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Using E-Z Reader to Simulate Eye Movements in Nonreading Tasks: A Unified Framework for Understanding the Eye–Mind Link

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Nonreading tasks that share some (but not all) of the task demands of reading have often been used to make inferences about how cognition influences when the eyes move during reading. In this article, we use variants of the E-Z Reader model of eye-movement control in reading to simulate eye-movement behavior in several of these tasks, including *z*-string reading, target-word search, and visual search of Landolt *C*s arranged in both linear and circular arrays. These simulations demonstrate that a single computational framework is sufficient to simulate eye movements in both reading and nonreading tasks but also suggest that there are task-specific differences in both saccadic targeting (i.e., decisions about where to move the eyes) and the coupling between saccadic programming and the movement of attention (i.e., decisions about when to move the eyes). These findings suggest that some aspects of the eye–mind link are flexible and can be configured in a manner that supports efficient task performance.

Keywords: attention, E-Z Reader, reading, saccades, visual search

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Eye movements have proven invaluable for studying the perceptual, cognitive, and motoric processes that are engaged during reading (Rayner & Pollatsek, 1989; Rayner, Pollatsek, Ashby, & Clifton, 2012); the viewing of scenes (Henderson & Hollingworth, 1999); and many other visual–cognitive tasks (e.g., visual search; Findlay & Gilchrist, 2003). In the domain of reading, there has been considerable progress in understanding how these different processes guide a reader's eyes through the text, and during the last decade this progress has resulted in several computational models that precisely describe what transpires in the mind of a reader and how this determines when and where the eyes move during reading (Engbert, Nuthmann, Richter, & Kliegl, 2005; McDonald, Carpenter, & Shillcock, 2005; Reichle, Pollatsek, Fisher, & Rayner, 1998; Reilly & Radach, 2006; Salvucci, 2001).[1]

Although there has also been considerable progress in understanding the eye–mind link in other visual–cognitive tasks, this progress has been slower—at least in part—because the demands of these tasks are much less constrained than those of reading. For example, whereas readers generally move their eyes from left to right across successive lines of text because this is required by both the spatial layout of the text and the sequential nature of spoken language, the patterns of eye movements that are observed during tasks such as scene viewing reflect both the variability of the physical layout of scenes and the goals of the viewer (Yarbus, 1967). This additional complexity has meant that there are fewer computational models of eye-movement control in nonreading tasks and that these models typically account for only limited aspects of the tasks being simulated (e.g., when or where the eyes move during scene viewing but not both; e.g., Nuthmann, Smith, Engbert, & Henderson, 2010; Torralba, Oliva, Castelhano, & Henderson, 2006; Zelinsky, 2008). These models have also been developed and evaluated only within each of their respective task domains, with little consideration of whether the theoretical assumptions of the models generalize to other tasks.

One particularly notable example of these previous attempts to simulate eye movements in a nonreading task—visual search—was reported by Najemnik and Geisler (2005, 2008). They created an ideal observer model in which the decision about where to move the eyes next was determined using the ideal observer's knowledge of the current posterior probabilities of an object's possible locations and a "visibility" or feature map, with the goal of moving the eyes to locations that maximize the probability of correctly identifying the location of the target after the fixation.

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The compiled (executable) code and source code for the programs (written in Java) needed to complete the simulations reported in this article are available at http://www.pitt.edu/~reichle/ezreader.html. This site also provides detailed instructions for how to run E-Z Reader simulations.

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[1] For a comprehensive review of these models, see either Reichle, Rayner, and Pollatsek (2003) or the 2006 special issue of *Cognitive Systems Research*.

This model predicts that observers will tend to fixate relatively proximal locations and that the distance moved is a function of visual acuity variables. Although human observers closely mirrored the behavior of the ideal observer, the task domain of the model is limited to searching for a sinusoidal pattern in a fairly homogeneous display, and as such, it is not clear whether the correspondence between human and model performance would generalize to other types of search tasks (e.g., ones involving photographic images of scenes or text where the location of individual objects is much more clearly defined). More important, the model is limited to explaining where—and not when—the eyes move. Finally, Najemnik & Geisler (2005) acknowledged that their model "is not meant to be a plausible model of human visual search" (p. 390) but instead provides a basis of comparison for understanding human performance.

Of course, this last criticism is equally applicable to models of eye-movement control during reading; because these models have been designed to explain readers' eye movements, there has been very little effort to determine whether the theoretical assumptions of the models generalize to other tasks.[2] That is, these models may only be formal descriptions of the eye–mind link during reading, with the unstated assumption that reading is a highly specialized task having little in common with other visual–cognitive tasks. On the other hand, these models may also describe what happens in nonreading tasks because reading may draw upon many of the same basic processes that are used to perform other visual–cognitive tasks.

Our main goal in this article is to answer this question by using one of the existing models of eye-movement control during reading, *E-Z Reader* (Pollatsek, Reichle, & Rayner, 2006c; Rayner, Ashby, Pollatsek, & Reichle, 2004; Rayner, Li, & Pollatsek, 2007; Reichle et al., 1998; Reichle, Rayner, & Pollatsek, 1999, 2003), to examine the perceptual, cognitive, and motoric processes that are involved in reading and in several other, nonreading tasks. By doing this, we intend to demonstrate that, although most of the basic principles of the E-Z Reader model (which are discussed in detail below) are applicable to other visual–cognitive tasks, the model's core assumption that the "trigger" to initiate saccadic programming is a preliminary stage of word identification (or in the context of other tasks, visual object identification) may be limited to reading or to other highly practiced, reading-like tasks. This is a novel hypothesis about how reading and reading-like tasks may differ from other visual–cognitive tasks, and it suggests that the primary differences that are observed between eye movements during reading and those during nonreading tasks may emerge from the unique demand characteristics of the former. This hypothesis also suggests that the E-Z Reader model can be construed as a more general theory for thinking about (and simulating) eye movements in a wide variety of task domains—a theory that is potentially general enough to explain eye movements in all visual–cognitive tasks but still precise enough to make quantitative predictions.

In the remainder of this article, we attempt to meet the above objectives by first providing a precise description of the E-Z Reader model and how its theoretical assumptions were motivated by what is known about the nature and time course of (a) word identification, (b) higher level language processing, (c) saccadic programming and execution, and (d) visual processing. The model's assumptions are then used as an organizational framework for discussing our hypotheses about how various perceptual, cognitive, and motoric processes in reading might be similar to or different from those in nonreading tasks. Our hypotheses about these similarities and differences are then evaluated using what has been learned from experiments involving several nonreading tasks. These hypotheses are also evaluated using the E-Z Reader model to simulate key results from several of these experiments. These simulations are intended to demonstrate which assumptions are sufficient to account for the similarities and differences in the patterns of eye movements that are observed in reading and nonreading tasks. We conclude this article by discussing the limitations of our work and what this indicates about possible future efforts to understand cognition in visual–cognitive tasks—especially in those that tend to be underconstrained, such as scene viewing.

The E-Z Reader Model of Eye-Movement Control in Reading

E-Z Reader is actually a family of computational models that has been developed over the years (Pollatsek et al., 2006c; Rayner, Ashby, et al., 2004; Rayner, Pollatsek, Drieghe, Slattery, & Reichle, 2007; Reichle et al., 1998, 1999, 2003; Reichle, Warren, & McConnell, 2009) to explain an increasingly large number of phenomena related to eye movements in reading (for a review, see Reichle, 2011). We provide a brief but precise description of the model and its assumptions next before we describe the simulations that are the focus of this article (see Reichle, Warren, & McConnell, 2009, for a more detailed exposition of the model). Figure 1 is a schematic diagram of the E-Z Reader model.

Word Identification

The core assumption of all versions of the model is that the type of attention that is necessary to process and identify printed words during reading is allocated serially—to only one word at a time. However, it is assumed that letters within a word are processed in parallel, at least for words less than 8–9 letters in length. The former assumption of serial processing across words stands in stark contrast to what is assumed in most alternative models of eye-movement control in reading, which assume that attention is allocated in parallel to support the simultaneous processing of multiple words (Engbert et al., 2005; Reilly & Radach, 2006) or that attention has little or nothing to do with eye-movement control (Feng, 2006; McDonald et al., 2005; Yang, 2006).

There is a second core assumption in all of the versions of the E-Z Reader model that is important in modeling the data: There is a decoupling between the signal to shift covert attention to the next word and the signal to make an eye movement to the next word. The versions of the E-Z Reader model that provide the best fit to the data assume that an early stage of word identification, called the *familiarity check* (L_1 in Figure 1), is the "engine" that causes the eyes

[2] Two notable exceptions to this claim are discussed below: EMMA (Salvucci, 2001), a model that has been used to simulate eye movements in both reading and several nonreading tasks (e.g., driving), and SWIFT (Engbert et al., 2005), a model of readers' eye movements that has been used to simulate the patterns of eye movements that are observed in a nonreading task called *z*-string reading (Nuthmann & Engbert, 2009).

to move forward during reading, whereas a later stage, corresponding to *lexical access* (L_2 in Figure 1), is the trigger to shift attention to the next word. The motivation for the distinction is that there is an appreciable latency to trigger even the simplest eye movements (Rayner, 1998, 2009). The familiarity check can be viewed as a "cheat" that is acquired during the course of learning to read that allows readers to anticipate when access to a word's meaning is imminent and, in so doing, move their eyes in a manner that supports efficient reading (see Reichle & Laurent, 2006). This cheat will be quite reliable and cost free if the probability is close to one that the lexical access stage is completed before the saccade to the next word is actually initiated.

Although a model in which one assumes that lexical access simultaneously triggers (a) a shift of covert attention and (b) an eye-movement program is consistent with many qualitative features of the reading data (Morrison, 1984), a direct comparison of such a model with E-Z Reader found that the former fit certain quantitative aspects of the data (e.g., parafoveal preview effects) far less well than the latter (Pollatsek et al., 2006c). Indeed, one question that our modeling of other visual–cognitive tasks addresses is whether this assumption that separate stages of cognitive processing trigger covert attentional shifts and saccades is special to reading (or possibly to other very highly practiced visual–cognitive tasks) or whether it is a general feature of eye movements in all visual–cognitive tasks.

In the E-Z Reader model, the mean time (in ms) required to complete the familiarity check on word$_n$, $t(L_1)$, is described by Equation 1. It is a function of the frequency of occurrence of word$_n$ in printed text per million words, as tabulated in various corpora (e.g., Francis & Kucera, 1982), and its within-sentence cloze predictability (Taylor, 1953), as measured by giving subjects the sentences up through word$_{n-1}$ and having them guess word$_n$. (In our exposition below, we use the term *predictability* to refer to the probability of word$_n$ being guessed from its prior context in such a norming study.) This is reflected in the upper branch of Equation 1, where word$_n$ is guessed from its sentence context (with probability p = predictability$_n$). We have assumed that the time required to complete $t(L_1)$ is 0 ms in this case. However, in the majority of instances (with probability $p = 1 -$ predictability$_n$), $t(L_1)$ is set equal to some non-zero value, as indicated by the lower branch of Equation 1. There, $t(L_1)$ is determined by three free parameters: α_1 determines the base time to complete the familiarity check (i.e., when frequency is 1 per million and predictability is zero); α_2 modulates how this time is attenuated by word frequency; and α_3 modulates how predictability attenuates this time on those occasions when the word is not actually guessed. (All of the model's free parameters, along with their interpretations and values, are listed in Table 1, and the procedures used to determine these parameter values are described in Appendix A.) Thus, in the model, a predictable word is actually guessed a small percentage of the time, but in most instances, predictability facilitates the processing of the word in what might be considered a priming-like mechanism. The actual time to complete L_1 during any Monte Carlo simulation is sampled from a gamma distribution with a mean of $t(L_1)$ and a standard deviation equal to $\sigma_\gamma \times t(L_1)$. Thus, consistent with what is observed (see, e.g., Rayner, 1998, 2009), less time is required (on average) to complete the familiarity check on frequent words and/or predictable words.

$$t(L_1) = \begin{cases} 0\ ms,\ with\ p = predictability_n \\ \alpha_1 - \alpha_2\ ln(frequency_n) - \alpha_3\ predictability_n,\ with\ p = 1 - predictability_n \end{cases} \qquad (1)$$

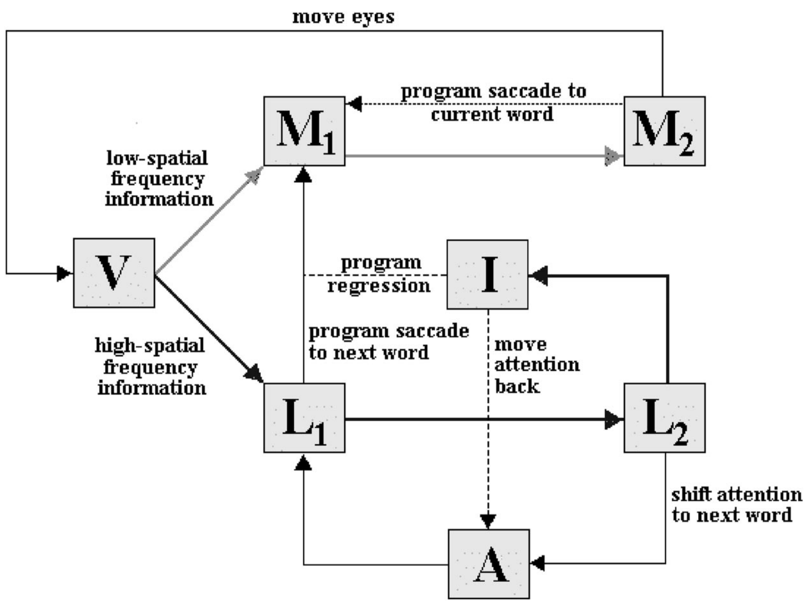

Figure 1. Schematic diagram of the E-Z Reader model of eye-movement control in reading (Reichle, Warren, & McConnell, 2009). The model components are labeled as follows: (a) V = preattentive visual processing; (b) L_1 = familiarity check; (c) L_2 = lexical access; (d) A = attention shift; (e) I = postlexical integration; (f) M_1 = labile saccadic programming; and (g) M_2 = nonlabile saccadic programming.

Table 1
E-Z Reader Parameter Interpretations With Their Default and New Values

Type of processing	Parameter	Interpretation	Old default values	New default values
Word identification	α_1	Mean maximum L_1 time (ms)	**98**	**104**
	α_2	Effect of frequency on L_1 time (ms)	**2**	**3.5**
	α_3	Effect of predictability on L_1 time (ms)	**27**	**39**
	Δ	Proportional difference between L_1 and L_2	**0.25**	**0.34**
	A	Mean attention-shift time (ms)	**50**	**25**
Higher level language processing	I	Mean integration time (ms)	25	25
	p_F	Probability of integration failure	0.01	0.01
	p_N	Probability of regression being directed to prior word	0.5	0.5
Saccadic programming and execution	M_1	Mean labile programming time (ms)	125	125
	ξ	Proportion of M_1 allocated to "preparatory" substage	0.5	0.5
	$M_{1,R}$	Additional time required for labile regressive programs (ms)	30	30
	M_2	Mean nonlabile programming time (ms)	25	25
	Ψ	Optimal saccade length (character spaces)	7	7
	Ω_1	Effect of launch-site fixation duration of systematic error	**7.3**	**6.0**
	Ω_2	Effect of launch-site fixation duration of systematic error	3	3
	η_1	Mean minimum random error (character spaces)	0.5	0.5
	η_2	Effect of saccade length on random error (character spaces)	0.15	0.15
	λ	Increase in refixation probability (character spaces)	**0.05**	**0.16**
	S	Saccade duration (ms)	25	25
Visual processing	V	Eye-to-brain transmission time (ms)	50	50
	ϵ	Effect of visual acuity	1.15	1.15
General	$\sigma\gamma$	Standard deviation of gamma distributions	0.22	0.22

Note. The parameter values that were evaluated in the simulations are indicated in bold font. Parameter values in the column labeled "Old Default Values" are those used in the simulations reported by Reichle, Warren, & McConnell (2009); values in the column labeled "New Default Values" were obtained as described in Appendix A.

The mean time (in ms) required to complete the second stage of word identification, $t(L_2)$, is given by Equation 2, where Δ is a free parameter that sets $t(L_2)$ to some fixated proportion of $t(L_1)$, as specified by the lower branch of Equation 1. In contrast to the familiarity check, this second stage of lexical processing always requires some amount of time to complete; thus, even when a word is guessed from its context (i.e., $t(L_1) = 0$ ms), $t(L_2)$ reflects whatever minimal amount of time is necessary to activate the word's meaning. However, as in the familiarity check, the actual value of $t(L_2)$ during any given Monte Carlo simulation is sampled from a gamma distribution with a mean of $t(L_2)$ and a standard deviation of $\sigma_\gamma \times t(L_2)$.

$$t(L_2) = [\alpha_1 - \alpha_2\, ln(frequency_n) - \alpha_3\, predictability_n]\Delta \quad (2)$$

Because the mean duration of $t(L_2)$ is some fixed proportion of the mean time to complete L_1, and because the mean times that are required to move both the eyes and attention are unaffected by parameters having to do with ease of word identification, the mean amount of time that is available for parafoveal processing of word$_{n+1}$ depends upon the mean time required to complete $t(L_2)$ on word$_n$. This relationship is depicted in the Figure 2, which shows how the preview time (i.e., the difference between when attention shifts to word$_{n+1}$ and when the eyes move to word$_{n+1}$) varies as a function of the duration of $t(L_2)$ on word$_n$. For simplicity, the figure shows the range of mean $t(L_2)$ durations only across the domain of a word's natural log frequency; as indicated above, however, the mean duration of $t(L_2)$ also varies as a function of a word's predictability. As the figure indicates, the amount of time that is available for parafoveal processing of word$_{n+1}$ decreases as the processing difficulty of word$_n$ increases, allowing the model to explain the finding that foveal processing load interacts with parafoveal preview (Henderson & Ferreira, 1990). The fact that less time is available for parafoveal processing from difficult-to-process words also allows the model to explain *spillover effects*, or the finding that fixations on words immediately

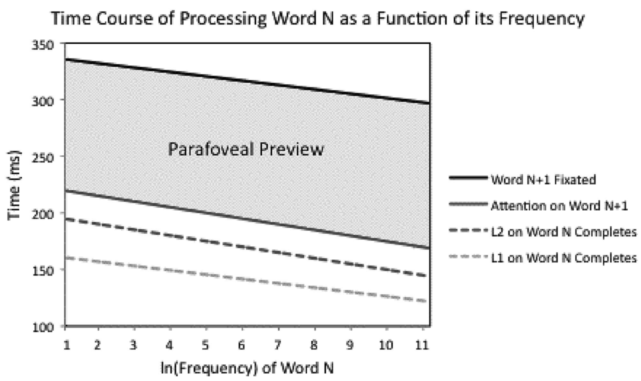

Figure 2. Time course of lexical processing as a function of the processing difficulty of word$_n$ and how this relationship modulates parafoveal preview of word$_{n+1}$. As indicated, the time courses of the two stages of lexical processing, $t(L_1)$ and $t(L_2)$, vary as a function of processing difficulty (e.g., frequency) of word$_n$. Because saccadic programming is initiated by the completion of L_1, and because the mean times to shift attention, $t(A)$, and to initiate a saccade, $t(M_1) + t(M_2)$, are constants, the amount of time available for parafoveal processing of word$_{n+1}$ (indicated by the shaded region) varies as a function of the processing difficulty of the fixated word. Note that the indicated durations are the expected values, ignoring visual acuity limitations (which would increase the durations) and including the 50-ms eye–mind lag associated with the preattentive visual processing of word$_n$ that is normally canceled out via parafoveal processing.

after difficult-to-process words are often inflated (Rayner & Duffy, 1986; Rayner, Sereno, Morris, Schmauder, & Clifton, 1989).

