighborhood size.

Another theoretical advancement of OB1 is its use of a spatiotopic sentence-level representation. This representation answers the question of how a parallel processing system can successfully identify multiple words without losing track of word order, hence meeting one of the major challenges raised against parallel processing systems by proponents of serial processing (Reichle et al., 2009a). Low-level visual information, which is used to associate activated words with plausible positions, can further be used to constrain word activation. This provides a valuable counterweight to the possibility that open-bigrams activated by multiple words in the visual field are combined to activate an incorrect word (e.g., "The butter flies through the room," *butter flies* would activate *butterflies* if not for the guidance of the spatiotopic representation). In accordance with this idea is the finding of Inhoff, Radach, Eiter, and Juhasz (2003) that target words are recognized faster after viewing length-accurate parafoveal previews, compared with length-inaccurate previews. Finally, a spatiotopic representation would explain how readers can make accurate long-range regressions to words earlier in the sentence (e.g., Inhoff et al., 2005; Macdonald et al., 1994).

Given the pivotal role of the spatiotopic representation in OB1, one may wonder how readers can be fairly successful in reading unspaced text (e.g., "youcandefinitelyreadthis"). Regarding this, it should be noted that while one can indeed read unspaced text, the removal of interword spaces undoubtedly has a negative impact on the ease with which the text is read (e.g., Epelboim, Booth, & Steinman, 1995; Perea & Acha, 2009; Rayner, Fischer, & Pol-

[6] In contrast, it is not clear how parafoveal letters should connect to lexical representations if those letters would be coded for their absolute position (e.g., Gomez et al., 2008)—especially given the increased positional noise at increased eccentricities. The SOLAR model of Davis (1999, 2010) forms an exception, as words away from fixation are activated quite similarly as those at fixation. However, it is not clear how the SOLAR model would be able to account for orthographic parafoveal-on-foveal effects.

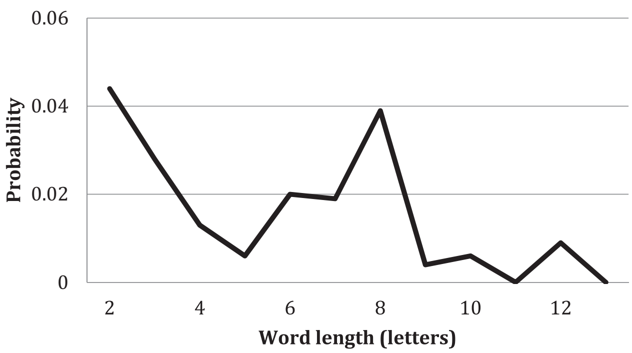

Figure 12. Probability that words were not correctly recognized, as modulated by word length.

latsek, 1998; Mirault, Snell, & Grainger, 2018). OB1 would deal with the removal of spaces by activating all words containing present bigrams, regardless of word length. Interestingly, earlier simulations of the model without length constraint did show fairly successful reading behavior, albeit with a 9% rate of unrecognized words (compared with 1% in the present simulations). It is possible that the human reading system would show a similar number of errors during unspaced reading but that postlexical processes (e.g., determining whether activated words fit with the prior context) correct for falsely identified words.

Further, whereas low-level visual information (e.g., word length) may not be available at first glance during unspaced reading, it is conceivable that readers nonetheless engage a sentence-level representation. For instance, Mirault et al. (2018) found that, even in unspaced reading, saccade amplitudes were influenced by the length of fixated as well as upcoming words, suggesting that readers mentally parse unspaced text into separate words at quite a rapid pace, conceivably driven by lexical identification processes as well as top-down expectations. In any case, accounting for reading of unspaced text remains an interesting challenge for ongoing model development, especially considering the possibility of accommodating alphabetic writing systems that do not use spaces, such as Thai (e.g., Winskel, Radach, & Luksaneeyanawinc, 2009).

Limitations and Future Directions

Although OB1 approaches experimentally observed reading behavior quite well, OB1 is not a perfect model of reading. One weakness is OB1's inability to recognize some words (see Figure 12), with words of Length 2 having the lowest recognition rate (95.6%). It may be that certain high-frequency short words have a dedicated representation that generally allows them to be activated directly, without having to rely on bigram-to-word activation. In this regard, it is interesting to note that the most frequent word in the English language, *the*, tends to be skipped even when it appears at an unpredictable and ungrammatical location (Angele & Rayner, 2013), suggesting that it has special status. In any case, the fact that some words were not recognized is informative in the sense that even skilled readers may err at times—either consciously or unconsciously—and it is likely that postlexical processes allow human readers to correct such mistakes (whereas OB1 cannot).

