Visual attention modulates the transition from fine-grained, serial processing to coarser-grained, more parallel processing: a computational modeling study

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Abstract

During reading acquisition, beginning readers transition from serial to more parallel processing. The acquisition of word specific knowledge through orthographic learning is critical for this transition. However, the processes by which orthographic representations are acquired and fine-tuned as learning progresses are not well understood. Our aim was to explore the role of visual attention in this transition through computational modeling. We used the BRAID-Learn model, a Bayesian model of visual word recognition, to simulate the orthographic learning of 700 4-to 10-letter English known words and novel words, presented 5 times each to the model. The visual attention quantity available for letter identification was manipulated in the simulations to assess its influence on the learning process. We measured the overall processing time and number of attentional fixations simulated by the model across exposures and their impact on two markers of serial processing, the lexicality and length effects, depending on visual attention quantity. Results showed that the two lexicality and length effects were modulated by visual attention quantity. The quantity of visual attention available for processing further modulated novel word orthographic learning and the evolution of the length effect on processing time and number of attentional fixations across repeated exposures to novel words. The simulated patterns are consistent with behavioral data and the developmental trajectories reported during reading acquisition. Overall, the model predicts that the efficacy of orthographic learning depends on visual attention quantity and that visual attention may be critical to explain the transition from serial to more parallel processing.

Keywords: Visual attention, Bayesian modeling, Length effect, Orthographic learning

1. Introduction

1.1. Theoretical background

During learning to read, children move from slow serial processing to faster, more parallel word recognition (Castles et al., 2018). This developmental trajectory was initially conceptualized as reflecting successive stages in reading acquisition (Frith, 1985). However, the self-teaching theory (Share, 1995, 1999; Share and Shalev, 2004) proposed to replace this stage-based model by an item-based model according to which the transition from serial letter-by-letter to more parallel processing would apply at the level of each individual item word. According to this theory, the first time the child encounters a new printed word, this word would be serially processed through phonological recoding (i.e., translation of each orthographic unit into its spoken form). When phonological recoding is successful, then the input orthographic information can be memorized, leading to enriching the reader's word-specific orthographic knowledge. Although some orthographic learning was demonstrated following a single encounter with the novel word, additional encounters contribute to shape well-specified word-specific orthographic representations (Bowey and Muller, 2005; Nation et al., 2007; Pellicer-Sanchez, 2016; Share and Shalev, 2004). The acquisition of new orthographic representations during reading (referred to as "orthographic learning" hereafter) allows fast recognition of previously encountered words, which is the hallmark of expert reading.

The self-teaching hypothesis is not age-specific. Most of the printed words beginning readers are exposed to are new words for them, which increases the probability of orthographic learning as soon as they have enough knowledge about print-to-sound mapping. However, readers are likely to be exposed to new words throughout their lifespan, so that orthographic learning through self-teaching is observed in both beginning and skilled readers (Bowers et al., 2005; Joseph and Nation, 2018; Joseph et al., 2014; Manis, 1985; Pagan and Nation, 2019). Interestingly, the capacity to build-up new words' orthographic knowledge across repeated exposures may be as efficient in beginning as in more advanced readers (van Viersen et al., 2022), suggesting that the same mechanisms are involved regardless of reading practice.

Orthographic learning is characterized by a reduction of both the word length effect (i.e., additional processing cost for longer words) and the lexicality effect (i.e., differences in processing between unknown vs. known words) in reading. Length effect on word reading speed decreases with reading expertise and the development of orthographic knowledge (Marinelli et al., 2016; Provazza et al., 2019; Zoccolotti et al., 2005). This is accompanied by changes in eye movements. Gaze duration and the probability of refixations is less influenced by word length in more advanced readers (Joseph et al., 2009; Rayner, 1998). A decrease of the length effect on reading times was also reported with repeated exposure to novel words in tasks of orthographic learning (Suarez-coalla et al., 2016). At fixed length, online measures of eye movements across repeated exposures to novel words and known words revealed larger learning effects for novel words (Ginestet et al., 2020; van Viersen et al., 2022). A larger decrease in gaze duration and fixation number across exposures was reported for novel words, showing a reduction of the lexicality effect with learning.