Finally, two processes are simultaneously evoked when word_n is identified. First, attention (A in Figure 1) shifts from word_n to word_{n+1}. The time required to shift attention, $t(A)$, is sampled from a gamma distribution with $\mu = A$ ms and $\sigma = \sigma_\gamma \times \mu$. Second, the meaning of the word is subjected to some minimal amount of higher level language processing. For the sake of exposition, we shall call this stage of postlexical language processing *integration* (I in Figure 1).

Higher Level Language Processing

This stage of higher level language processing is meant to encompass whatever minimal level of postlexical processing is necessary for the reader to know that comprehension is proceeding without difficulty, making it unnecessary to interrupt the default forward movement of the eyes. This stage can thus be conceptualized as corresponding to the amount of processing that is "good enough" to support some minimal level of comprehension (Ferreira, Bailey, & Ferraro, 2002; Ferreira & Patson, 2007; Swets, Desmet, Clifton, & Ferreira, 2008; see also Sanford, 2002; Sanford & Garrod, 2005). In this conceptualization, this stage might include the operations of connecting a word into the phrasal structure that has been constructed, as well as some of the semantic operations (e.g., assignment of case roles) that are necessary to integrate the meaning of the word into the overall semantic representation that is being constructed.

The time required to complete integration, $t(I)$, is also sampled from a gamma distribution with $\mu = I$ ms and $\sigma = \sigma_\gamma \times \mu$. The completion of this integration stage can influence ongoing processing in two ways. First, if word_n is not integrated prior to the identification of word_{n+1}, both the eyes and attention are directed back to word_n, under the assumption that readers will not continue progressing through the text when postlexical processing lags too far behind lexical processing. Second, with some probability, determined by a free parameter p_F, postlexical integration can simply fail and cause both the eyes and attention to be directed backwards. The latter situation can occur when, for example, a reader fails to correctly parse the syntactic structure of a sentence (Frazier & Rayner, 1982; Rayner, Carlson, & Frazier, 1983). With both types of integration failure, however, the eyes and attention are directed back to word_n with probability p_N and to an earlier location (e.g., word_{n-1}) with probability $1 - p_N$. This last assumption is meant to capture any uncertainty that readers might have locating the source of their comprehension difficulty. Finally, because the predictability of any given word at least partially reflects whatever linguistic processing has been completed on prior words, predictability attenuates the time required to complete L_1 and/or L_2 on word_n only if word_{n-1} has been successfully integrated.

Saccadic Programming and Execution

All of the remaining model assumptions have to do with saccadic programming and execution. Based on work by Becker and Jürgens (1979), which indicated that saccadic programming is completed in two stages, saccadic programming in E-Z Reader is also completed in two stages: a preliminary *labile stage* (i.e., M_1 in Figure 1) that can be canceled by the initiation of subsequent saccadic programs, followed by a *nonlabile stage* (i.e., M_2 in Figure 1) that is not subject to cancellation. If the eyes are on word_n, for example, and the familiarity check completes on word_n, a saccadic program to move the eyes to word_{n+1} will be initiated. If lexical processing of word_{n+1} happens to proceed in a timely manner, so that the familiarity check on it completes before the labile stage of the program to fixate word_{n+1} is completed, the program to fixate word_{n+1} will be canceled and be replaced by a new program to move the eyes to word_{n+2}. Thus, word_{n+1} would be skipped. However, if the familiarity check on word_{n+1} is not completed before the end of the labile stage of the program to fixate word_{n+1}, the program transitions to the second, nonlabile stage, causing word_{n+1} to be fixated. On average, the model predicts that words that are easy to identify (e.g., frequent words) will be skipped more often than words that are less easy to identify, consistent with what is observed (Rayner, 1998, 2009).

The labile stage of programming is further assumed to be divided into two substages: an initial system *preparation* substage that engages the oculomotor system, making it ready to program a saccade, followed by a *transformation* substage that converts the saccade target from spatial coordinates to a distance or muscle force metric. If a saccadic program is initiated and is in the system-preparation substage when a second saccadic program is initiated, whatever time has elapsed in preparing the oculomotor system is applied to the second saccadic program (i.e., there is no cost associated with preparing the second saccade). However, if the first saccadic program has reached the transformation substage when the second is initiated, whatever time has been spent converting the spatial coordinates of the saccade target to a distance metric will be lost due to the fact that the saccade target has changed (i.e., there is a cost associated with changing the saccade target). The first of the two substages of labile saccadic programming is assumed to require some proportion ξ of the actual time required to complete the labile saccadic programming stage, $t(M_1)$, which is sampled from a gamma distribution with $\mu = M_1$ ms and $\sigma = \sigma_\gamma \times \mu$. Similarly, the time required to complete the nonlabile saccadic programming stage, $t(M_2)$, is also sampled from a gamma distribution with $\mu = M_2$ ms and $\sigma = \sigma_\gamma \times \mu$. Because there is evidence that inhibition of return makes it more difficult to move the eyes to a location that was just fixated (Rayner, Juhasz, Ashby, & Clifton, 2003), the labile programming stage for regressive saccades requires some additional amount of time to complete. Thus, in the model, the additional mean time (in ms) to complete the labile stage of programming for regressive saccades is represented by the parameter $M_{1,R}$. Finally, the time required to complete the saccade, $t(S)$, is a constant, S ms.

In E-Z Reader, a saccade is posited to be directed toward the *optimal viewing position* (OVP). This is the center of the word, which has been shown to be the location from which a short to moderately long word can be most rapidly processed (O'Regan & Lévy-Schoen, 1987). However, because of both systematic and random error, saccades usually land at a location other than the intended target (usually short of the OVP on the *preferred viewing location*, or PVL; Rayner, 1979). The lengths of the executed saccades (in character spaces) are therefore the sum of three components: the intended saccade length, systematic error, and random error, as given by Equation 3.

$$\textit{saccade length} = \textit{intended saccade length} + \textit{systematic error} + \textit{random error} \quad (3)$$

The random error component causes the fixation landing-site distributions to be approximately normal, with variability increasing with the length of the intended saccade. In the model, the random error component (in character spaces) is sampled from a Gaussian distribution with $\mu = 0$ and a standard deviation given by Equation 4, where η_1 and η_2 modulate the effect of saccade length on saccadic error variability.

$$\sigma = \eta_1 + (\eta_1 \times \textit{intended saccade length}) \quad (4)$$

The systematic error (on average) causes short saccades to overshoot their intended targets and long saccades to undershoot their targets. In the model, the systematic error (in character spaces) is described by Equation 5, where the free parameter Ψ is the *optimal saccade length* (i.e., the saccade length that results in neither overshooting nor undershooting) and the free parameters Ω_1 and Ω_2 control the degree to which the launch-site fixation duration (*fix*) modulates the systematic error, increasing it for saccades following short fixations. Together, these assumptions are sufficient to allow the model to predict landing-site distributions that are centered on words and normal in shape but that shift toward the beginning of the words and become more variable with increasing saccade length and/or following short fixations, consistent with what has been reported (Engbert & Krügel, 2010; McConkie, Kerr, Reddix, & Zola, 1988; McConkie, Kerr, Reddix, Zola, & Jacobs, 1989; O'Regan, 1990; Rayner, 1979; Rayner, Sereno, & Raney, 1996).

$$\textit{systematic error} = (\Psi - \textit{intended saccade length})\{[\Omega_1 - \ln(\textit{fix})]/\Omega_2\} \quad (5)$$

Finally, after each saccade, there is some probability (p, given by Equation 6) that an "automatic" corrective saccade will be initiated. The probability of making this type of corrective saccade is a function of the saccadic error, or absolute distance (in character spaces) between the saccade target or OVP of the word being attended and the actual fixation location, as modulated by a free parameter λ. The assumption underlying this is that a corrective saccade is likely to be initiated if the efference copy (Carpenter, 2000) of the primary saccade indicates that the initial fixation location affords a poor view of the word that is being processed. Because the corrective saccades are directed toward the center of the word, they are likely to result in more rapid lexical processing. This assumption allows the model to predict that fixations near either end of a word are more likely to be followed by a refixation (Rayner et al., 1996; Vitu, McConkie, Kerr, & O'Regan, 2001).

$$p = \max(\lambda|\textit{fixation} - \textit{OVP}|,1) \quad (6)$$

Visual Processing

After each saccade, the visual information from the new viewing location is assumed to propagate from the retina to the brain so that it can be used to continue lexical processing, which continues using information from the previous viewing location during the saccade and for the duration of the "eye–mind lag" (which requires V ms to complete in the model). This preliminary stage of visual processing is assumed to be preattentive, with low-spatial frequency information about word boundaries being used by the oculomotor system to select the upcoming saccade target and high-spatial frequency information about letter and/or word features being used to identify the individual letters and words. By assumption, lexical processing continues using whatever visual information was acquired during the preceding fixation until new information from the new fixation location becomes available. The source of this continuing availability of information from the prior fixation is visual short-term memory (Logie, 1995; Luck & Vogel, 1997; Phillips, 1974). This persisting information would be replaced by the information from the new fixation when this new information reaches the relevant cortical processing areas.

Limitations of visual acuity also attenuate the rate of lexical processing, in accordance with the observation that longer words and/or words farther from the center of vision require more time to identify than short words and/or words closer to the center of vision (Rayner & Morrison, 1981; Schotter, Angele, & Rayner, 2011). In the E-Z Reader model, this is accomplished by including the assumption that the time required to complete the familiarity check, $t(L_1)$, is also attenuated by visual acuity, as a function of *foveal eccentricity*, or the mean absolute distance in character spaces between each of the letters of word$_n$ and the current fixation location. This adjusted time (in ms) is described by Equation 7, where ε is a free parameter that modulates the effect of eccentricity, *fixation* is the current fixation location, and *letter* indicates the location of each of the N letters in word$_n$. Thus, consistent with what is observed (see, e.g., Rayner, 1998, 2009), less time is spent fixating on short words and words whose centers are closer to fixation. (Note that there is no explicit assumption about how word length influences the time to process a word; word length effects on fixation times result from Equation 7.)

$$t(L_1) \leftarrow t(L_1)\ \varepsilon^{\Sigma|\textit{fixation}-\textit{letter}|\ /\ N} \quad (7)$$

Finally, by assumption, the duration of the second stage of lexical processing (i.e., $t(L_2)$, as specified by Equation 2) is not modulated by visual acuity under the assumption that this latter stage of word identification corresponds to the activation of semantic codes, which is both time consuming and obligatory (because subsequent language processing is dependent upon these codes). This assumption is consistent with the results of an experiment (Reingold & Rayner, 2006) that manipulated the visual quality of target words (e.g., by using faint fonts). This manipulation increased fixation durations on the target words but did not lengthen fixations on the post-target words. These findings can be readily explained as follows: The degraded visual information slowed the completion of L_1 and thereby lengthened the fixations on the target words, but it did not affect L_2 and hence the amount of parafoveal processing that the post-target words received from the targets. This is because the mean time required either to actually move the eyes or to move attention is a constant in E-Z Reader. Thus, because the parafoveal processing time the post-target word receives would be unaffected by the visual quality of the target word, there would be no effect of visual quality on fixation times on the post-target word (see Figure 2).

Applying the E-Z Reader Assumptions to Nonreading Tasks

With the preceding description of the E-Z Reader model, it is now possible to discuss how each of its specific assumptions might be used to understand eye movements in other visual–cognitive tasks. This analysis is organized according to four general groups of assumptions: (a) those related to the processing and identification of words (and in the context of nonreading tasks, other visual objects); (b) those related to whatever higher level (linguistic or cognitive) processing is necessary to perform that task of interest; (c) those related to the programming and execution of saccades; and (d) those related to visual processing. Our goal is to first briefly review the empirical and theoretical factors that motivated these assumptions and to then consider how these assumptions might have to be modified to explain other visual–cognitive tasks.

Word (and Object) Processing

As indicated, the E-Z Reader model's core assumptions about word identification are (a) that only one word is attended, lexically processed, and identified at a time and (b) that an early stage of word identification, the familiarity check, is the "trigger" that initiates saccadic programming to move the eyes from one word to the next, but that the completion of a subsequent stage of word identification, corresponding to lexical access, causes attention to shift from one word to the next.

The first of these assumptions—that attention is allocated serially from word to word—was motivated by what has been learned about (a) attention in the domain of visual search, (b) eye-movement experiments that have directly examined how attention is allocated during reading, and (c) an analysis of the task constraints that are imposed by reading. Because these considerations have been discussed at length elsewhere (see, e.g., Reichle, Liversedge, Pollatsek, & Rayner, 2009), we do not discuss them again here but instead simply acknowledge that the question of how attention is allocated in nonreading tasks is an open one. In the simulations that are reported below, we assume that attention is allocated serially because this makes the modeling tractable and because it provides a basis for generating interesting (and testable) hypotheses. The assumption is also consistent with key results from one task that is markedly different than reading—the viewing of natural scenes. This work shows that short-term recognition memory is close to chance for objects in a scene that are not actually fixated (Henderson & Hollingworth, 1999). This indicates that, to some approximation, the processing of objects in a scene for meaning is also a serial process and that the serial processing assumption in reading may generalize to a wide range of nonreading visual tasks.

The second of the previously mentioned word-identification assumptions—that a preliminary stage of word identification triggers saccadic programming—was motivated by a number of basic eye-movement experiments, an analysis of the temporal constraints provided by these results, and consideration of what has been learned about (word) identification in the domain of recognition memory. For example, simple eye-movement experiments in which subjects must move their eyes to target locations (e.g., Becker & Jürgens, 1979; Rayner, Slowiaczek, Clifton, & Bertera, 1983) indicate that the minimal saccadic latency, or time required to initiate a saccade, is approximately 180–220 ms. If one subtracts the duration of the eye-to-mind lag (i.e., the minimal 50 ms needed for visual information about the saccade target location to reach the brain; Clark, Fan, & Hillyard, 1994; Foxe & Simpson, 2002; Mouchetant-Rostaing, Giard, Bentin, Aguera, & Pernier, 2000; VanRullen & Thorpe, 2001) from the minimal saccadic latency, this provides an estimate of the minimal time required to program a saccade: 130–170 ms. Because most fixation durations in reading are 200–220 ms in duration (Rayner & Pollatsek, 1989), a simple model in which the completion of lexical access of word$_n$ is the trigger to begin programming an eye movement to word$_{n+1}$ is not plausible because such a model would allow only 30–90 ms for the identification of words (i.e., the difference between the observed fixation durations and the inferred minimal saccade programming times).

One solution to this paradox is to simply assume that the trigger to initiate saccadic programming is some earlier stage of lexical processing—one that is completed more rapidly than meaning access (which has been estimated to require 150 ms; Rayner & Pollatsek, 1989) but predictive of meaning access. In the E-Z Reader model, this hypothesized early stage of lexical processing L_1 was dubbed the familiarity check, consistent with the distinction made in some theories of recognition memory between a rapidly available feeling of familiarity and a slower retrieval process (for a review, see Yonelinas, 2002). These theories hold that people can discriminate previously studied items from new items on the basis of their familiarity; during recognition, the previously studied items resonate with information stored in long-term memory and thus produce a stronger feeling of familiarity than do the new, unstudied items. In the context of the E-Z Reader model, this feeling of familiarity varies as a function of a word's frequency of occurrence and predictability, so that easier-to-identify words produce a stronger feeling of familiarity than less frequent or less predictable words (Reichle & Perfetti, 2003). This in turn means that a word's familiarity is predictive of how long it will take to identify, thereby providing a way to decide when to initiate saccadic programming so as to avoid fixations that are either too short or too long (Reichle & Laurent, 2006).

Of course, one might posit that an object's familiarity influences the decision about when to initiate saccadic programming in other visual–cognitive tasks. However, this might only happen in tasks that are highly practiced and in which performance is reasonably optimal, in the sense that there is a point during object processing that allows the task can be performed both quickly and with a reasonable degree of accuracy. The former condition is necessary because the objects must be represented in long-term memory if they are to engender a feeling of familiarity. The latter condition is likely because accurate performance can be obtained by simply waiting until each object is fully identified. That is, if there is no well-defined point at which one can be fairly sure that one is reasonably likely to have processed the object correctly, one is risking making many mistakes by initiating a saccade too soon—especially given that the only cost of waiting until the object has been fully identified is that the fixation duration on that object will be unnecessarily long. Therefore, in the simulations reported below, we leave open the possibility that the tasks being simulated might be better accounted for by a model that allows some variable amount of "slippage" between whatever preliminary stage of object identification might initiate saccadic programming and the stage of full identification that—by hypothesis—causes attention to shift to the next object. For example, in scanning arrays of Landolt *C*s for letter *O* targets (Williams & Pollatsek, 2007), we suspect, the two signals are tightly coupled, with full stimulus identification causing both the eyes and attention to shift to the next stimulus. These hypotheses will be evaluated using the simulations that are reported below.