The implementation of higher order feedback processes, involving syntactic and/or semantic constraints, may alleviate this shortcoming of the model. As proposed in Snell, Meeter, et al. (2017), activated words may be categorized syntactically (e.g., noun, verb), and be appended to a syntactic sentence-level representation that follows the grammatical rules of a given language. Feedback from this higher layer to individual word representations (in the form of activation or inhibition, for syntactically legal and illegal words respectively) would constrain the recognition process for those words. For example, if the article *ein* is surrounded by a verb at $n - 1$ and a noun at $n + 1$, syntactic feedback would strongly activate *ein* as one of the few plausible articles for position n, while inhibiting syntactically implausible words such as the verb *eingestallt*. Indeed, as discussed in the Models of Eye-Movement Control in Text Reading section, Snell and Grainger (2017) provided evidence in favor of this theory, as word recognition was found to be better in grammatical than in ungrammatical contexts.

Another imperfection is that OB1 did not capture the lexical lag and successor effects (e.g., Kennedy & Pynte, 2005) that were present in the Potsdam experimental data. Orthographic overlap is a prerequisite for OB1 to display interactions among words in the fovea and parafovea (i.e., bigram-to-word excitation and word-to-word inhibition). This implies that, if anything, word viewing times should be increased by highly frequent adjacent words, as the nodes belonging to those adjacent words should exert more inhibition on the node belonging to the foveal word. Yet, the experimental data showed a reversed pattern with the higher frequency $n + 1$, leading to a shorter gaze duration on word n and suggesting that this lexical successor effect is not driven by direct word-to-word dynamics as displayed by OB1. It rather seems that high-frequency successors demand fewer processing resources, subsequently leading to stronger activation of the fixated word.

Applying this conception, future implementations of OB1 may adopt a different approach to how visuospatial attention is distributed. In its current form, the model follows the proposal of Ans et al. (1998) with an attentional distribution that has a variable width tuned to recent success and failure in word recognition. An alternative approach would be to let the width of the attentional gradient be influenced by the speed with which parafoveal words become active, with increased activation leading to a narrowed attentional distribution centered on the fixated word. As such, the gradient width would not be determined by failure and success, but rather by anticipated failure and success. Future simulations should point out whether such an adjustment allows OB1 to effectively account for lexical lag- and successor effects.

Finally, in the current implementation of the model, the attentional gradient width dynamic is only used to allow the model to find an optimal size of the attentional window for the input it

Table 2
Average Fixation Duration (in ms) and Refixation Probability Across Conditions

Condition	Single fixation duration	Gaze duration	Refixation probability
Repetition	200	210	.13
Control	205	243	.20
Baseline	203	242	.19

receives. In the future, this dynamic may be explored in more detail, as it possibly accounts for the progression of reading with increased skill—from reading letter-by-letter in beginning readers to reading whole words in experienced readers (e.g., Rayner, 1998). Suboptimal deployments of attention, such as one where the gradient width is too large given the reader's skill (e.g., Collis, Kohnen, & Kinoshita, 2013; Geiger et al., 2008), which leads to increased parafoveal interference, might account for cases of poor reading and dyslexia. OB1 provides a suitable theoretical framework for putting such scenarios to the test.

Concluding Remarks

In conclusion, we believe that OB1-reader provides an important step in the convergence of the neighboring domains of single-word recognition and eye-movement control in text reading. The model's architecture successfully accounts for a wide range of phenomena, including phenomena that were not explained by other models of text reading (e.g., neighborhood size effects, orthographic parafoveal-on-foveal effects). The architecture further allows one to track not only normal reading, but also reading development (e.g., manipulating the width of the attentional window to simulate differences between beginning and skilled readers) and, potentially, processes involved in dyslexia. Finally, the connectionist approach of the model allows for easy expansion, such as the implementation of syntactic constraints as discussed earlier. Future research will reveal how well OB1-reader fares in exploring these various domains and components.

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