The importance of orthographic learning in the transition from novice to expert reading is now well established. However, much is still unknown about the mechanisms involved in orthographic learning. According to the self-teaching theory, phonological recoding is the primary mechanism by which an orthographic representation is acquired (Share, 1995, 1999; Share and Shalev, 2004). The models of reading acquisition that implement the self-teaching mechanisms (Perry et al., 2019; Pritchard et al., 2018; Ziegler et al., 2014), assume that phonological recoding relies on the mapping of graphemes onto phonemes. Knowledge about grapheme-to-phoneme mapping allows generating phonemic sequences that can trigger the activation of known spoken words in phonological memory. When an existing phonological word is sufficiently activated, then an orthographic representation is set up in long-term memory which is connected to the word phonological representation and its meaning. Simulations within these computational models have shown that most novel words could be successfully learned through phonological recoding (Perry et al., 2019; Pritchard et al., 2018; Ziegler et al., 2014). In contrast, the role of visual processing in orthographic learning is minimized in the self-teaching theory (Share, 1999) and computational modeling suggests that orthographic learning is more sensitive to phonological than visual deficits (Perry et al., 2019; Ziegler et al., 2014). However, these models make a number of simplifying assumptions about the mechanisms of visuo-orthographic processing and orthographic memorization. First, they do not implement the mechanisms of visual acuity, lateral interference and visual attention that are known to modulate letter identity processing within strings (Pelli et al., 2007; Waechter et al., 2011) but rather postulate that accurate identity information is immediately available for all the letters within the input string. Second, they assume that the word complete orthographic representation is acquired in a "one-shot" manner, after a single exposure (Perry et al., 2019; Pritchard et al., 2018; Ziegler et al., 2014). This would predict an abrupt shift from serial to parallel processing at the item level after a single exposure, which contrasts with behavioral evidence that successive exposures to words gradually shape orthographic representations (Ginestet et al., 2020; Joseph et al., 2014; Nation et al., 2007; Pagan and Nation, 2019; Pellicer-Sanchez, 2016; Suárez-Coalla et al., 2014).

Despite the importance of phonological recoding in reading acquisition, there is behavioral evidence that phonological processing cannot be the sole mechanism involved in the development of orthographic knowledge. Self-teaching studies on typical readers have shown that successful phonological recoding only weakly predicted orthographic learning at the item level, suggesting that other mechanisms were further involved (Bosse et al., 2015; Cunningham, 2006; Cunningham et al., 2002; Nation et al., 2007; Tucker et al., 2016). The dissociations reported in developmental dyslexia between word-specific orthographic knowledge and phonological recoding lead to the same conclusion, showing that good orthographic knowledge might develop despite very poor phonological recoding skills while, conversely, good phonological recoding skills provided no guarantee of good orthographic knowledge acquisition (Castles, 1996, 2006; Howard, 1996; Valdois et al., 2011, 2003). Furthermore, demonstrations that humans can acquire orthographic knowledge from artificial scripts that do not have any connection to phonology (Chetail, 2017; Lelonkiewicz et al., 2020), and that nonhuman animals can acquire knowledge about printed words without any language or phonological skills (Grainger et al., 2012; Scarf et al., 2016), suggest less phonological dependency in the development of orthographic knowledge than currently postulated.