Higher Level Language (and Cognitive) Processing

As indicated, the E-Z Reader model's assumptions about higher level (i.e., postlexical) linguistic processing were derived from several key experimental findings in the reading literature that suggest that ongoing higher level linguistic processing is sluggish, often lagging behind lexical processing and having little or no influence on the forward movement of the eyes, but that problems associated with such processing can rapidly intervene, resulting in a pause or regression back to the source of processing difficulty (Reichle, Warren, & McConnell, 2009). For example, if a word is encountered that is anomalous from its prior context, such as *carrot* in "John used a pump to inflate the large carrot for dinner," the fixation on that word is lengthened relative to when the word is consistent with its prior context (Rayner, Warren, Juhasz, & Liversedge, 2004; Warren & McConnell, 2007; Warren, McConnell, & Rayner, 2008). Unsurprisingly, these lengthened fixation durations are usually followed by regressions back to earlier parts of the sentence to determine whether there is any sense that could be made of the sentence. Similar pauses and/or regressions can be induced by manipulations that disrupt the syntactic structure of the sentence (e.g., garden-path sentences that cause readers to initially misparse a sentence; Frazier & Rayner, 1982; Rayner, Carlson, & Frazier, 1983), lending additional support to the assumption that higher level processing can rapidly intervene to influence the forward movement of the eyes.

Although the E-Z Reader model's assumptions about how integration affects attention and oculomotor programming allow the model to predict when an interword regression is likely to occur, these assumptions are admittedly quite speculative in that they fail to specify precisely why integration falters or how the reader goes about repairing faulty comprehension. As Reichle et al. (2009) explicitly indicated, such an account seemingly requires a much more sophisticated model of language processing and how it fails—a level of detail that is simply beyond the scope of the model's current (fairly simple) assumptions. These simple assumptions are nevertheless useful, because they provide a framework for thinking about how higher level language processing interacts with the systems that are involved in identifying words, shifting attention, and programming saccades. And in the context of nonreading tasks, the integration stage provides a nice "placeholder" to think about how the higher order goals of the task being performed (e.g., the types of goals that might be conveyed through verbal instructions about how to perform that task) might influence task performance. At one extreme, such goals might markedly effect the observed patterns of eye movements, as is evidenced by the different patterns of eye movements that were exhibited by Yarbus' (1967) subjects when they were given different instructions for viewing a painting (e.g., "What were the people doing prior to the moment depicted in the painting?" vs. "What are the material circumstances of the people in the painting?"). The nature of the task demands had clear effects on where the subjects looked; the *scan paths* or patterns of looking differed markedly as a function of the questions that were asked of the subjects as they viewed the painting. But while it is clear that the questions affected how subjects engaged in looking at the painting, the precise nature of the cognitive processes underlying the observed differences have not been specified.

Because of this, and because many of the tasks that are simulated below might involve very little in the way of higher level cognitive processing (e.g., scanning arrays of Landolt *C*s; Williams & Pollatsek, 2007), we have adopted a minimalist approach and attempted to simulate the tasks making as few assumptions about higher level processing as possible. In most instances, this strategy has meant that the E-Z Reader model's current assumptions about how higher level processing affects progressive eye movements has simply been "disabled," allowing us to examine how object processing and identification affect the patterns of first-pass eye movements in the absence of any specific assumptions about higher level processing. As indicated in the General Discussion section, we suspect that explorations of these assumptions will provide the most interesting hypotheses for future research. That being said, we now turn to the third set of model assumptions—those involving saccadic programming and execution.

Saccadic Programming and Execution

As noted above, the E-Z Reader model's assumptions are that (a) saccades are programmed in two stages; (b) that the saccades are directed toward the centers of words but that, because of some combination of random and systematic error, they often deviate from their intended targets; and (c) that initial fixations near the ends of words are more likely to be rapidly followed by corrective saccades because such saccades often afford better viewing positions (i.e., fixations closer to the centers of the words). These assumptions about saccadic programming and execution were motivated by key results from experiments involving both basic oculomotor tasks and reading.

For example, both the assumption that saccades are programmed in two discrete stages, where the first stage is labile and that the second is not, and the durations of these stages were motivated by the results of the seminal double-step experiment of Becker and Jürgens (1979). In this experiment, subjects were instructed to rapidly move their eyes to saccade targets (small dots) that appeared at various random viewing locations. On some proportion of the trials, the target would appear at one location and then, after some short, variable length delay, instantaneously move to a second location. When this delay was long, subjects moved their eyes to both locations, with the fixation on the first location often being very short. With shorter delays, however, the subjects often moved their eyes directly to the second target location, indicating that the initial saccade program (i.e., the program that would have otherwise caused the eyes to move to the first target location) had been canceled. The length of the delay indicates that the labile stage of programming is much longer than the nonlabile stage, although precise estimates of the durations of the two stages are difficult to obtain.

The second set of assumptions—that saccades are directed toward word centers but often miss their targets because of error—

was derived from analyses of fixation landing-site distributions during reading (McConkie et al., 1988, 1989; McConkie et al., 1991; O'Regan, 1990, 1992; O'Regan & Lévy-Schoen, 1987; Rayner, 1979; Rayner et al., 1996). In these analyses, the landing positions of large number of fixations were analyzed as a function of the launch-site fixation location and duration, the length of the word being targeted, and so on. The plots indicated that the distributions are in fact Gaussian in shape and centered near the middle of the target words but that they are missing "tails" that reflect instances where the saccade under- or overshot its intended target. These analyses also indicated that intended saccades that are approximately seven character spaces in length have minimal mean saccadic error (i.e., there was no tendency to either undershoot or overshoot their targets). In contrast, shorter/longer intended saccades tended to over-/undershoot their target by approximately half a charter space for each character space that the intended saccade was shorter/longer than the optimal saccade length. In a similar manner, these analyses showed that the systematic error is modulated by the launch-site fixation duration, with longer fixations typically being followed by more accurate saccades. Finally, these analyses show that the random error component increases with the length of the intended saccade, causing long saccades to be less accurate than shorter saccades.

The last assumption—that refixations are more likely following initial fixations near either end of a word—is based on analyses of refixation probabilities as a function of initial landing positions (McConkie et al., 1988, 1991; Rayner et al., 1996; Vitu et al., 2001). This work shows that refixations during reading are more likely following initial fixations near the beginnings and ends of words and that the refixations are most often directed toward the centers of the words being processed. Theoretical analyses suggest that these refixations are "corrective" in that they provide a way to quickly move the eyes from poor viewing locations, where lexical processing is slow, to more optimal viewing locations, where lexical processing is more rapid (e.g., Nuthmann, Engbert, & Kliegl, 2005).

Because the E-Z Reader model's assumptions regarding saccade programming and execution are derived from a combination of reading and nonreading tasks, it should come as no surprise that the assumptions should generalize to a wide variety of visual–cognitive tasks. The precise metrics of the saccades, however, might be expected to vary considerably, depending upon the nature of the task. For example, although the optimal saccade length has been estimated to be approximately seven character spaces in analyses of the eye movements of English readers (McConkie et al., 1988), these estimates might be expected to vary as a function of language and/or writing system (e.g., shorter in "denser" writing systems, such as Chinese).[3] Similarly, the propensity to make refixations might be expected to change depending upon the nature of the task being performed; for example, reading-like tasks might result in more refixations because of the requirement to identify objects. These possibilities are explored in the simulations reported below by using a single set of assumptions about saccade programming and execution but allowing the metrics of saccadic programming and/or execution to vary.

Visual Processing

As was true for saccadic programming and execution, the E-Z Reader model's visual-processing assumptions were motivated by basic facts about the visual system and not inferences derived from specific reading experiments. For example, the duration of the eye-to-brain lag was estimated using a variety of different methods (e.g., electrophysiological responses to the onset of visual stimuli; Clark et al., 1994), and, as such, this constraint should be invariant across visual–cognitive tasks.

Similarly, the fact that the type of high visual acuity required to identify words is largely limited to the central 2° of the visual field, to a region of the retina called the fovea, follows directly from what is known about the basic physiology of vision and the well-established fact that visual acuity declines very rapidly from central to peripheral vision. (The fact that this decline in visual acuity specifically slows word identification was corroborated by Rayner & Morrison, 1981; see Schotter et al., 2011, for a more recent review.) Of course, the degree to which limitations in visual acuity slow the identification of different visual stimuli may vary as a function of the precise nature of the stimuli and the task. For example, one might predict that the rate at which Chinese words are identified might be affected by visual acuity to a greater degree than the rate at which English words are identified because the former comprise densely packed configurations of (often complex and small) features. Likewise, visual acuity might affect reading more than scene viewing to the extent that words are more difficult to identify than visual objects. Thus, in using E-Z Reader to simulate a variety of nonreading tasks, one might expect that between-task differences in the nature of the stimuli being identified and/or the task demands (e.g., identify each object vs. locate a distinctive object) might require different assumptions about how much limited visual acuity affects task performance.

Simulations of Several Nonreading Visual–Cognitive Tasks

Unless otherwise noted, the simulations that are reported below use the version of E-Z Reader that was just described and the model's standard parameter values (listed in the column labeled "New Default Values" in Table 1; see Appendix A). For simulations involving the reading of actual text, we have used the corpus of sentences that were initially used by Schilling, Rayner, and Chumbley (1998) to examine word-frequency effects. We have used the Schilling et al. sentences on a number of occasions to examine a variety of reading-related topics via simulations using the E-Z Reader model (see, e.g., Pollatsek, Juhasz, Reichle, Machacek, & Rayner, 2008; Pollatsek et al., 2006a, 2006b, 2006c; Rayner, Pollatsek, et al., 2007; Rayner, Reichle, Stroud, Williams, & Pollatsek, 2006; Rayner et al., 2004; Reichle, Pollatsek, & Rayner, 2007; Warren, White, & Reichle, 2009). Our general approach has been to manipulate the properties of specific target words within those sentences. Because the model's parameter values have been selected to maximize its overall fit to the sentences, it is possible to examine how specific target-word manipulations affect simulated eye movements using the sentences as

[3] Several models of eye-movement control in reading allow the parameters that control saccade programming (e.g., the optimal saccade lengths) to take on different values depending upon the tasks being performed (e.g., reading vs. *z*-string scanning; Nuthmann & Engbert, 2009) and whether the saccade is progressive or regressive and/or being directed within or between words (e.g., McDonald et al., 2005).

frames, so that the model is engaged in the normal sequence of processing upon encountering the target words that were the focus of our specific manipulations of interest.[4]

Simulation of Fixation-Duration (i.e., "When") Measures

Although it is obviously important that an eye-movement model can explain both fixation-duration measures (e.g., how long people look at regions of interest and the duration of individual fixations) and exactly where the eyes land on a fixation, the "when" and "where" issues are, to some extent, separable. Certainly, in terms of the E-Z Reader model outlined above, the when decision is determined by ongoing processing of the attended stimulus, whereas the where decision depends on certain assumptions that are independent of this (e.g., exactly where in a word the original saccade is intended to land and the error in executing this saccadic movement). As a result, we first concentrate on how the pattern of fixation durations changes across tasks and how the E-Z Reader model should be adapted (if at all) to model these other tasks. We then, in the following section, discuss the details of where eye movements land. As will be seen, consistent with the claim above, our simple assumptions about saccade targeting (e.g., that the eyes are directed toward the centers of words and other visual objects) are sufficient to accurately predict fixation times.

Our strategy in the simulations reported below was to first examine whether the basic framework of the E-Z Reader model could be used to simulate eye movements in three nonreading tasks that have sometimes been used in the debate about eye-movement control during reading: (a) visual search for a specific target word; (b) *z*-string "reading"; and (c) visual search for an *O* in clusters of Landolt *C*s. In the first task, target-word search (Rayner & Fischer, 1996; Rayner & Raney, 1996), subjects are instructed to scan sentences for a particular target word (e.g., *zebra*) and to indicate all occurrences of the target word with button presses. In the second of these tasks, *z*-string reading (Nuthmann & Engbert, 2009; Nuthmann, Engbert, & Kliegl, 2007; Rayner & Fischer, 1996; Vitu, O'Regan, Inhoff, & Topolski, 1995), subjects are instructed to "pretend" that they are reading sentences in which all of the letters in each of the sentences have been replaced by the letter *z*, but with capitalization, spaces, and punctuation preserved (e.g., the sentence fragment "The cat, black as soot,. . ." would thus be converted to "Zzz zzz, zzzzz zz zzzz,. . ."). Finally, in the Landolt-*C* task (Williams & Pollatsek, 2007; see also Hooge & Erkelens, 1998; Trukenbrod & Engbert, 2007; Vanyukov, Warren, Wheeler, & Reichle, in press), subjects are instructed to search through an array of Landolt *C*s (i.e., rings with a small segment missing, making them look like *C*s) and to indicate whether there was also a letter *O* in the display with a button press. The "gap" size (measured in terms of number of pixels) in the Landolt *C*s was varied, making the task of discriminating them from the target *O*s more or less difficult.

All of these nonreading tasks are similar in that they logically require little or no language processing (e.g., an illiterate person can scan through sentences and decide whether *zebra* is present based on pattern matching). However, the speed of processing in the target search is likely speeded by the familiarity of the target word. Moreover, because the cognitive operations required to perform the tasks differ from those of reading, each of the tasks has been used to make inferences about the specific nature of eye-movement control in reading, with the general approach being to compare the eye movements that are observed when subjects perform each of the tasks to those that are observed during reading. This has led to the following type of argument:

> (a.) If the eye-movement patterns in these nonreading tasks are similar enough to those of natural reading, then the visual and oculomotor constraints that are common to both these nonreading tasks and reading are sufficient to explain eye-movement behavior in reading (Nuthmann & Engbert, 2009; Vitu et al., 1995).
>
> (b.) Therefore, it is unlikely that language processing is the primary engine that is driving eye movements during reading.

Although there are admittedly many similarities between the eye movements that are observed in both reading and nonreading tasks, there are also several important differences. In the sections that follow, we describe the results of several simulations using variants of the E-Z Reader model of eye-movement control in reading. These simulations collectively show how the observed similarities and differences between reading and nonreading tasks can emerge from the framework of a single eye-movement control system, solely as a function of the specific task demands that are placed upon subjects. This is because the primary engine in the E-Z Reader model that is driving the eyes forward is "satisfactory processing" of the fixated stimulus. This seems to be a reasonable assumption about what is driving the eyes forward in these other tasks (with the possible exception of the *z*-string reading task), although what satisfactory processing means in these tasks will differ from those in reading because the demands of these tasks are different than those of reading. After presenting these simulations, we indicate why these between-task similarities and differences actually provide evidence favoring the hypothesis that ongoing language processing normally intervenes to influence eye movements during reading. In short, our simulations are intended to provide a unified account of eye movements in both reading and nonreading tasks.

Rayner and Fischer (1996). Our first set of simulations are of the tasks used by Rayner and Fischer to directly compare the patterns of eye movements that are observed during reading to those observed in two nonreading tasks: target-word search and *z*-string reading. We chose to simulate this particular experiment because the eye-movement data in the three tasks were collected using the same apparatus and subject pool and—in the case of reading and target-word search—exactly the same text materials, making between-task comparisons and theoretical inferences easier. (The figures below show the observed and simulated results on common scales to facilitate between-task comparisons.) There are

[4] The simulations were completed using sentence frames rather than the actual materials because fitting the model to specific materials is prohibitively expensive (see, e.g., the Appendix of Reichle et al., 1998) and because the effects of the simulated manipulations (e.g., the frequency of specific target words) are often localized, influencing the eye movements on the target words and—at most—the words preceding and/or following those words (cf. Kliegl, Nuthmann, & Engbert, 2006; Rayner, Pollatsek, et al., 2007).

clearly many different fixation duration measures that could be used. To keep the exposition understandable, we have focused on two: *single-fixation duration* and *gaze duration*. The former is a widely used measure that assesses the duration of an individual fixation, and the latter is perhaps a more widely used measure that assesses the total time spent on a word during the first pass through the text. Another widely used measure, *first-fixation duration*, is largely redundant with single-fixation duration, and another, *second-fixation duration*, can often be estimated from the differences between gaze duration and single-fixation duration (see Inhoff & Radach, 1998) but is less reliable because it is based on much less data.

Reading. Because our simulations used the Schilling et al. (1998) corpus as sentence frames to examine how the task differences between reading and the two other nonreading tasks influenced various eye-movement measures on specific target words, it was first necessary to calibrate the model using the data from the reading condition of Rayner and Fischer (1996). To do this, we first factorially manipulated both the frequencies (187 per million vs. 3 per million) and lengths of the target words (i.e., making them 5, 6, 7, 8, and 9 letters in length) so that we could examine how these variables affected readers' eye movements (in exactly the same manner as did Rayner and Fischer). Because the target words were unpredictable in their original sentences, the cloze predictability values of the target words were set equal to 0.01 in our simulations. We then completed three grid searches of the model's parameter space (as described in Appendix B) to find the parameter values that allowed the model to minimize the mean absolute deviations between the observed and simulated single-fixation and gaze durations for the target words of each length. These parameter values are displayed in Table 2.

As Table 2 indicates, the best fitting parameter values ($\alpha_1 = 162$, $\alpha_2 = 7.5$, $\alpha_3 = 19$, $\Delta = 0.97$, $\lambda = 0.3$) meant that the rate of lexical processing for the simulated subjects in the reading task in the Rayner and Fischer (1996) experiment was slower than for those in the Schilling et al. (1998) experiment (cf. Tables 1 and 2). This difference is plausibly due to between-subject differences in the two experiments, as well as differences between the sentences used in the two experiments. More important, as Panel A of Figure 3 indicates, these modest changes in the parameter values were sufficient to simulate the mean observed single-fixation durations and gaze durations on both the high- and low-frequency target words, both in terms of their absolute values (i.e., average absolute difference between observed and simulated *M*s = 16 ms) and of how both dependent measures were affected by word frequency. The one discrepancy between the observed and simulated values occurred with the low-frequency target words, where the model predicted gaze durations that were shorter than those that were actually observed. However, as Panels A and B of Figure 4 show, this discrepancy is largely due to the low-frequency nine-letter words, which tended to be the recipients of longer gaze durations than one might predict on the basis of the gaze durations on the words of other lengths. One possible explanation for this result is that those words were also associated with more difficult postlexical processing.

Target-word search. The model was next used to simulate the first nonreading task reported by Rayner and Fischer (1996): a target-word search in which subjects were instructed to rapidly search through the same text that was used during reading and to indicate all occurrences of a specific target word, *zebra*. The key results from this task (and from a similar experiment by Rayner & Raney, 1996) are that, relative to those for reading, the single-fixation durations and gaze durations tended to be quite short and seem to be much less influenced by word frequency (see Panel B of Figure 3).

To better understand these findings, we once again used the Schilling et al. (1998) corpus as sentence frames to examine how the demands of the target-word search task affected the patterns of eye movements on specific target words. This was done by factorially manipulating both the frequencies (187 vs. 3 per million) and lengths of the target words (i.e., 5-, 6-, 7-, 8-, vs. 9-letters) in exactly the same manner as in our previously reported simulation of reading. To more accurately simulate the specific demands of the word-search task, we disabled the model's postlexical processing (i.e., $I = 0$ and $p_F = 0$) under the assumption that such activity would be unlikely to occur during the task. We then completed three successive grid searches of the model's parameter space (see Appendix B) to find the parameter values that minimized the mean absolute deviations between the observed and simulated single-fixation and gaze durations for the target words of each length. The best fitting parameter values are shown in Table 2.

Table 2
Best Fitting Parameter Values for the Three Simulated Tasks Used by Rayner and Fischer (1996): Reading, Target-Word Search, and Z-String Reading

			Z-string reading	
Parameter	Reading	Target-word search	Simulation 1	Simulation 2
α_1	162	39	219	233
α_2	7.5	0	n/a	n/a
α_3	19	44	n/a	n/a
Δ	0.97	0	0	0
λ	0.3	0	0.27	0.26

Note. In Simulation 1, all saccades were directed toward the optimal-viewing positions (i.e., centers) of the *z* strings; in Simulation 2, refixations were directed toward the ends of *z* strings and required additional time to program. "n/a" indicates that the parameter has no interpretation in the context of the task being simulated (e.g., because *z* strings are not predictable, the parameter that modulates the effect of predictability, α_3, has no interpretation in the *z*-string reading task).

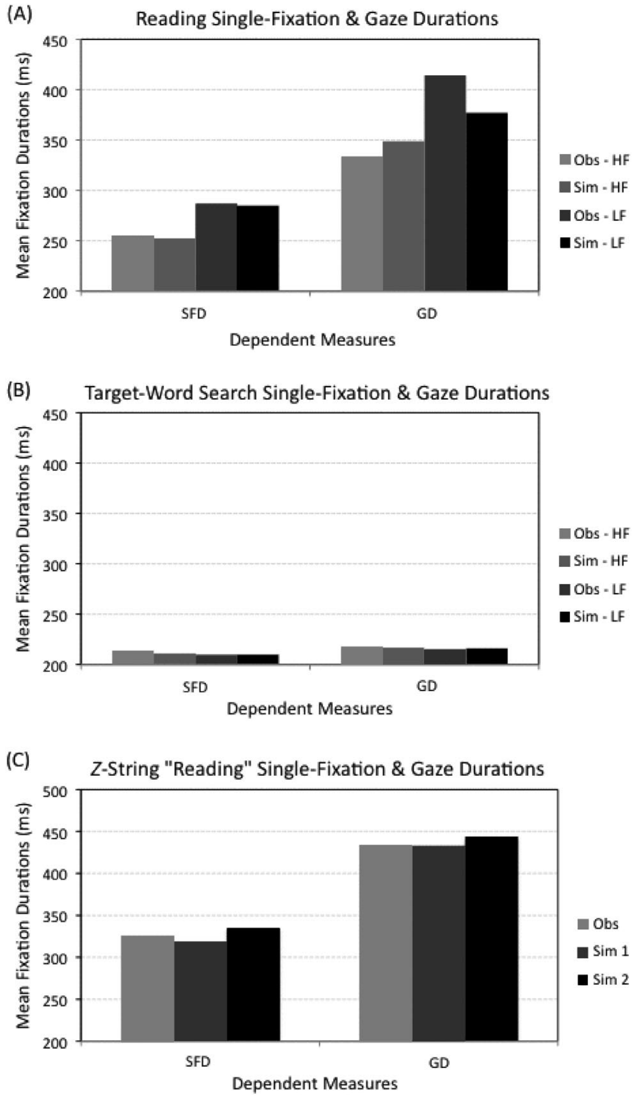

Figure 3. Mean observed (Rayner & Fischer, 1996) and simulated single-fixation (SFD) and gaze durations (GD) in three tasks: (A) reading; (B) target-word search; and (C) *z*-string "reading." Panels A and B show these dependent measures for high-frequency (HF) and low-frequency (LF) target words in reading and target-word search. Panel C also shows simulations completed using centers (Sim 1) versus ends (Sim 2) of *z* strings as refixation targets.

As Panel B of Figure 3 shows, the model accurately simulated the mean observed single-fixation and gaze durations, with the mean absolute difference between the observed and simulated means being only 1.2 ms. The simulation also captured two important aspects of the target-word search data: (a) relative to reading, both the single fixations and gaze durations during target-word search are much shorter in duration (cf. Panels A and B in Figure 3), and (b) both measures are only slightly affected by word frequency. It is also important to note that the best fitting parameter values that were obtained for the target-word search task differed in several important ways from those obtained for reading. First, the parameters that control the maximal time to complete lexical processing during reading (α_1 = 162 and Δ = 0.97) are markedly reduced in target-word search (α_1 = 39 and Δ = 0). To give some sense of this reduction, according to the model, the time required to identify a completely unpredictable three-letter word with a frequency of occurrence of one per million during reading is 385 ms; in contrast, the maximal time to "identify" the same word during target-word search is 93 ms. Thus, in contrast to reading, where each word is presumably processed up to the point where its meaning has been accessed, the target-word search task most likely entails only some minimal degree of lexical processing. This hypothesis is consistent with the fact that the target-word search task actually requires little or no language processing per se but can instead be performed on the basis of a superficial orthographic analysis: processing each word to the point where it can be discriminated from the target word. Because such decisions can probably be made using gross information such as word length and/or the identities of a few letters, individual words can be processed much more rapidly than during reading.

Second, the non-zero parameter estimate for α_3 (= 44 ms) during target-word search suggests that word processing is not always absent. Subjects seem to be occasionally encoding the meaning of individual words and possibly portions of the text as well, even though doing so is not required by the task. This may be encouraged by a strategy of processing the text well enough to predict that the target word is unlikely to be the next word. However, the fact that the best fitting value for λ is zero indicates that words are virtually never refixated for the sake of facilitating word encoding, suggesting that subjects are expending only minimal effort to understand the text.

Finally, it is interesting that the best fitting value of the Δ parameter is zero, effectively eliminating the L_2 stage so that the completion of the L_1 stage initiates both saccadic programming and shifts of attention to the next word. This result is theoretically significant because it suggests that the decoupling between the signal to move the eyes and the signal to move attention that is posited to occur during normal reading may be a visual routine that is relatively specific to reading and may not apply to many non-reading tasks. In the context of reading, such a routine is a heuristic that allows readers to fixate on words long enough for them to be encoded, but not longer than necessary. The best fitting parameters in our simulations of the target-word search task suggest that this heuristic is not adaptive in the context of performing that task; instead, subjects may have rapidly learned to locate the target words as quickly as possible by initiating saccadic programming and attention shifts after some minimal amount of visual processing has been completed (e.g., enough processing to "know" that the currently fixated word did not contain the first letter of the target word in the first position). This suggests that the link between cognition and eye-movement control is flexible, with the link being adjusted to accommodate new task demands. This hypothesis is explored below.

Z-string reading. The three articles using *z*-string reading (Nuthmann & Engbert, 2009; Rayner & Fischer, 1996; Vitu et al., 1995) have produced the following remarkably consistent (and possibly surprising) finding: Relative to the fixations that are observed during normal reading, those that occur during *z*-string reading tend to be longer in duration even though the task requires no language processing. In particular, in the data from Rayner and Fischer (1996) shown in Panel C of Figure 3, both the observed

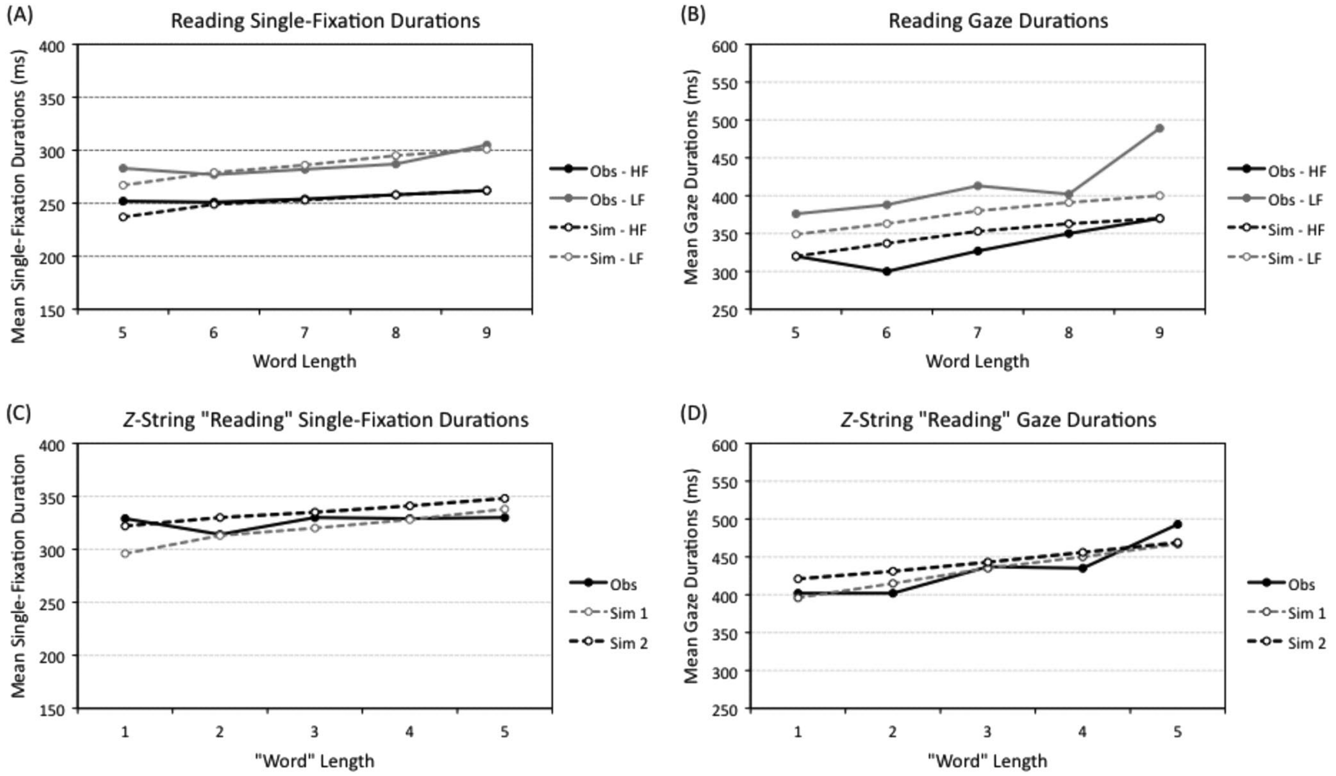

Figure 4. Mean observed (Rayner & Fischer, 1996) and simulated single-fixation and gaze durations in reading (Panels A and B) and *z*-string "reading" (Panels C and D) as a function of word/*z*-string length (5–9 letters). Panels A and B show these dependent measures for high-frequency (HF) and low-frequency (LF) target words in reading. Panel C also shows simulations completed using centers (Sim 1) versus ends (Sim 2) of *z* strings as refixation targets.

gaze duration and the single-fixation duration measures are markedly longer in the *z*-string condition than in the normal reading condition. Moreover, these durations are not modulated by word frequency, which is of course not applicable to the *z* string that replaces a word. However, because all of the letters of the text in *z*-string reading condition are replaced by *z*s, the "words" do differ in terms of their length. The challenge in explaining *z*-string reading using E-Z Reader therefore is to explain both the inflated fixation-duration measures and the effect of *z*-string length.

To simulate the eye movements in the *z*-string reading task, we used a variant of our sentence corpus in which all of the letters were replaced by *z*s. All of the word cloze predictabilities were therefore set to zero, and because the model uses log frequency to predict fixation time (and the log of zero is minus infinity), all of the word frequencies were set equal to one (so that the log frequency would equal zero).

In addition, the value of the Δ parameter was set equal to zero. We did this for three related reasons. Most notably, because there was no meaningful processing of the fixated word to be done, it seemed that positing two stages for such meaningless processing was close to nonsensical. Second, because there was nothing to be processed on the fixated word that required attention, positing a second stage in which attention remains on the fixated word after the command to move the eyes has been issued has no impact on what is being observed (i.e., it is a completely "invisible" stage in the model for these data, with no discernible effect). Third, because we obtained a zero value of Δ in the preceding simulation of the target-word search task, we thought it would be of interest to determine whether the assumption of a zero value of Δ would be adequate to explain the data in all three of our nonreading tasks.

Finally, because *z* strings are by definition devoid of any semantic content, we disabled the model's assumptions about postlexical processing (i.e., $I = 0$ and $p_F = 0$) because it is unclear what such processing corresponds to in this task (see Appendix B). We then found the values of α_1 and λ that minimized the mean absolute deviation between the observed and simulated single-fixation and gaze durations on the *z*-string target words (i.e., the same 5-, 6-, 7-, and 8-letter target words used in the previous simulation but with the letters replaced with *z*s).

The procedure for finding the best fitting parameter values was completed twice: first as just described and then again using two additional assumptions about the programming of refixation saccades. These two assumptions were that refixations are directed toward the ends (rather than centers) of *z* strings and that these nonstandard refixations require some additional amount of time (i.e., the duration of the eye–mind lag, 50 ms) to program. The rationale for these additional assumptions is discussed below, in the section on simulating fixation-location measures, but for the sake of completeness, we report simulation results using both the standard and additional refixation assumptions even though the latter had very little effect on the fixation-duration measures.

The two sets of best fitting parameter values are shown in Table 2, with the columns labeled "Simulation 1" and "Simulation 2" respectively showing the best fitting parameters obtained using the standard model and the model that included the two additional refixation assumptions.. As Panel C of Figure 3 shows, both of the simulations captured the main trends in *z*-string reading, allowing the model to generate single-fixation and gaze durations that were fairly long (mean absolute difference between the observed and simulated $Ms = 11.3$ ms for Simulation 1 and 10.5 ms for Simulation 2). Also, as Panels C and D of Figure 4 show, the simulations accurately predicted the effect of *z*-string length, with longer *z* strings being the recipients of longer single-fixation and gaze durations than shorter *z* strings.

It is worth mentioning that the changes in parameter values relative to the simulation of reading (see Table 2) also provide an explanation of how *z*-string reading is different from normal reading. First, ignoring the obvious changes in the model that eliminate frequency and predictability effects, it is interesting that the parameter that determines the maximal time to complete the first stage of lexical processing and hence (according to the model) when saccadic programming will be initiated is longer during *z*-string reading ($\alpha_1 = 219$ ms and 233 ms for Simulations 1 and 2, respectively) than reading ($\alpha_1 = 162$ ms). This suggests that the overall reduction in fixation durations that is observed during reading reflects facilitation from lexical processing and that the signal to initiate saccadic programming in *z*-string reading may instead reflect some type of deadline corresponding to the maximal time that is normally allotted for lexical processing. As is discussed below, this interpretation is consistent with results from a recent eye-movement experiment (Reichle, Reineberg, & Schooler, 2010) that examined mindless "reading" during the reading of actual text.

It is also interesting that the decoupling between the signal to shift attention and the signal to initiate saccadic programming (as determined by the non-zero value of the parameter Δ that is posited to occur during reading) was not necessary to simulate *z*-string reading. This result suggests that the decisions about when to move the eyes may be more or less tightly coupled to the decisions about when to shift attention. During reading, the two appear to be decoupled, allowing individual fixations to be as short as possible while also allowing the words of the text to be encoded and identified as efficiently as possible. In contrast, *z*-string reading seems to benefit from a coupling between saccadic programming and attention shifts; the decision to start programming a saccade off a *z* string appears to correspond to some type of signal that enough time has elapsed to move the eyes forward (which appears to be a function of the length of the *z* string). This suggests that the separation between the two processes that is posited to occur during reading by the E-Z Reader model reflects a strategy that may be specific to reading and that may not generalize to other (nonreading) tasks. This also suggests that the trigger to begin saccadic programming in *z*-string reading may have little to do with whatever processing is actually being done to the *z* strings. Thus, contrary to the explanation offered by Nuthmann and Engbert (2009), the movement of the eyes during *z*-string reading may have little to do with ongoing visual encoding or lexical processing per se but may instead reflect internal decisions about when to move the eyes in order "to look like those in reading."

Finally, one unexpected outcome of these simulations is that the values of the parameter that modulates the tendency to make automatic refixations (i.e., λ; see Equation 6) were actually larger than in the simulations of reading, raising the question of why *z*-string reading should increase (rather than decrease) the propensity to refixate when nothing is actually being read. We suspect that this paradoxical result reflects the tendency to maintain the forward momentum of the eyes during *z*-string reading. As we show below, an increased tendency to make refixations during *z*-string reading is actually rational behavior if the majority of those refixations move the eyes forward, either to the end of the current *z* string or the beginning of the next. This hypothesis is discussed below, in the section on fixation-location measures.

Williams and Pollatsek (2007) and Williams, Pollatsek, and Reichle (2011). In this pair of studies, subjects were instructed to search through arrays containing eight 4-character clusters of Landolt *C*s to decide whether a single target letter *O* was present in the array. The orientation of the gaps in the *C*s varied pseudorandomly, with equal numbers of gaps appearing in each of the four cardinal orientations. The size of the gaps was held constant in a cluster (including the nontarget *C*s in the cluster containing the target *O*), but the size of the gaps in a cluster varied across the conditions of interest, with an equal number of clusters containing gap sizes of varying numbers of pixels. (Although the size of the gap was counterbalanced, it is likely that, from the subject's perspective, the size of the gap varied randomly from cluster to cluster.) In the first experiment (Williams & Pollatsek, 2007), the stimuli were arranged in a linear array, so that the stimuli superficially resembled sentences in which the letters in the words were either *C* or *O*. In the second experiment (Williams et al., 2011), the stimuli were arranged in a circular array (like a clock face), with individual clusters of Landolt *C*s being located at eight positions along the circumference of an imaginary circle (i.e., at 0° and increments of 45°). The two experiments thus allow one to examine how the spatial arrangement of the stimuli do (or do not) affect subjects' decisions about when and where to move their eyes in the service of performing the task. In both the actual experiments and the simulations reported below, only the patterns of eye movements obtained during target-absent trials were examined.