Indeed, it has been shown that orthographic learning was facilitated when more visual information on the input letter-string was simultaneously available during the learning phase (Bosse et al., 2015). This suggests that the mechanisms involved in visuo-orthographic processing may represent additional components that contribute to orthographic learning, independently of phonological skills. Some insights on these mechanisms comes from studies on the length effect in reading (Barton et al., 2014). The fact that longer words (familiar or not) are fixated for longer than shorter words and have a higher probability to be refixated (Hautala et al., 2011; Kliegl et al., 2004; Loberg et al., 2019; Lowell et al., 2014; McDonald, 2006; Rayner et al., 1996; Vitu et al., 1990) was interpreted as following from the fact that more letters would fall in regions of poorer visual acuity in longer words, thereby reducing the probability of successful identification (Engbert et al., 2002; Reichle et al., 2003). However, length effects on eye movements have also been reported when words were equated for their spatial extent, so that visual acuity decline was similar for all words whatever their length (Hautala et al., 2011; McDonald, 2006). Evidence for a length effect beyond the influence of visual acuity was interpreted as potentially reflecting differential crowding effects, assuming that more letters suffered from crowding (i.e., interference from adjacent letters) in longer than in shorter words (Hautala et al., 2011; McDonald, 2006). However, visual acuity and crowding can hardly account for the evolution of eye movement behavior in condition of orthographic learning, in which readers are repeatedly exposed to the same set of words (at fixed length) (Ginestet et al., 2020; Joseph and Nation, 2018; Joseph et al., 2014; Pagan and Nation, 2019; Pellicer-Sanchez, 2016).

Visual attention is a third mechanism involved in letter-string processing that might further affect orthographic learning. Behavioral studies have mainly focused on the visual attention span (VAS), a measure of multielement parallel processing (Frey and Bosse, 2018; Valdois, 2022). VAS is known to relate to reading acquisition (Valdois et al., 2019) and children with higher VAS show higher reading fluency (Bosse and Valdois, 2009) and higher orthographic knowledge (Niolaki et al., 2020). By reference to the "Theory of Visual attention" (Bundesen, 1990), VAS was found to reflect the amount of visual attention available for multielement processing (Bogon et al., 2014; Dubois et al., 2010; Lobier et al., 2013). Neuroimaging studies revealed that VAS related to the activation of the superior parietal lobules within the dorsal attentional network (Lobier et al., 2012; Peyrin et al., 2011; Reilhac et al., 2013). Only a few behavioral studies have examined whether VAS was involved in orthographic learning. In an experiment conducted in adults, Ginestet et al. (2020) showed that orthographic learning and eye movement patterns across exposures were modulated by VAS. Using a self-teaching paradigm without eye-movement monitoring in children, Marinelli et al. (2020) showed that VAS contributed to promote orthographic learning.

Interestingly, VAS was further described as relating to the length effect in reading. Lower length effects on word and pseudo-word reading latencies were reported in individuals with higher VAS (van den Boer et al., 2013) and exaggerated length effects were found in individuals suffering from a VAS reduction (Juphard et al., 2004; Valdois et al., 2011, 2003). In addition to visual acuity and crowding, these findings suggest that visual attention might be involved not only in the way words are processed (i.e., in a strict serial or more parallel manner), but further in the capacity to acquire new orthographic representations.

1.2. The present study

The main contribution of the present study was to investigate the role of visual attention in orthographic learning using a modeling approach. For this purpose, we started from BRAID, a word recognition model that implements the three mechanisms of visual attention, visual acuity and lateral interference that are known to affect letter identification within strings (Ginestet et al., 2019; Phenix, 2018; Phénix et al., 2018; Saghiran et al., 2020). In BRAID, the spatial distribution of visual attention was modeled by a Gaussian probability distribution, so that the letters near the focus (i.e., peak) of attention were better recognized while the number of letters that were allocated attention was dependent on attention dispersion. Computational studies have shown that variations in visual attention dispersion modulated word recognition (Valdois et al., 2021a) and the word length effect in tasks of lexical decision, naming and progressive demasking (Ginestet et al., 2019; Saghiran et al., 2020). The initial word recognition model was extended in BRAID-Learn, a model of orthographic learning (Ginestet, 2019; Ginestet et al., 2022). The model incorporates a mechanism of visual attention exploration that optimizes the gain of information on letter identity within the input string over time through modulation of the two parameters of attentional focus location and attention dispersion.

Ginestet et al. (2022) showed that BRAID-Learn successfully simulated the evolution of eye-movement patterns across repeated exposure to novel words by skilled readers. This was mainly due to the interaction of bottom-up sensory information modulated by visual attention and top-down lexical feedback from the newly acquired orthographic representation. However, the study focused on words of fixed length and attention quantity in the model was defined by its default value, thus remaining constant through simulations.