Landolt-*C* search of linear arrays. One key finding of these experiments was that, as gap size with a cluster increased, so did the relative ease of performing the task. This pattern is evident in Panel A of Figure 5, which shows the mean first-fixation and gaze durations (collapsed across the different cluster positions) as a function a gap size for target-absent clusters: As gap size increased, the mean durations of both measures decreased. (A similar gap-size effect was observed with target-present clusters; however, gaze durations on target-present clusters were longer overall, possibly because subjects usually maintained their gaze on the cluster while executing their manual responses.) A second key finding of the experiment was that the gap size in a cluster only affected fixation time on that cluster. That is, it did not have an effect on the gaze duration on the prior cluster (which is consistent with our data in reading and with predictions of the E-Z Reader

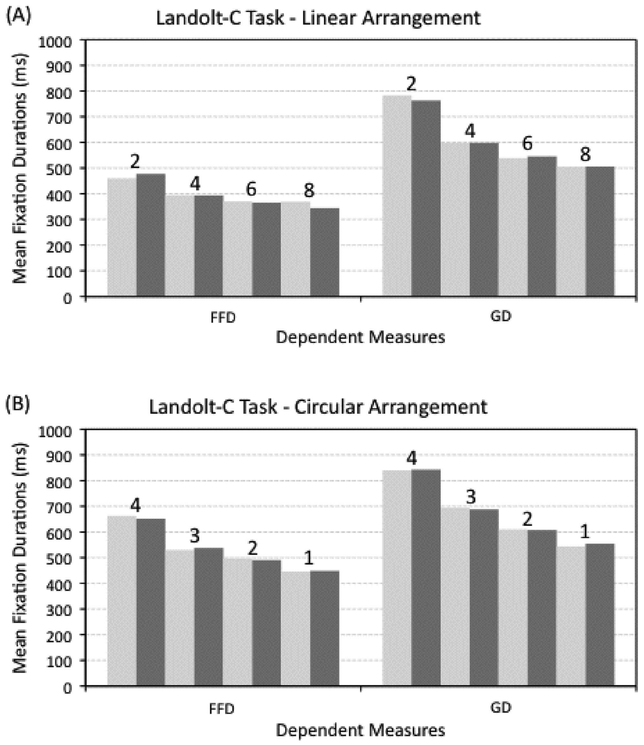

Figure 5. Panel A: Mean observed (Williams & Pollatsek, 2007) and simulated first-fixation durations (FFD) and gaze durations (GD) during visual search as a function of Landolt-*C* gap size (2–8 pixels, as indicated by the numbers above the bars in the figure). Panel B: Mean observed (Williams et al., 2011) and simulated FFD and GD during visual search as a function of Landolt-*C* gap size (1–4 pixels, as indicated by the numbers above the bars in the figure).

model for reading). More significant, it did not have a spillover effect on fixation times on the subsequent cluster (which is contrary to both the reading data and predictions of the E-Z Reader model for reading).[5] Another marked but easy-to-overlook difference between this task and reading concerns the absolute durations of the two fixation-duration measures: As Panel A of Figure 5 clearly shows, both the first-fixation and gaze durations were much longer in the Landolt-*C* task than in reading (cf. Figures 3 and 5). The challenge is therefore to explain these key findings using the assumptions of E-Z Reader.

To simulate the Landolt-*C* search task, we gave the model a corpus containing 48 arrays of Landolt *C*s, each containing eight 4-character clusters with the clusters separated by blank spaces (as in the experiment by Williams & Pollatsek, 2007). We assumed that each cluster was treated as a functional unit or word, with attention being allocated to one cluster at a time. As with the *z*-string reading simulation reported above, each cluster was assumed to have a frequency of one and a predictability of zero. Of greater importance, the value of the Δ parameter was set equal to zero because this assumption is necessary to account for the absence of spillover effects in experiments involving the Landolt-*C* task (Williams & Pollatsek, 2007; Williams et al., 2011). Thus, it is crucial to see whether setting Δ equal to zero would give a satisfactory fit of other aspects of the data.

Two additional assumptions were necessary to account for the observed differences between this task and reading. First, as in our simulations of the *z*-string reading and word-search tasks, postlexical processing was disabled (i.e., $I = 0$ and $p_F = 0$). Second, to simulate the observed differences in the ease of discriminating nontarget clusters from targets in the 8-, 6-, 4-, and 2-pixel gap conditions, it was necessary to assume that the limiting effect of visual acuity (see Equation 7) was more pronounced as gap size decreased. This was done by varying the values of ε across conditions from 2.04 in the 8-pixel gap condition to 2.75 in the 2-pixel gap condition. We would argue that this assumption is reasonable given the inherent difficulty of discriminating Landolt *C*s from *O*s and the fairly homogeneous nature of the Landolt-*C* stimuli. Moreover, in contrast to reading, there is no equivalent of a word representation to facilitate letter identification via top-down processing.

The best fitting values of the α_1, λ, and ε parameters were then found (as described in Appendix B), using the mean absolute deviation between the observed and predicted means as our goodness-of-fit metric. The best fitting parameters are listed in Table 3. As Panel A of Figure 5 shows, our assumptions about how subjects performed the Landolt-*C* search task were sufficient to explain the overall increase (relative to reading) in the observed first-fixation and gaze durations (cf. Figure 3A and Figure 5A) and the effect of gap size on both measures (i.e., mean absolute deviation = 9.3 ms).

As Table 3 indicates, the best fitting parameter values differ substantially from those obtained in reading. First, the parameter that controls the maximal rate of word or object processing is modestly reduced in the Landolt-*C* task (i.e., $\alpha_1 = 119$ ms) relative to reading ($\alpha_1 = 162$ ms). However, in the Landolt-*C* task, the rate of processing is considerably slower because of the severe restrictions imposed by visual acuity limitations. For example, the Landolt-*C* clusters containing the smallest gap sizes are presumably the most difficult to discriminate from the letter *O*; according to the parameter values, such clusters will on average require 304 ms of processing (i.e., = 50 ms of visual processing + 254 ms to complete the L_1 stage of processing) before enough information has been extracted from the cluster to know that it does not contain an *O* and to consequently initiate saccadic programming to move the eyes and covert attention to the next cluster. Consistent with this account is the fact that this task required substantially larger values of the parameter that modulates the probability of making automatic refixations (i.e., $\lambda = 0.48$) than in any of the previously reported simulations, suggesting that the clusters were often refixated to afford better views of the difficult-to-discriminate Landolt-*C* stimuli.

Together, the results of this simulation again suggest important differences between eye-movement control during reading and nonreading tasks, most notably, that the decisions about when to move the eyes during the former tasks are determined by factors that may be unique to reading (and perhaps a few other highly

[5] One concern we had was that the lack of spillover effects may simply reflect the failure to extract information from the cluster about to be fixated. However, a pilot display-change experiment with the clusters showed this was not the case; fixation times on a cluster were longer when there was no parafoveal information.

Table 3
Best Fitting Parameter Values for the Landolt-C Search Tasks Involving Linear (Williams & Pollatsek, 2007) and Circular (Williams et al., 2011) Arrangements of Stimuli

Parameters	Linear arrangement	Circular arrangement
α_1	119	128
Δ	0	0
λ	0.41	0.12
ϵ	2.04, 2.17, 2.33, 2.75	1.7, 1.84, 2.03, 2.41

Note. The four increasing values of epsilon correspond to conditions involving decreasing Landolt-*C* gap sizes.

practiced visual tasks). We shall return to the issue of how, in the context of reading, such decision-making routines might be learned below, after we examine one final task that is designed to examine how the spatial arrangement of the stimuli that are being processed might affect eye guidance.

Landolt-C search of circular arrays. As indicated, the main difference between this study (Williams et al., 2011) and the previous one (Williams & Pollatsek, 2007) was that, in the former, the Landolt-*C* clusters that were arranged into a circle, with the four stimuli within each cluster arranged into a square. (Although the screen resolution of the monitors used in the two experiments also differed, thereby requiring different number of pixels to render stimuli having different gap sizes, the absolute gaps sizes were comparable across the experiments.) As such, the experiment provides an ideal test case to determine if the assumptions of our model are applicable to viewing tasks in which the individual elements that are being examined are arranged in a nonlinear configuration (e.g., visual search for objects in scenes). Of course, the unique arrangement of the stimuli required three additional, task-specific assumptions.

The first assumption pertains to how the model viewed the Landolt-*C* clusters in performing the simulated task. For the sake of simplicity, we adopted the assumption that the stimuli would be examined in a clockwise or counterclockwise manner, starting with the cluster at the top of the display. This assumption is consistent with what was observed by Williams et al. (2011); in their experiment, 90% of the intercluster saccades systematically moved their subjects' eyes in either a clockwise or counterclockwise manner.

The second assumption is related to saccadic error. Because the Landolt-*C* clusters were arranged in two dimensions, it was necessary to assume that saccades could deviate from their intended targets in both the *x*- and *y*-directions. The Gaussian component of the saccadic error could thus cause a fixation to deviate by some distance and some angle (i.e., 0–360°) relative to the intended target. Therefore, any given saccade could cause the eyes to overshoot or undershoot their intended target and could similarly move the eyes to the left or right of their intended target.

The final assumption is related to how visual acuity attenuated the rate of lexical processing (see Equation 7). In all of the previous simulations, this processing rate was a function of the mean linear distance (in character spaces) between the point of fixation and each of the letters in the word being processed. For example, in the previously reported simulation of the Williams and Pollatsek (2007) study, each of the Landolt *C*s corresponded to one letter in a four-letter word. However, in the present simulation, this processing rate was a function of the mean of the Euclidean distances between the point of fixation and each of the four Landolt *C*s within the cluster being processed. This assumption was adopted because it was the simplest possible extension of the standard assumption.

With these three assumptions, we completed grid searches of the parameter spaces to find the best fitting parameters for this task in exactly the same manner as in our simulation of the Williams and Pollatsek (2007) study (e.g., setting the value of the Δ equal to zero, disabling postlexical processing). The best fitting parameter values are listed in Table 3. As can be seen, these parameters are similar to those obtained in our previous simulation involving the linearly configured Landolt *C*s. This convergence across the two Landolt-*C* task simulations lends additional support to our assumption that the demands of the tasks are extremely similar. That is, relative to reading, the primary determinant of the time required to process a Landolt *C* to a degree that is sufficient to discriminate it from an *O* is not lexical processing per se but is instead visual acuity. As Panel B of Figure 5 shows, the time required to perform this discrimination increased as gap size decreased, as indicated by the fact that both first-fixation and gaze durations became longer as the gap size of the stimuli decreased. As Figure 5 also shows, the model simulated this pattern very accurately, both in terms of the absolute durations of the measures and how those measures were modulated by gap size (mean absolute observed-simulated deviation = 6.2 ms).

As indicated previously, the primary reason for performing this simulation was to demonstrate that the basic principles of the E-Z Reader model are sufficient to explain the patterns of eye movements that are observed in a task that—in many ways—is markedly different from reading, which was the task that the E-Z Reader model was designed to explain. That is, the Williams et al. (2011) task—in stark contrast to reading—involved neither linguistic processing nor movement of the eyes along a linear trajectory. Thus, the success of this simulation in explaining the fixation-duration data suggests that the model's core principles might indeed be applied to a range of other visual–cognitive tasks (e.g., searching for objects in a visual scene). It also provides a template for how these principles might be applied to other tasks (e.g., by embedding the model's principles within the framework of a few general assumptions about the goals of a task and/or how it is performed). We return to and discuss this possibility at length, below.

Simulation of Fixation-Location (i.e., "Where") Measures

Although the decisions about when versus where to move the eyes are largely independent in the E-Z Reader model, we nonetheless thought it was important to know whether the general principles of the model—in conjunction with the specific assumptions and parameter values used in the simulations reported above—were also sufficient to explain the various fixation-location measures that were reported in each of our simulated experiments. Therefore, the simulations reported below were completed using exactly the same assumptions and parameter values as those reported in the previous section.

Rayner and Fischer (1996). As with our discussion of the fixation-duration measures, we report our findings for reading first, then target-word search, and then *z*-string reading.

Reading. To evaluate the model's capacity to simulate where the eyes move during reading, we examined the three dependent measures that were reported by Rayner and Fischer (1996): (a) the distributions of first-fixation landing sites on 5- to 9-letter high- and low-frequency target words (see Figure 6); (b) the probabilities of making refixations on 5- to 7-letter high- and low-frequency target words as a function of initial fixation location (see Figure 7); and (c) the durations of single fixations as a function of their location on 5- to 7-letter high- and low-frequency target words (see Figure 8).

As Figure 6 indicates, the model accurately simulated the basic characteristics of the observed initial-fixation landing-site distributions (i.e., mean absolute difference between observed and simulated *M*s = 0.048). Figure 7 indicates that the model also simulated the finding that refixations are more likely following initial fixations near the beginnings and ends of words, although the model tended to overpredict the overall probability of making a refixation (i.e., mean absolute difference between observed and simulated *M*s = 0.305). Finally, as Figure 8 shows, although the model was less accurate in simulating how single-fixation durations are modulated by their locations (i.e., mean absolute difference between observed and simulated *M*s = 50 ms), the nature of this discrepancy is interesting because the predicted results actually conform more closely to the canonical inverted-*U* patterns that are typically observed and that give the inverted-optimal viewing position (IOVP) effect its name (i.e., single fixations near the centers of words tend to be longer in duration than those near the

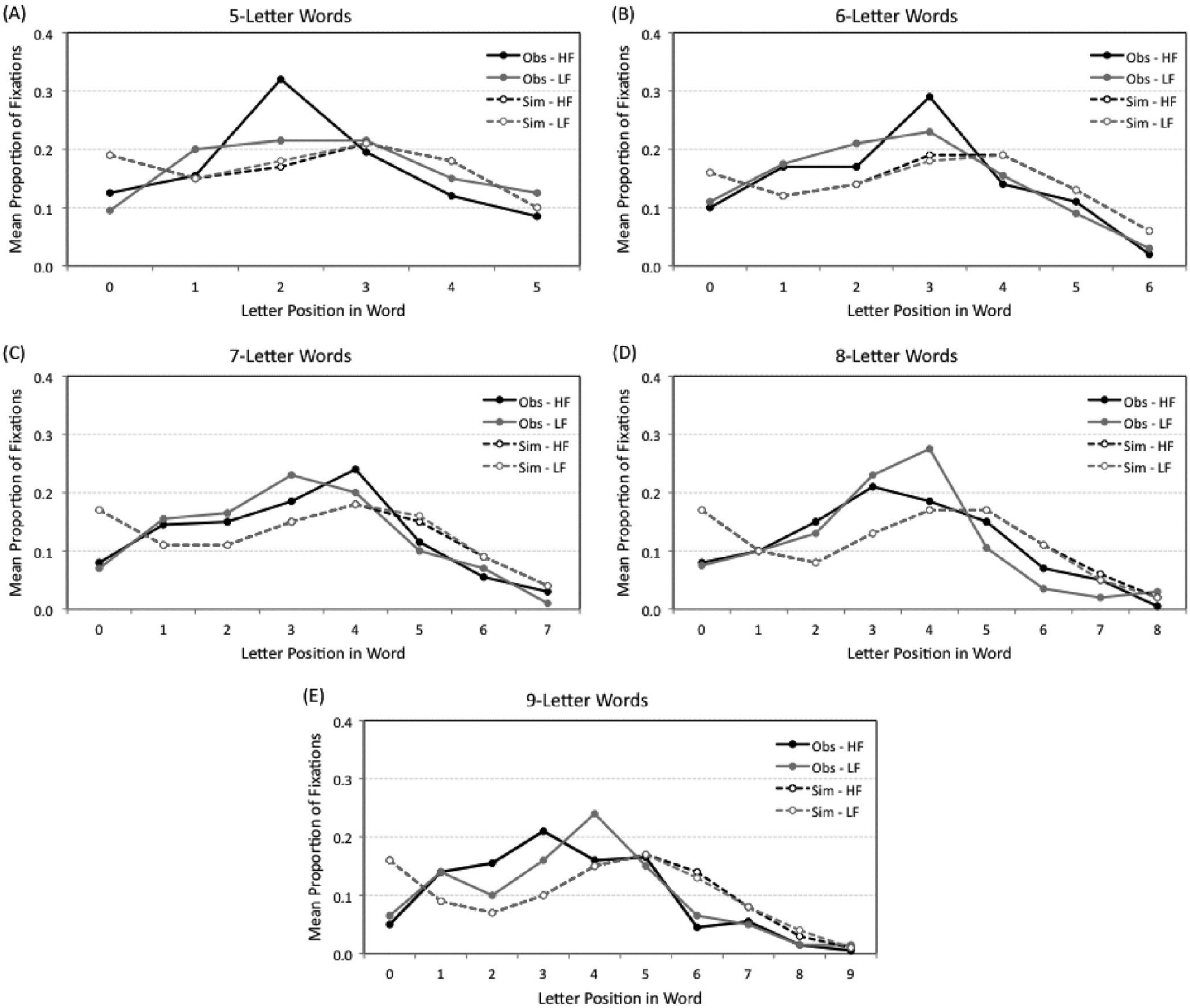

Figure 6. Mean observed (Rayner & Fischer, 1996) and simulated first-fixation landing-site distributions for high-frequency and low-frequency target words in reading, as a function of their length (5–9 letters in Panels A–E, respectively).

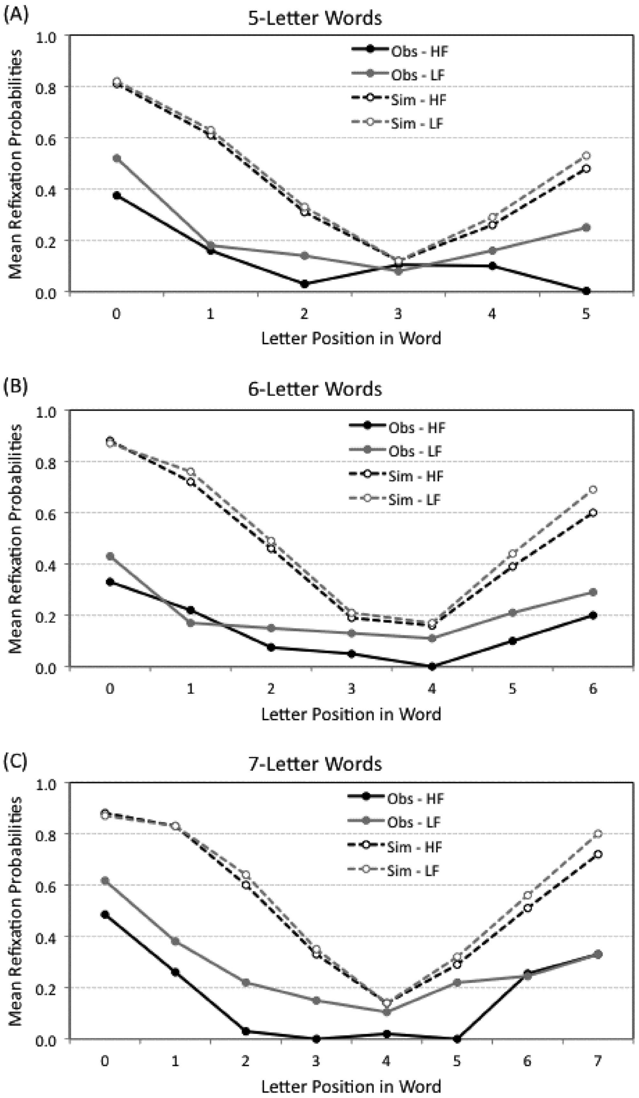

Figure 7. Mean observed (Rayner & Fischer, 1996) and simulated refixation-probability distributions as a function of the first-fixation landing site for high-frequency and low-frequency target words in reading, as a function of their length (5–7 letters in Panels A–C, respectively).

beginnings and ends of words; see, e.g., Vitu et al., 2001; Reingold, Reichle, Glaholt, & Sheridan, in press). Because these discrepancies between the observed and simulated data are fairly minor, and because the purpose of simulating the normal reading condition was to provide a baseline with which to compare the nonreading tasks, we made no attempt to obtain better fits by adjusting other model parameters.

Target-word search. We next moved to predicting the target-word search data and examined the one dependent measure reported in this task—the distributions of first-fixation landing sites for 5- to 9-letter words (see Figure 9). As Figure 9 indicates, the model accurately simulated the observed landing-site distributions (mean absolute observed-simulated deviation = 0.06), capturing the finding that the observed landing-site distributions tend to be more platykurtic (i.e., flatter, with more observations in the tails of the distributions) during target-word search than reading, especially for the shorter words.

Z-string reading. Finally, we examined the model's capacity to explain where the eyes move by simulating the three dependent measures reported by Rayner and Fischer (1996) for this task: (a) the distributions of first-fixation landing sites on 5- to 9-letter words (see Figure 10); (b) the probabilities of making refixations on 5- to 7-letter words as a function of initial fixation location (see Figure 11); and (c) the durations of single fixations as a function of their location on 5- to 7-letter words (see Figure 12). These simulations were completed twice: Simulation 1 used the standard model, and Simulation 2 included the additional assumptions that refixations are directed toward the ends (rather than centers) of *z* strings and that they require extra time (i.e., 50 ms) to program.

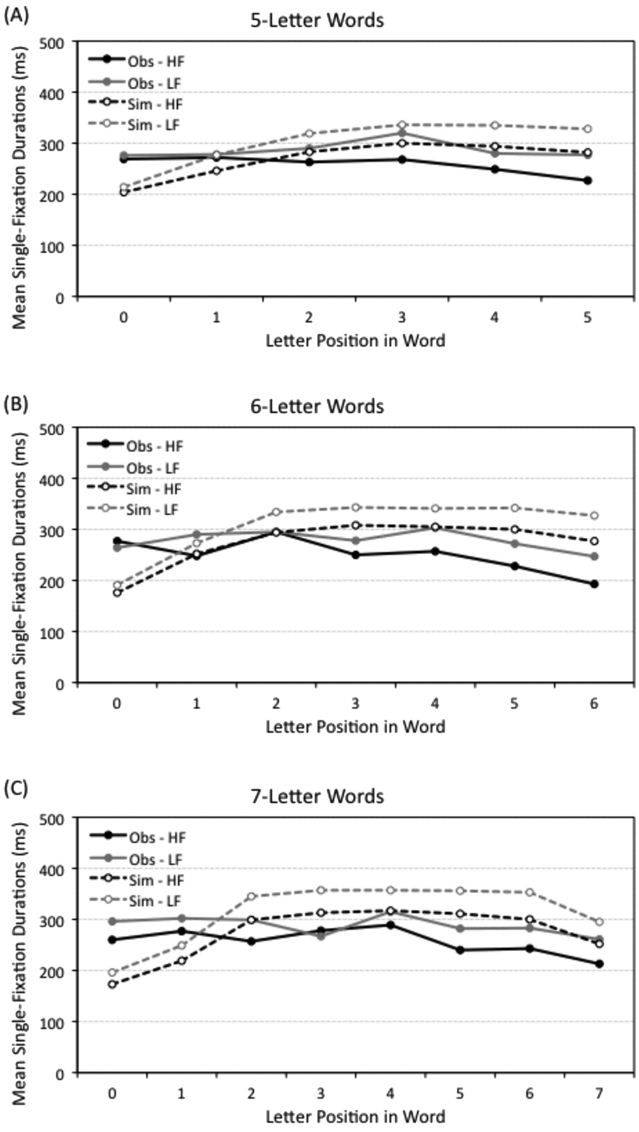

Figure 8. Mean observed (Rayner & Fischer, 1996) and simulated single-fixation durations as a function of their within-word location for high-frequency (HF) and low-frequency (LF) target words in reading, as a function of their length (5–7 letters in Panels A–C, respectively).

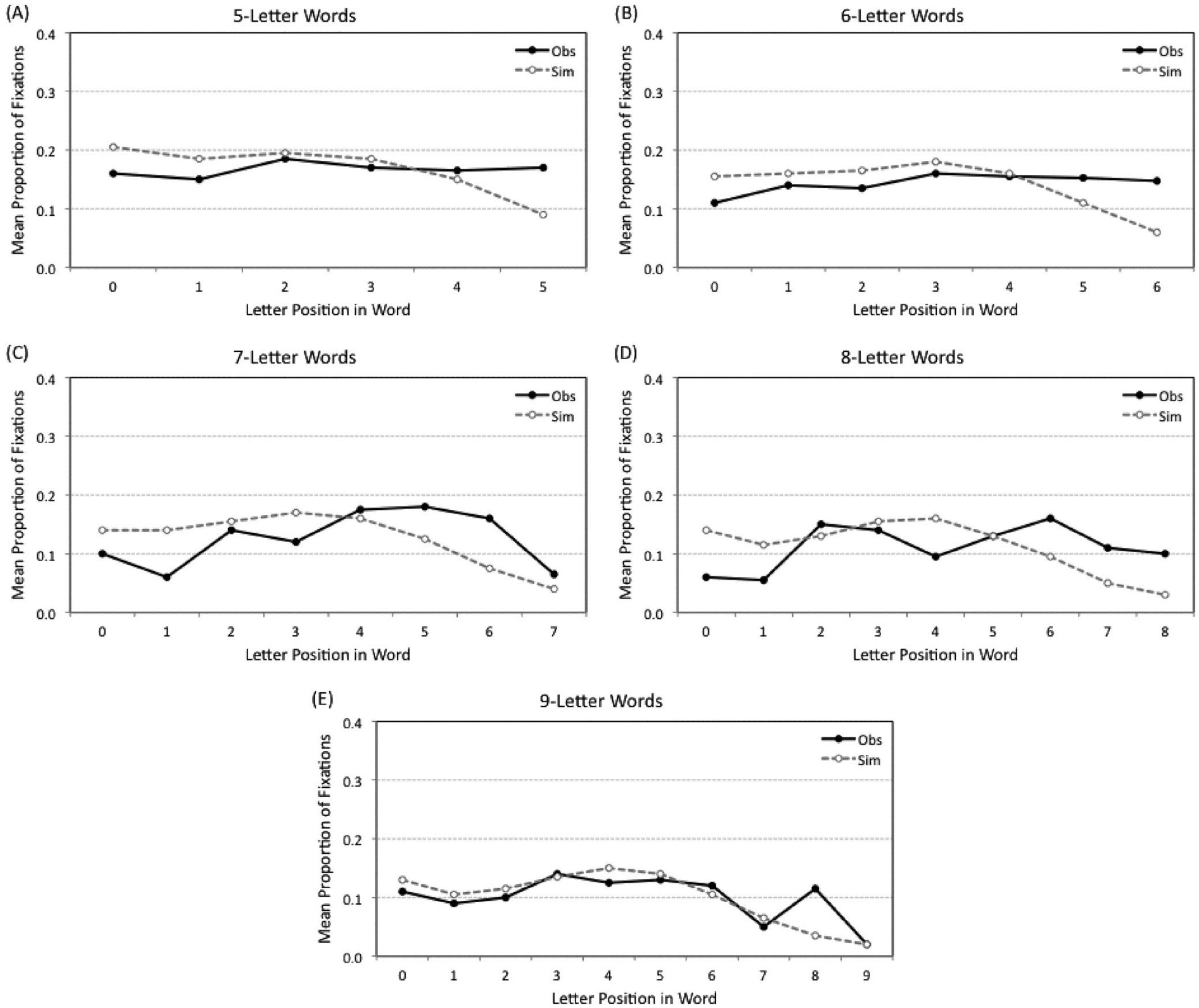

Figure 9. Mean observed (Rayner & Fischer, 1996) and simulated first-fixation landing-site distributions for target words in target-word search, as a function of their length (5–9 letters in Panels A–E, respectively).

The former assumption was adopted on the grounds that, during the *z*-string reading task, subjects have little incentive to interrupt the forward momentum of their eyes (e.g., they make fewer regressions; Nuthmann & Engbert, 2009; Rayner & Fischer, 1996; Vitu et al., 1995) and, as a result, might simply direct all refixations toward the ends of the *z* strings so as to maintain their progression through the text. That is, these refixations are not really attempted refixations per se but are instead a population of short forward saccades that are made to maintain the forward momentum of the eyes. The latter assumption was adopted because these refixation programs are not based on efference copies of the primary saccade programs (i.e., the two types of saccades are directed toward different targets), suggesting that the former should require more time to complete than the latter. For the sake of simplicity, we therefore assumed that refixations require an additional 50 ms to program because this corresponds to the duration of the eye-to-mind lag and thus the minimal time required to use visual feedback to program a refixation. (Two additional simulations that were completed using 0 ms and 100 ms produced similar results.)

As Figure 10 shows, the model does a fairly good job reproducing the observed initial-fixation landing-site distributions, with the two simulations performing about equally well (mean absolute observed-simulated deviations = 0.03 vs. 0.04 for Simulations 1 and 2, respectively). However, as Figure 11 shows, the two simulations do not reproduce the observed refixation-probability distributions equally well. In Simulation 1, the model erroneously predicts an asymmetrical *U*-shaped pattern, similar to what is observed during reading (mean absolute observed-simulated deviation = 0.32). In Simulation 2, the model correctly predicts that refixations are more likely following an initial fixation near the beginning than middle of

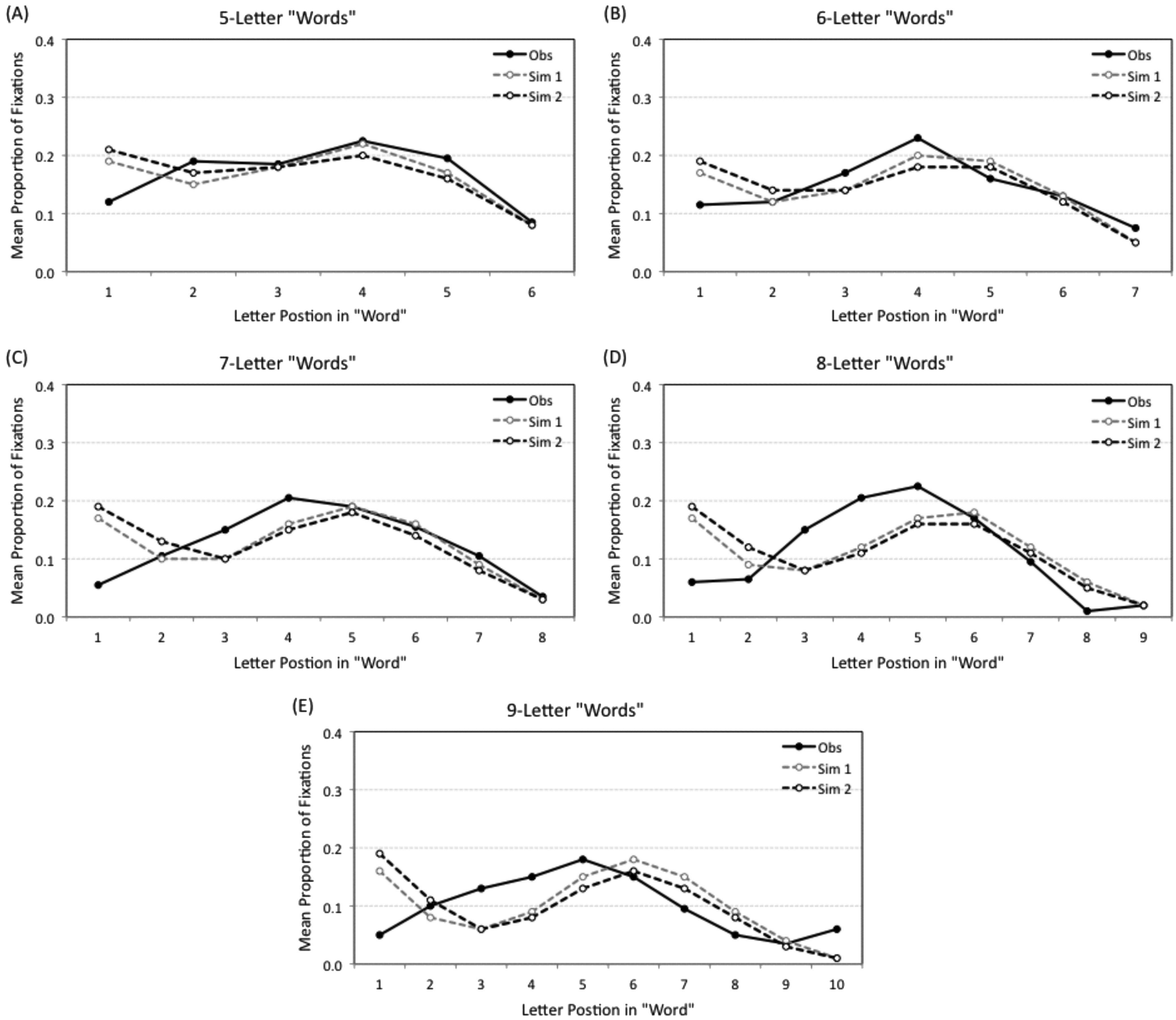

Figure 10. Mean observed (Rayner & Fischer, 1996) and simulated first-fixation landing-site distributions for target "words" in *z*-string reading, as a function of their length (5–9 letters in Panels A–E, respectively). The simulations were completed using centers (Sim 1) versus ends (Sim 2) of *z* strings as refixation targets.

a *z* string and that this likelihood is reduced even further following an initial fixation near the end of a *z* string (mean absolute observed-simulated deviation = 0.14). This (nearly) monotonic pattern in Simulation 2 contrasts with what is observed in reading (cf. Figures 7 and 11). It obviously reflects the additional assumptions about how refixations are programmed and provides some justification for their inclusion.

This conclusion is also supported by Figure 12, which shows single-fixation durations as a function of the location within a given *z* string. As can been seen, Simulation 2 captured the mean absolute durations fairly well (i.e., mean absolute observed-simulated deviations = 33 ms) and reproduced the canonical inverted-*U* shape that has been reported with *z* strings (e.g., Vitu et al., 2001). In contrast, Simulation 1 performed less well, both in terms of mean absolute durations (i.e., mean absolute observed-simulated deviation = 62 ms) and its canonical inverted-*U* shape. The fact that Simulation 2 provides a better account of how single-fixation durations are modulated by their location than does Simulation 1 therefore provides some additional support for our hypothesis that, during *z*-string reading, subjects may have adopted a strategy of almost always directing their refixations in the forward direction, perhaps to maintain a more rapid progress through the text. This suggests that the saccade-targeting routines that are employed by subjects may be task dependent and that these routines may involve decisions about where to direct both the primary saccades that

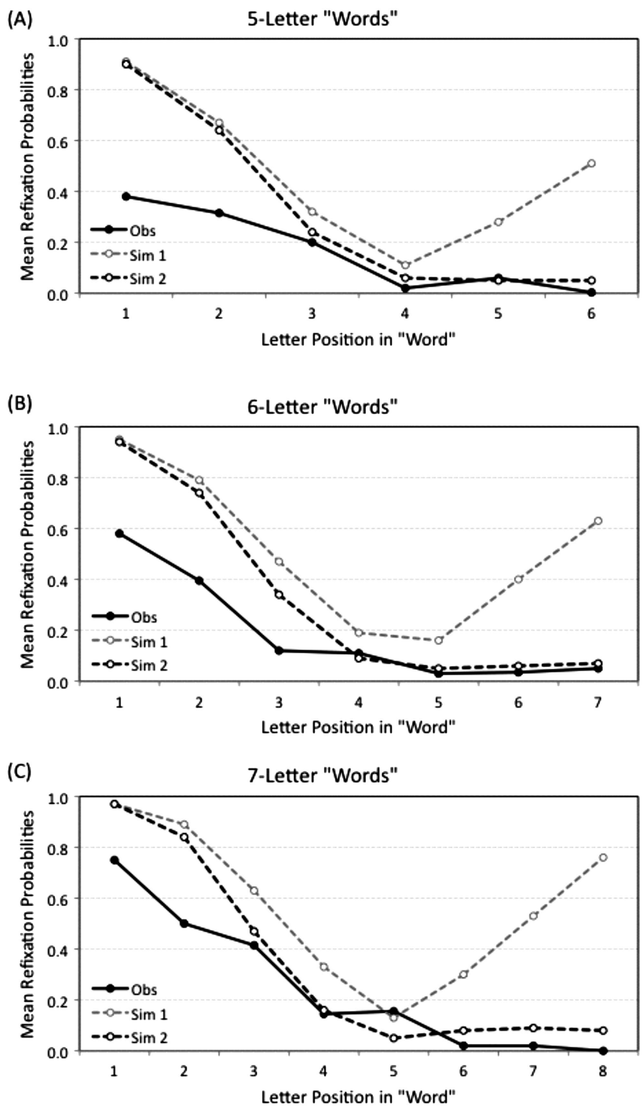

Figure 11. Mean observed (Rayner & Fischer, 1996) and simulated refixation-probability distributions as a function of the first-fixation landing site for target "words" in *z*-string reading, as a function of their length (5–7 letters in Panels A–C, respectively). The simulations were completed using centers (Sim 1) versus ends (Sim 2) of *z* strings as refixation targets.

move the eyes from one word to the next and the corrective saccades that normally result in refixations.