Our purpose in the present study was to provide a more plausible implementation of visual attention processing in BRAID-Learn. Indeed, behavioral studies have shown that VAS increased with age during childhood (from first to fifth grade) (Bosse and Valdois, 2009) and that inter-individual variations in VAS accounted for differences in orthographic learning (Ginestet et al., 2020). As VAS reflects the amount of visual attention available for processing (Valdois, 2022), this suggests that a plausible model of orthographic learning should be able to simulate the consequences of variations in visual attention quantity on processing. Our main contribution was thus to introduce a new visual attention quantity parameter in the model and examine the effect of attention quantity variations on orthographic learning through simulations.

Second, despite behavioral evidence that the length effect on word and pseudo-word reading decreases with reading expertise (Marinelli et al., 2016; Provazza et al., 2019; Zoccolotti et al., 2005), evidence is lacking on the evolution of length effects over repeated exposure to known or novel words in condition of orthographic learning. To fill this gap and provide new insights for future behavioral studies, we examined the model's predictions depending on the attention quantity available for processing when repeatedly exposed to known or novel words that varied in length. We used the model as an experimental substitute to study the length effect all other factors otherwise equal. For this purpose, a single set of words was considered as known words in a first series of simulations, in which the target words' orthographic information was part of the model's word knowledge, but as novel words in a second series of simulations conducted after removing target words' orthographic knowledge from the model database.

Assuming that higher visual attention quantity would allow the model to accurately identify more letters simultaneously, we expected longer stimuli to be more proficiently processed as attention quantity increases. More proficient processing was expected to result in shorter processing time (i.e., fewer iterations) and a smaller number of attentional fixations during the visuo-attentional exploration of the input word. Novel words that do not benefit from top-down lexical knowledge at the first exposure, would be processed less efficiently than known words; moreover this difference would be magnified with low attention quantity. However, orthographic learning being initiated at the first exposure, novel word processing would improve across exposures due to increasingly strengthened top-down support from the newly acquired orthographic representation of the target novel word. Assuming that higher attention quantity allows processing more letters efficiently, orthographic knowledge acquisition would be more effective at each exposure, leading to more proficient learning of the novel word orthographic representation. This would also result in a stronger length effect decrease, both on processing times and number of attentional fixations, across exposures as visual attention quantity is higher.

The rest of this paper is structured as follows. First, we describe the BRAID-Learn model, with a particular focus on the visual-attention component. Second, we detail the material and procedure used in the experiment. Third, we present the simulation results, which we discuss and relate to behavioral data.

2. The BRAID-Learn model

2.1. General outline of the model

The BRAID-Learn model shares the core of its architecture with the three-layer architecture used, among others, by the classical Interactive Activation model (IA; McClelland and Rumelhart, 1981). It also features an additional, original layer modeling visual attention, along with mechanisms for orthographic learning. The resulting architecture is shown in Figure 1. The BRAID-Learn model is a hierarchical, probabilistic model, defined by a joint probability distribution over its variables. As it is not relevant for the scope of the current study, and as completely defining the model requires space, we do not describe entirely its mathematical definition or its resulting properties here. However, they can be found elsewhere (Ginestet, 2019; Phenix, 2018). Instead, in this section, we provide the necessary elements to detail how orthographic learning processes are implemented, and how visuo-attentional properties affect the learning process.