Williams and Pollatsek (2007) and Williams et al. (2011). To further evaluate the E-Z Reader model's capacity to simulate where the eyes move during nonreading tasks, we simulated the fixation-location data in the two other types of search tasks discussed above—where subjects searched for *O*s that were embedded in either linear or circular arrays of Landolt *C*s.

Landolt-C search of linear arrays. The primary analysis was of the locations of the fixation landing-site means and how these means varied as a function of the Landolt-*C* gap size. The locations of both the observed and simulated means are shown in Panel A of Figure 13. As the figure shows, the observed mean locations were not affected by gap size and tended to fall near the rightmost edge of the first character within a cluster. The model accurately captured both aspects of these data (mean absolute observed-simulated deviation = 0.12 characters).

Landolt-C search of circular arrays. The primary analysis was again of the locations of the fixation landing-site means and their relation to Landolt-*C* gap size. Panel B of Figure 13 shows the distance in pixels between the first-fixation location on a Landolt-*C* cluster and its center as a function of its gap size. The figure also shows that the model accurately predicted these distances and the absence of any effect of gap size (mean absolute observed-simulated deviation = 1.61 pixels). These results, in conjunction with the simulated fixation-duration results reported earlier, indicate that the basic assumptions of the model were

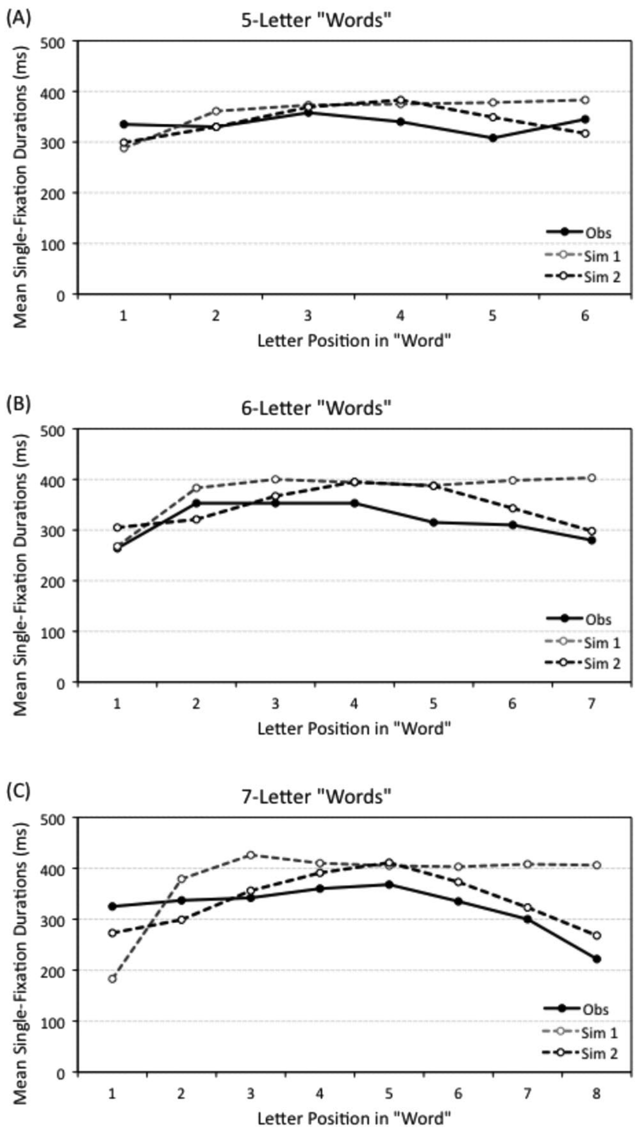

Figure 12. Mean observed (Rayner & Fischer, 1996) and simulated single-fixation durations as a function of their within-string location for target "words" in *z*-string reading, as a function of their length (5–7 letters in Panels A–C, respectively). The simulations were completed using centers (Sim 1) versus ends (Sim 2) of *z* strings as refixation targets.

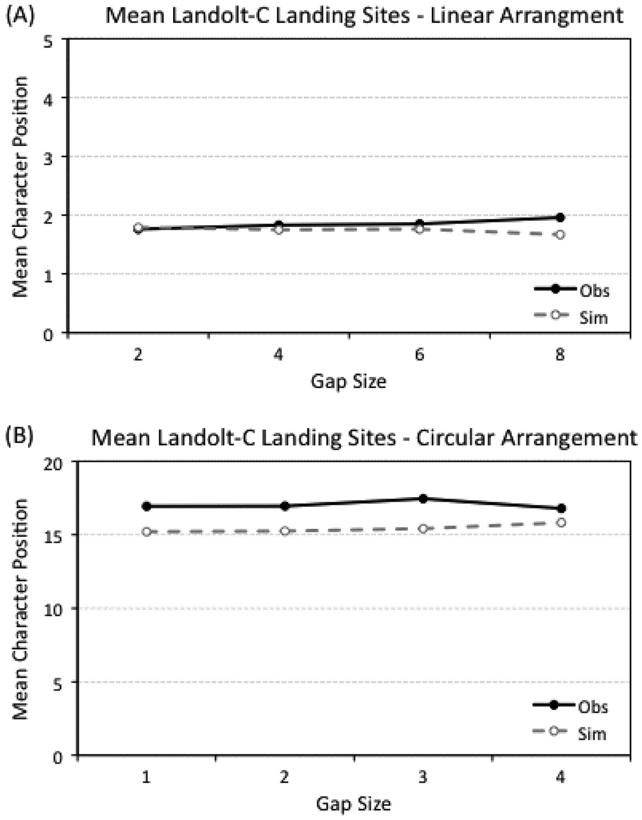

Figure 13. Panel A: Mean observed and simulated first-fixation landing sites in the Landolt-*C* task as a function of gap size (2–8 pixels). The positions are coded using 0 for the blank space to the left of a Landolt-*C* cluster, a 1 for the first character in a cluster, and so on. Panel B: Mean observed and simulated distance (in pixels) between the centers of the Landolt-*C* clusters and the first-fixation landing-site distributions, as a function of gap size (1–4 pixels).

sufficient to simulate both when and where the subjects moved their eyes in performing this task—a task that, as already said, has demand characteristics that are very different from those of reading. We discuss this issue of between-task differences and how these differences might be expected to influence eye movements in other nonreading tasks below, in the final section of this article.

General Discussion

We have shown that a cognitive-control, serial-attention-shift model can simulate the eye movements that are observed in three tasks that do not require language processing and—because they engender patterns of eye movements that are somewhat similar to those that are observed in natural reading—these tasks have sometimes been used to argue against a tight coupling between cognition and eye movements in reading. What the simulations specifically demonstrate is that the architecture of the systems that guide eye movements in tasks such as reading is flexible enough to accommodate tasks other than reading, even when the array is not linear (Williams et al., 2011). One might argue that this is not surprising. Reading has been around for only a few millennia (Dehaene, 2009; Robinson, 1995), which means that the processes that guide eye movements in other tasks (e.g., search for an object in the environment) almost by definition have had to be co-opted and coordinated (through extensive practice) to support the task of reading.

Two fundamental theoretical differences between reading and the three nonreading tasks that were simulated that are suggested by our simulations are (a) the trigger to begin programming a saccade from one object (e.g., words, *z* strings, Landolt-*C* clusters) to the next may often be synchronized with the trigger to shift attention in tasks other than reading for comprehension; and (b) the overall time that is required to trigger the saccade can vary and can be more or less modulated by cognitive variables (e.g., word frequency). Of course, our simulations do not provide definitive proof that these conjectures are true; as such, they should be viewed as working hypotheses that warrant further investigation. What they do strongly suggest, however, is that the visual routines that guide eye movements during reading can emerge through practice performing a task that has unique task demands—rapidly identifying words in their correct (canonical) order on the printed page (Pollatsek & Rayner, 1999; Rayner, Pollatsek, Liversedge, & Reichle, 2009).

This last conjecture is supported by recent computational work in which artificial reading agents are given the task of learning to move their eyes and attention in order to "read" as efficiently as possible (Liu & Reichle, 2010; Reichle & Laurent, 2006; Reichle, Liu, & Laurent, 2011). These reading agents, which learn via reinforcement learning algorithms (Sutton & Barto, 1998), quickly learn about cues that happen to be predictive of how long it will take to identify a word (e.g., word length) and then use this information to learn to initiate saccadic programming prior to full word identification. In essence, the agents learn how to perform a "familiarity check" so that the saccadic programming will be completed (with the eyes moving) just as a word is being identified. This indicates that a system that is capable of associating whatever cues are predictive of lexical-processing ease/difficulty to the decision about when to move the eyes off a word can learn the type of visual routine that is instantiated by the E-Z Reader model and that—more generally—can be characterized by the decoupling of eye movements from the movement of covert attention.

Finally, it is important to note that at least four other tasks have been used to study the eye–mind link and to make inferences about the specific nature of eye-movement control in reading—mindless reading (i.e., lapses of attention during the reading of real text), the solving of equations, driving, and scene viewing. Although we do not attempt to simulate these tasks, we discuss the theoretical issues that must be considered if models such as E-Z Reader are to account for eye movements in these tasks. As we shall make clear, at least two of the tasks, equation solving and driving, in principle, pose no problems for models like E-Z Reader because the tasks have in fact been simulated using a model very similar to E-Z Reader—*EMMA* (Salvucci, 2001; see Reichle, 2011). As for E-Z Reader, the core assumptions of the EMMA model are that (a) attention is allocated serially, to only one object (e.g., word) at a time and (b) ongoing cognitive processing (i.e., the visual encoding of objects) is what determines when the eyes move from one object to the next. As such, the simple fact that the model is able to simulate both equation solving and driving provides an existence proof against any possible claims that these tasks defy any explanation by models that incorporate either serial-attention or cognitive-control assumptions. We now discuss the four tasks in turn.

Equation Solving

As mentioned, Salvucci (2001) used the EMMA model of eye-movement control to simulate eye movements in an algebraic equation-solving task. In this paradigm, subjects had to solve for unknown variables while their eye movements were monitored. Importantly, the patterns of eye movements were both systematic and indicative of the different possible strategies that subjects used in solving the equations, such as first encoding pairs of values and calculating intermediate quantities before encoding the next pair of values. The patterns of eye movements associated with these strategies thus suggest a fairly tight coupling between whatever cognitive processes were necessary to solve the equations and both when and where subjects looked.

Driving

Salvucci (2006) also used EMMA (Salvucci, 2001) to simulate certain aspects of viewing behavior during driving. Again, because EMMA is quite similar to E-Z Reader, it should not be difficult to simulate eye movements in driving if one were to "plug in" the driving-specific assumptions of EMMA into E-Z Reader. As with the equation-solving task, this suggests that the task demands of driving are probably similar enough to reading that they may result in the development of similar visual routines (e.g., serial attention allocation combined with rapid cues for knowing when to move the eyes). Moreover, in stark contrast to scene perception (see below), the task demands that are placed on the driver are fairly well specified, making it a useful paradigm for studying the eye–mind link.

Mindless Reading

Reichle et al. (2010) recently examined lapses of attention (i.e., mind wandering) during the actual reading of text by employing a behavior-sampling procedure (Schooler, Reichle, & Halpern, 2004) in conjunction with eye tracking. In the experiment, subjects read a novel (over multiple days) and were instructed to press a button whenever they caught themselves "zoning out." The subjects were also prompted by the computer every 2–4 min to indicate whether they had been zoning out "just then." The fixations from the 10 s preceding both the "yes" and "no" responses to the probes, as well as those preceding self-caught mind wandering, were analyzed.

The results of these analyses indicated that the first-fixation durations, gaze durations, and total-viewing times on words were longer during mind wandering (i.e., prior to self-caught and probe-caught zone outs) than during normal reading (i.e., prior to making "no" responses to the mind-wandering probes). Moreover, although word frequency and whether or not a word was clause final or sentence final influence all three measures during normal reading (Hirotani, Frazier, & Rayner, 2006; Rayner, Kambe, & Duffy, 2000; Warren et al., 2009), they were absent in all but the total viewing times during mindless reading. (The fact that these effects tended to appear in the later measure suggests that, upon gaining awareness of their mind wandering, subjects tended to make regressions back to earlier parts of the text, presumably to ameliorate their comprehension failures.) Together, these results suggest that, during mindless reading, the cognitive processes that normally determine when the eyes will move during reading either are absent or are considerably attenuated. This suggests that the signal to begin saccadic programming during mindless reading occurs much later than it does during normal reading and that it is not modulated by either lexical or higher level (e.g., syntactic) language processing. The overall pattern of results during mindless reading is thus consistent with what was observed during *z*-string reading and, as such, should be amenable to simulation using the same assumptions that were used to simulate *z*-string reading. These results also suggest that cognitive processes that support language processing during reading do not operate by inhibiting or otherwise slowing a more "primitive" system that rapidly and automatically generates eye movements. Instead, the results suggest that rapid progression of eye movements during reading may largely be driven by the specific task of trying to comprehend the text.

Scene Viewing

The final task that has been used to make inferences about the eye–mind link in reading is the one that we are most intimately familiar with (since we do it so frequently) and that is arguably the least understood—scene viewing. Although there are several procedures for making the task of scene viewing better defined, perhaps the best known is that of Yarbus (1967), who monitored subjects' eyes when viewing a painting under different sets of instructions (e.g., "What were the people doing prior to moment depicted in the painting?" vs. "What are the material circumstances of the people in the painting?"). The nature of the task demands had clear effects on where the subjects looked; the scan paths (i.e., patterns of looking) differed markedly as a function of the questions that were asked of the subjects as they viewed the painting.

A more recent demonstration that task demands are the primary influence of scan paths rather than low-level visual features comes from an experiment in which subjects were asked to search for objects in a scene (e.g., Henderson, Brockmole, Castelhano, & Mack, 2007). Henderson et al.'s experiment indicated that people mainly fixated in regions where objects were likely to be (e.g., rarely fixated the sky) and also indicated that low-level features, such as salience, predicted little of where people fixated. Thus, although it is clear that the (explicit or implicit) tasks that subjects are engaged in while looking at a scene are likely to be the primary engine that drives where subjects fixate, there is little in the way of a theory of the universe of tasks people would be engaged in while viewing scenes.

As mentioned earlier, one notable finding about scene viewing is that short-term recognition memory is close to chance for objects in a scene that are not actually fixated (Henderson & Hollingworth, 1999). Thus, although there is abundant evidence that the gist of a scene can be extracted in a single fixation (Biederman, 1972; Boyce & Pollatsek, 1992; Kirchner & Thorpe, 2006; Potter, 1975, 1976), this result indicates that, to some approximation, processing objects (and perhaps other detailed information) in a scene for meaning is also a serial process and that the serial processing assumption in reading may generalize to a wide range of nonreading visual tasks. However, most scene-viewing tasks may be too open-ended to make strong inferences about the factors that determine when and where subjects move their eyes.

Thus, although we suspect that too little might be known about what happens in scene viewing to completely simulate eye movements (i.e., both where the eyes go and when they move), we can say that, as the scene-viewing task is naturally conceived of (i.e., free viewing of a scene to comprehend what is in it), there are no results that preclude an explanation that is based on the assumptions of serial-attention allocation or cognitive control of eye movements. The finding of Henderson and Hollingworth (1999) cited in the prior paragraph supports the former claim; the latter claim is consistent with the simple fact that cognition seems to influence when the eyes move in all of the other tasks that we have discussed. We do note that there have been a number of recent attempts to simulate where the eyes go (e.g., Itti & Koch, 2000; Torralba et al., 2006; Zelinsky, 2008) and simulations of when the eyes move (Nuthmann et al., 2010). As impressive as these models are, it remains the case that none of them can simultaneously account for simulating where the eyes go and when they move. As such, we view the simulations that were reported in this article as being important first steps toward more unified accounts of eye-movement control across a variety of visual–cognitive tasks.

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Appendix A

Simulations of Benchmark Reading Phenomena

The parameter values used in the simulations reported by Reichle, Warren, and McConnell (2009) were selected to allow the E-Z Reader model to simulate patterns of fixation-duration measures observed in reading. As such, the simulations were completed without regard to fixation-location measures, using the same default saccade-targeting parameters first reported by Reichle et al. (1999) and used in every reported simulation to date (for a list of the model's parameters, their interpretations, and their default values, see Table 1; see also Reichle, 2011). Although this approach is reasonable because the factors that determine where the eyes move during reading are largely independent of those that determine when the eyes move (Rayner & Pollatsek, 1981), our primary goal was to examine both types of measures in both reading and nonreading tasks. As such, it was first necessary to find parameter values that were adequate to simulate when and where the eyes move during reading. This appendix describes how such parameters were selected.

As one might guess, the process of selecting parameter values was guided by several a priori constraints. The first was that the parameters had to give plausible estimates of the process durations that they control. For example, several recent electrophysiological experiments have indicated that effects of lexical variables (e.g., word frequency) can be discerned as rapidly as 120 ms after stimulus onset (Assadollahi & Pulvermüller, 2001, 2003; Penolazzi, Hauk, & Pulvermüller, 2007; Reichle, Tokowicz, Liu, & Perfetti, 2011; Sereno, Rayner, & Posner, 1998). Such results clearly delimit the lower bounds of values that are plausible for the model's lexical-processing parameters (i.e., α_1, α_2, and α_3). We therefore considered only those combinations of parameter values that, when ignoring predictability (see Equations 1 and 7), provided a minimal estimate of 120 ms or more for the time required to complete the first stage of lexical processing (i.e., $t(L_1) \geq 120$ ms).