The model includes four submodels. The letter sensory submodel focuses on low-level mechanisms involved in letter identification within the input string. Letter identification at this level is modulated by inter-letter visual similarity, implemented through a letter confusion matrix adapted from experimental data (Townsend, 1971) and by two mechanisms of visual

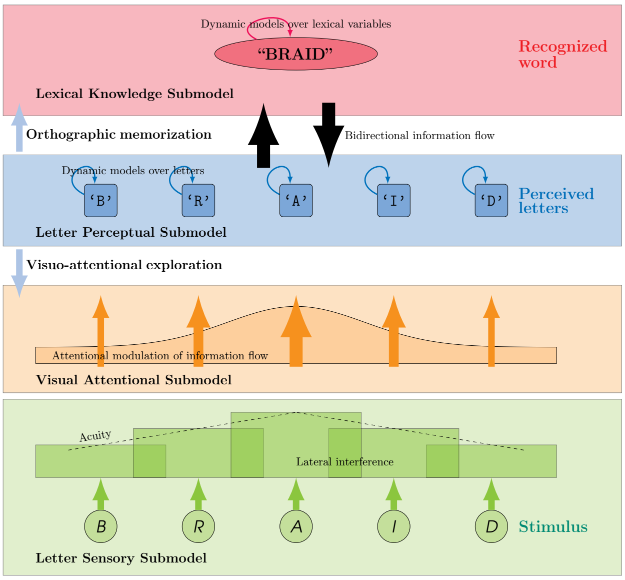

Fig. 1: Conceptual representation of the BRAID-Learn model. The four submodels are represented as colored blocks, and arrows represent information flow or specific processes (blue arrows). This structure is illustrated here on a 5-letter stimulus. See text for details.

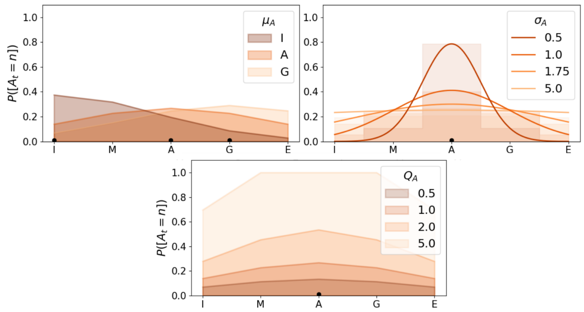

Fig. 2: Illustration of visuo-attentional distributions on the 5-letter input word "IMAGE". Top left: attention distribution for a few values of parameter μ_A^t, which defines the position of attentional focus at time t. Top right: attention distribution for a few values of parameter σ_A^t, which defines attentional dispersion. Bottom: attention distribution for a few values of parameter Q_A, which defines the total attention quantity available for processing.

acuity and lateral interference. The acuity gradient penalizes letter identification proportionally to the distance of the letter to gaze position. Letter identification is further affected by interference from neighboring letters so that inner letters suffer more interference than outer letters.

In the letter perceptual submodel, evidence about the identity of letters accumulates over time, to build dynamically evolving perceptual representations of the letters in the input string. These perceptual representations receive sensory information from the letter sensory submodel, in a bottom-up manner. They are further influenced by top-down information from the lexical knowledge submodel, so that identity information accumulates faster at the perceptual level for letters that belong to previously known words. (Note that, in the context of the current orthographic learning experiments, top-down knowledge about gradually improving orthographic traces is facilitatory. However, this is not a general property of the model. When top-down information from lexical knowledge is discongruent with the stimulus letters, for instance in priming simulations, it can slow down letter perception.)

The lexical knowledge submodel is configured to represent the spellings of a large database of words. The current simulations were run using a dataset of 79,673 English words, taken from the English Lexicon Project (Balota et al., 2007). The submodel further includes a mechanism that evaluates lexical membership and allows determining whether the input stimulus is a known word or a novel word.

BRAID-Learn further includes a visuo-attentional submodel that controls the flow of information from the sensory to the perceptual submodel. Given the key role of visual attention in letter identity processing and orthographic learning, this submodel is described in more detail below.