Similarly, although estimates of the time required to shift covert attention across one degree of visual angle give a range of possible values (e.g., 4 ms: Posner, 1978; 8 ms: Tsal, 1983; 17 ms: Sagi & Julesz, 1985a; 25 ms: Jolicoeur, Ullman, & Mackay, 1986; 30 ms: Sagi & Julesz, 1985b; 33 ms: Eriksen & Shultz, 1977; 38 ms: Ibos, Duhamel, & Hamed, 2009; 50 ms: Bergen & Julesz, 1983), our previous assumption that attention requires 50 ms to shift from one word to the next was probably too conservative, especially given that an extensive literature on visual search indicates that the time to both shift attention from one stimulus to another and perform some amount of perceptual analysis of those stimuli is typically 25–50 ms per item (e.g., Horowitz & Wolfe, 1998; Wolfe, Alvarez, & Horowitz, 2000; for a review, see Wolfe, 1994). We therefore decided to use a more "middle of the road" estimate for the time associated with covert attention shifts, adopting the assumption that such shifts on average require 25 ms to complete (i.e., $A = 25$ ms).

(*Appendices continue*)

The second constraint was that our model should be able to simulate certain important phenomena that have been accepted as important benchmarks that any viable model of eye-movement control in reading must be able to explain (e.g., spillover effects; Rayner & Duffy, 1986). For the present purposes, this constraint had one important consequence: our adoption of the assumption that, in the context of reading, the Δ parameter that controls the degree of decoupling between the signal to initiate saccadic programming and the signal to shift attention had to take on some intermediate value (i.e., $0.3 \leq \Delta \leq 0.7$).

Finally, although the values of the parameters controlling saccadic programming durations (i.e., $M_1 + M_2 = 150$ ms) were actually congruent with recent estimates (e.g., 136 ms: Reingold et al., in press), a series of pilot simulations indicated that the values of the parameters controlling saccade metrics were probably suboptimal. In particular, the parameter that modulates the systematic range error as a function of the fixation duration on the launch-site word (i.e., Ω_1; see Equation 5) was causing the predicted range error to be too large. For that reason, we decided to evaluate our model's performance using a range of values that would produce a systematic range error of approximately 0.25–0.5 character spaces at normal (e.g., 200 ms) fixation durations.

To find new default parameter values that could simultaneously allow the E-Z Reader model to simulate both fixation durations and locations, we completed three successive grid searches of the model's parameter space, with each search using more statistical subjects and smaller increments in parameter values. These grid searches focused on those parameters that control the rate of lexical processing and saccadic targeting because these should prima facie vary across populations, materials, and—importantly for the present article—task domains. As discussed above, the ranges of parameter values were selected on the basis of their plausibility (e.g., minimum and maximum word identification latencies) and knowledge of their prior default values; the remaining parameters (see Table 1) were set equal to their prior default values.

The first grid search used 250 statistical subjects per condition and permutation of parameter values, and it varied six parameters over the following domains using the indicated increments: $\alpha_1 \in [80, 110]$, increment = 5; $\alpha_2 \in [3, 5]$, increment = 1; $\alpha_3 \in [10, 30]$, increment = 5; $\Delta \in [0.3, 0.7]$, increment = 0.1; $\lambda \in [0.05, 0.3]$, increment = 0.05; and $\Omega_1 \in [6.0, 7.5]$, increment = 0.5. The second grid search used 500 statistical subjects per condition/parameter combination, with parameter domains centered on the best fitting parameters from the first search, and used the following increments: $\alpha_1 = 2.5$; $\alpha_2 = 0.5$; $\alpha_3 = 2.5$; $\Delta = 0.05$; $\lambda = 0.025$; and $\Omega_1 = 0.25$. The third search used 1,000 statistical subjects and the following increments: $\alpha_1 = 1$; $\alpha_2 = 0.5$; $\alpha_3 = 1$; $\Delta = 0.01$; $\lambda = 0.01$; and $\Omega_1 = 0.1$. The final simulations (reported next) were based on 1,000 statistical subjects per condition and the best fitting parameter values obtained from the third grid search. These parameter values are listed in the column labeled "New Default Values" in Table 1.

Our goodness-of-fit metric measured the model's capacity to fit both the mean distributions of fixation landing sites and refixation probabilities for four- to eight-letter words that were reported by McConkie and his colleagues (McConkie et al., 1988; 1989), as well as the mean fixation duration and probability measures from the Schilling et al. (1998) sentence corpus (as reported in our previous simulations; see Reichle, 2011). This was done by first calculating the root-mean-squared deviation (*RMSD*) between the simulated and observed values for the landing-site and refixation-probability distributions for words of each length. The mean *RMSD* was then calculated across word lengths and the two types of distributions, with smaller values indicating better correspondences between the simulated and observed distributions. Next, the *RMSD* between the simulated and observed fixation duration and probability measures was calculated for the five frequency classes of words in the Schilling et al. corpus, with smaller values of this measure also indicating better correspondences between the observed and simulated values. Finally, the two *RMSD*s were averaged to give a single composite measure of the model's overall performance. This last step was necessary because we wanted to improve the model's capacity to simulate where the eyes move without compromising the model's capacity to simulate when the eyes move. In the discussion that follows, the first *RMSD* is subscripted with a "where" as a reminder that it measures the model's capacity to simulate the first-fixation landing-site distributions and refixation-probability distributions. In a similar manner, the second *RMSD* is subscripted with a "when" as a reminder that it measures fixation durations and probabilities.

As Figure A1 shows, the best fitting parameter values allowed the model to accurately simulate where the eyes look during reading ($RMSD_{\text{where}} = 0.046$). As Panel A of Figure A1 shows, the model predicted the Gaussian-shaped first-fixation landing-site distributions reported by McConkie et al. (1988), although the model did show a slight tendency to overpredict the proportion of initial fixations near the beginnings of words. Panel B shows that the model also correctly predicts the asymmetrical, *U*-shaped refixation-probability distributions reported by McConkie et al. (1989). Finally, Panels C and D respectively show the predicted durations of single and first (of one or more) fixations as a function of their within-word locations. Although observed values are not reported here (because they were not reported by McConkie et al., 1988, 1989), the simulated curves closely resemble canonical ones reported by others (e.g., Reingold et al., in press; Vitu et al., 2001), exhibiting a distinct inverted-optimal viewing position (IOVP) effect, or the finding that first fixations near the centers of words tend to be longer in duration than those near the beginnings or endings of words. These simulations thus indicate that—at least to a first-order approximation—our model can account for where the eyes move during reading.

As Figure A2 show, the best fitting parameter values also allowed our model to accurately fit the Schilling et al. (1998) fixation duration and probability means ($RMSD_{\text{when}} = 0.164$), although admittedly not quite as well as the parameters previously

(*Appendices continue*)

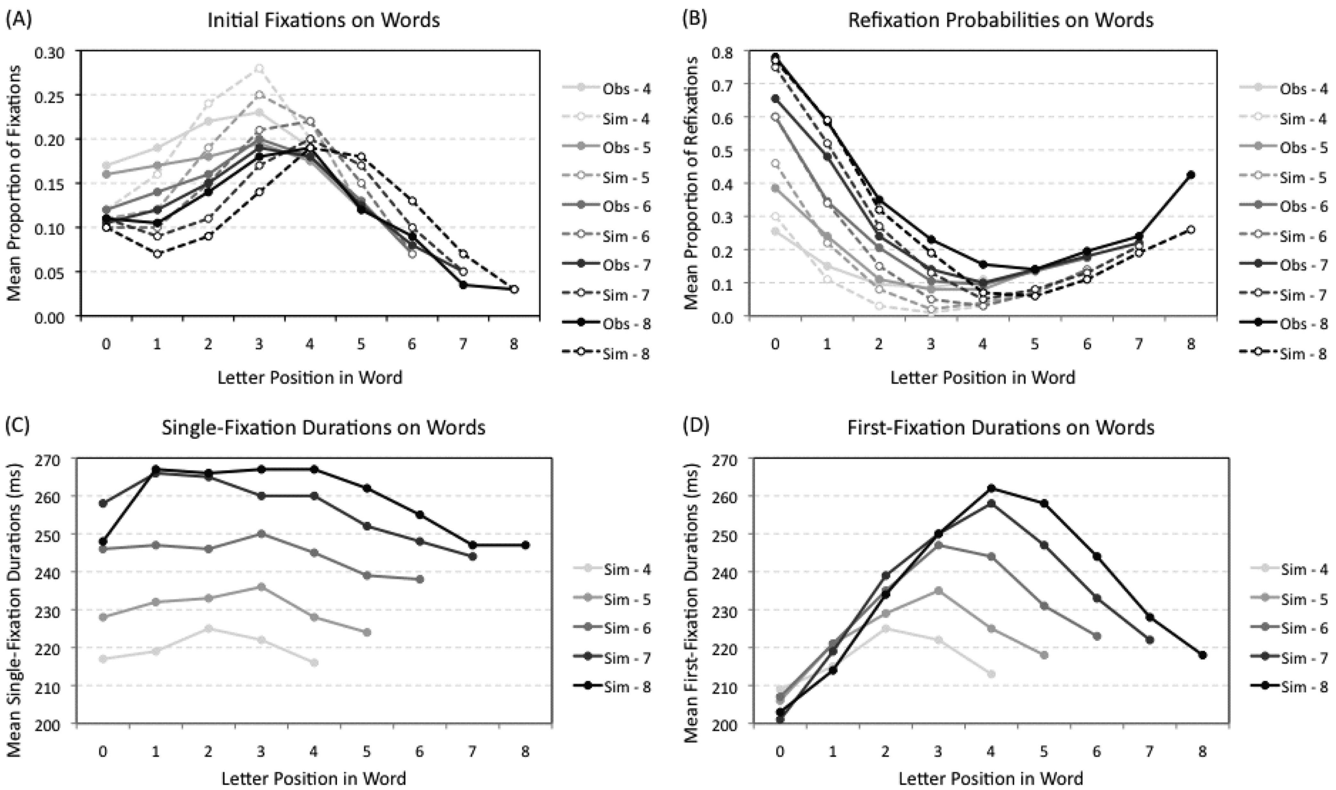

Figure A1. Panel A: Mean observed (McConkie et al., 1989) and simulated first-fixation landing-site distributions for 4- to 8-letter words. Panel B: Mean observed (McConkie et al., 1989) and simulated refixation-probability distributions for 4- to 8-letter words. Panel C: Mean simulated single-fixation durations as a function of their within-word locations. Panel D: Mean simulated first-fixation (of one or more fixations) durations as a function of their within-word locations. (Panels C and D show only the simulated distributions because the observed distributions were not reported by McConkie et al., 1989.) The simulations were completed with the E-Z Reader model's new default parameter values (Reichle et al., 2009; see Table 1) and indicate that those parameters are adequate to simulate the complex interaction of when and where the eyes move during reading.

used by Reichle, Warren, and McConnell (2009) ($RMSD_{\text{when}}$ = 0.105). Two points warrant mentioning, however. The first is that the previous fits may have actually capitalized on error variance and as such may be indicative of overfitting the data (see Pitt, Myung, & Zhang, 2002). The second is that the new parameters still allow the model to fit the Schilling et al. data better than most of the previously used best fitting parameter values (see Reichle, 2011). That being said, we contend that our model provides a reasonable account for when the eyes move during reading.

Finally, two other aspects of the new parameter values merit discussion (see Table 1). First, although the intercept parameter (α_1) that determines the mean maximum time to complete L_1 is only 104 ms, it is important to note that the time required to identify words also includes the preattentive stage of visual processing and is always lengthened by the slowing effect of limited visual acuity. For example, the mean minimum time to identify the most frequent word in the language (i.e., *the*, which has a token frequency of 69,975 per million) when it is centrally fixated is 143 ms. Similarly, the mean maximum time to identify a three-letter word with a frequency of 1 per million when it is centrally fixated is 200 ms. The mean times required to complete the familiarity check on these two example words are 121 ms and 164 ms, respectively. These ranges of predicted times are consistent with recent estimates of when word frequency modulates event-related potential (ERP) components associated with lexical processing. For example, Sereno et al. (1998) reported that word frequency modulated ERP components within 132 ms of word onset. And more recently, Reichle, Tokowicz, et al. (2011) found such effects even earlier (102–134 ms after word onset) when the ERP data were aligned to the onsets of the saccades off the words.

The second is related to the utility of our restriction on the domain of possible values of the Δ parameter; this was evaluated in one final simulation using the Schilling et al. (1998) sentence materials to examine the frequency effects on both their target words and the post-target words (i.e., spillover effects). The target words were either high frequency (M = 141 occurrences per million) or low frequency (M = 2 occurrences per million) and were matched on predictability and length; the post-target words

(*Appendices continue*)

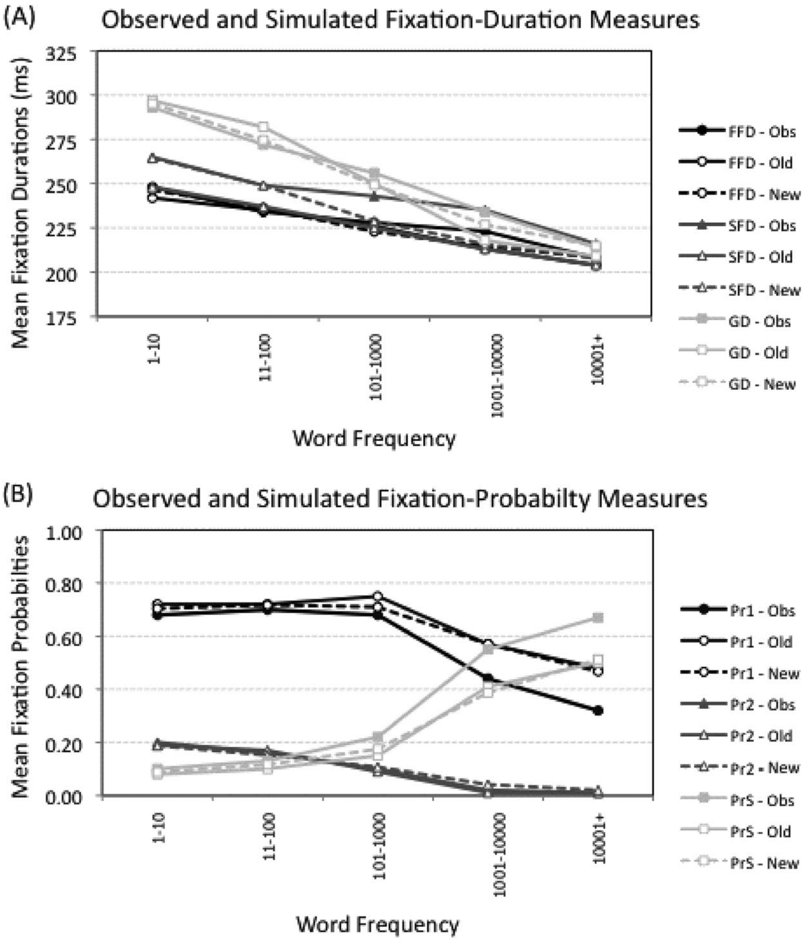

Figure A2. Mean observed (Schilling et al., 1998) and simulated first-fixation (FFD), single-fixation (SFD), and gaze durations (GD) and probabilities of skipping (PrS), making one fixation (Pr1), or making two or more fixations (Pr2) on five frequency classes of words. The simulations were completed with both the old (Reichle et al., 2009) and the new default parameter values (see Table 1).

were of variable frequency, predictability, and length. Using these materials, the model predicted a 39-ms frequency effect for gaze durations on the target words, along with a 9-ms spillover effect for gaze durations on the post-target words. These results are congruent with observations that spillover effects are typically one third to one half the size of frequency effects (e.g., Rayner & Duffy, 1986; Rayner et al., 1989) and indicate that our decision to consider only intermediate values of the Δ parameter was justified.

(*Appendices continue*)

Appendix B

Procedures for Identifying Best Fitting Parameter Values

For each simulation of reading and target-word search (Rayner & Fischer, 1996; Rayner & Raney, 1996), the parameter values that minimized the mean absolute differences between observed and simulated dependent measures were obtained by completing three grid searches of the parameter space using smaller parameter increments and more statistical subjects with each successive search. The first grid searches used 250 statistical subjects per condition and permutation of parameter values and varied five parameters over the following domains using the indicated increments: $\alpha_1 \in [40, 150]$, increment = 10; $\alpha_2 \in [0, 8]$, increment = 1; $\alpha_3 \in [0, 40]$, increment = 10; $\Delta \in [0, 1]$, increment = 0.1; and $\lambda \in [0, 0.4]$, increment = 0.05. The second grid searches used 500 statistical subjects per condition/parameter combination and used parameter domains that were centered on the best fitting parameters from the first searches with the following increments: α_1 = 2.5; α_2 = 1; α_3 = 2.5; Δ = 0.025; and λ = 0.025. The third searches were identical to the second but used 1,000 statistical subjects and were centered on the best fitting parameters from the second searches using the following increments: α_1 = 1; α_2 = 1; α_3 = 0.5; Δ = 0.01; and λ = 0.01. The final simulations of these tasks (and of all other tasks reported in this article) are based on 1,000 statistical subjects per condition and the best fitting parameter values obtained from the third grid searches.

The best fitting parameter values for both *z*-string reading (Rayner & Fischer, 1996) and the Landolt-*C* search tasks (Williams & Pollatsek, 2007; Williams et al., 2011) were obtained using grid searches that were identical to those used in the aforementioned tasks except that the parameter modulating the effects of word frequency (i.e., α_2) and predictability (i.e., α_3) were not varied because the frequencies and predictabilities of the stimuli were set equal to 1 and 0, respectively. Furthermore, because the Landolt-*C* task required subjects to make fine visual discriminations, the parameter modulating the effect of visual acuity was also varied across the three grid search, using $\varepsilon \in [1.15, 3]$ and an increment 0.05 in the first search and increments of 0.025 and 0.01 in the second and third searches, respectively. The only other constraint that was unique to the grid search for the Landolt-*C* task parameters was that the values of ε were allowed to vary across the four gap-size conditions, conditional upon those values being monotonically related to task difficult (i.e., values of ε had to increase with decreasing gap size).

In the reading simulations, the values of p_F and p_N (which have no default values but instead varied across the simulations reported by Reichle et al., 2009) were set equal to 0.01 and 0.5, respectively. These values were selected on the basis of their plausibility and pilot simulations indicating that they allowed the model to fit to observed data reasonably well. In the simulations of the nonreading tasks, postlexical processing was disabled (by setting I = 0 and p_F = 0) because the interpretation of such processing is much less clear in these tasks.

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