2.2. *The visuo-attentional submodel*

The visuo-attentional submodel acts as a filter between the sensory and the perceptual submodels. Its main element is a Normal probability distribution, noted $P(A^t \mid \mu_A^t\ \sigma_A^t)$, whose parameters μ_A^t and σ_A^t describe how visual attention is spatially distributed over the input letter string: the μ_A^t parameter represents the position of the focus of visual attention at time t (see Figure 2, top left), whereas the standard deviation σ_A^t parameter characterizes visual attention dispersion (see Figure 2, top right). Each letter in the input letter string, and therefore each position of the stimulus, is allocated a certain amount of visual attention, defined by this probability distribution. The amount of visual attention allocated to each position defines the amount of sensory evidence propagated from the sensory to the perceptual submodel. Due to the shape of the Gaussian distribution, less evidence on letter identity accumulates in the perceptual submodel when the distance from the attentional focus increases (Figure 2, top left). Letter identity processing is further modulated by visual attention dispersion. The smaller the attentional dispersion, the more attention is concentrated around the attentional focus, favoring efficient processing of a few letters, to the detriment of the others. The quality of perceptual representations is thus strongly modulated by the parameters of visual attention.

In previous simulations using either BRAID or anterior versions of the BRAID-Learn model, the total amount of attentional resources available for processing was implicitly equal to 1 (its default value). In the context of the present study, we have defined the parameter Q_A to explicitly represent the attention quantity. It is a multiplicative coefficient applied to the distribution of attention with the precaution that the amount of attention allocated to each position cannot exceed 1. Whatever the values of μ_A^t and σ_A^t, the higher Q_A, the more attention is available for the processing of the attended letters, so that perceptual representations accumulate more identity evidence on these letters at each time-step, resulting, overall, in faster processing. The effect of parameter Q_A on the attention value at each position is illustrated on Figure 2 (bottom plot).

2.3. Orthographic learning in BRAID-Learn

In the model, orthographic learning consists in the transfer of letter identity information from the perceptual submodel to the lexical knowledge submodel. As a result, orthographic learning is more efficient when perceptual information is of higher quality (i.e., providing enough information on letter identity at each position).

For the purpose of the current simulations, we consider that the model is given a task, in which the stimulus must be freely explored at each exposure, with no time-limit, until getting a precise enough perceptual representation of the input letter string. At the end of each exposure, the lexical membership mechanism evaluates whether perceptual information corresponds to a known word, by comparing the perceived letters to known words' letters. If this is the case, then the existing orthographic trace of the most likely word (a word recognition process, not detailed here, also proceeds in parallel) is updated by combining it with the perceptual representation of letters. Let us write (using a simplified notation) $P(P \mid S)$ the probability distribution about letters P given the stimulus letter sequence S, computed at the end of the exposure (i.e., the perceptual representation of letters), $P(L_n \mid [W = w])$ the probability distribution over letters for word w in the set of known words W, after n exposures (i.e., the orthographic trace of word w), θ_n the learning rate after n exposures (it decreases exponentially across exposures), and finally U the uniform distribution over the letter space. The probability distribution of the updated orthographic representation after $n + 1$ exposures is as follows:

$$P(L_{n+1} \mid [W = w]) \propto P(L_n \mid [W = w]) \times \Big(\theta_n \times P(P \mid S) + (1 - \theta_n) \times U\Big).$$

If, on the contrary, the perceptual information does not correspond to any word in the lexicon, then, a new orthographic trace is created. This trace is initialized with the perceptual representation of letters at the end of the first exposure. At each subsequent encounter with the "novel" word, the corresponding orthographic trace is gradually reinforced. Orthographic learning is said to be successful when the trace of an already encountered word is updated at subsequent encounters or when a new trace is created for a novel word at the first encounter.

The influence of lexical feedback on letter perception in the model is driven by lexical membership evaluation, so that the more likely the stimulus is to be a word, the stronger the lexical feedback. As a result, gradual strengthening of the orthographic trace makes novel word processing more and more efficient across exposures. A more detailed description of the mechanisms of lexical feedback and trace creation and updating can be found elsewhere (Ginestet et al., 2022).

2.4. Visuo-attentional exploration of a stimulus

The main goal of visuo-attentional exploration in the model is to favor efficient letter perception accumulation during processing. For this purpose, the model automatically selects the visuo-attentional parameter values that would allow gaining more information on letter identity during a given exposure. The entropy of probability distributions in the letter perceptual submodel is computed to estimate the quality of perceptual representations. The entropy is close to maximal during the first iterations of processing due to limited information on letter identity within the input string. Conversely, it would be small if letters were perfectly perceived (i.e., if perceptual representations were Dirac probability distributions). Thus, a decrease in entropy characterizes letter identity information gain at the perceptual level. Measuring entropy for each letter position allows identifying those letters for which perceptual information is lacking, thus indicating where attention should shift to significantly decrease entropy. How this might be performed with an optimization approach was described in a previous study (Ginestet et al., 2022). However, optimizing information gain entailed systematically exploring the parameter space to predict the entropy decrease for all possible combinations of visual attention parameters. This was computationally costly. Here, instead, we used a heuristic-based, approximate algorithm that provides visuo-attentional exploration behaviors that are qualitatively comparable to those produced by our previous algorithm (a quantitative assessment of this approximation is beyond the scope of the current paper).

Here, we more specifically focus on how location of the attentional focus moves over the input string to increase the gain of information on letter identity at each exposure and boost perceptual evidence accumulation. We then expose how visual attention dispersion is affected during processing and then provide an illustrative example, through the processing of the novel word "HOLPING".

Displacement of the visuo-attentional focus during exploration. The heuristic algorithm proceeds as follows. Initially, the position of the gaze and attentional focus μ_A^t is set according to stimulus length and attentional quantity (note that gaze position always coincide with the attentional focus position in the simulations). Following eye movement behavioral findings (Rayner, 1998; Vitu et al., 1990), the attentional focus is located slightly left of the word center, except for the smallest value of attention quantity ($Q_A = 0.5$), for which the initial position is located on the first letter of the word. This shift towards the beginning of words was motivated by the fact that virtually a single letter could be processed at once in this condition, so that no information could accumulate on the initial letter of the input stimulus when the focus of attention was located farther away on the right.

Then, at each time-step, the difference in entropy, between the probability distributions of the perceptual representation of the letter under the attentional focus and all other positions is computed. When this difference exceeds a given threshold T_{shift} (empirically set to 1.5 nats, with 1 nat the unit for information quantity when entropy is computed using the natural logarithm, as we do, instead of the more usual bit when it is computed with the base 2 logarithm), then a visuo-attentional shift is initiated towards that position. As a result, except for the initial position of the focus of attention, all subsequent displacements of the attention focus are computed by the model depending on the quality of identity evidence previously accumulated at the perceptual level. As in the terminology of eye movement studies, we will refer to time intervals when attention does not move as an "attentional fixation", between attentional displacements, and therefore count the number of attentional fixations.

As previously (Ginestet et al., 2022), the entropy difference was modulated by a motor cost parameter, noted α. This parameter considers the magnitude of the next displacement to penalize large attentional shifts. Several displacements of the focus of visual attention, thus several attentional fixations, can occur in a single exposure, as far as each displacement contributes to minimize entropy. Visuo-attentional exploration is stopped whenever the average entropy on letters falls below threshold T_{avg} (also empirically set to 1.5 nat), so that letter identity processing is considered terminated for the current exposure.

Modulation of visual attention dispersion during exploration. The model also automatically adjusts attentional dispersion during the exploration of the input letter string. The initial dispersion of visual attention is set to its default value $\sigma_A^t = 1.75$. At the end of the first displacement of the visuo-attentional focus during attentional fixation, a new value is selected by the exploration algorithm as a function of information accumulation speed during this first attentional fixation, relative to a "reference" information accumulation profile.

This reference profile was obtained as follows: for each length, we randomly selected 100 words from the lexicon, and performed letter and word recognition during 1,000 iterations, with a single fixation, and all parameters of the model at their default values. In particular, gaze and attention position were slightly left of the center position. We then measured the evolution of entropy for all these words, and computed their average. An example reference profile is shown Figure 3 (green curve of top left plot).

At the end of the first attentional fixation, if information accumulation was faster than in the reference, the model adopts a large attentional dispersion for the rest of stimulus exploration. If, on the other hand, information accumulation was slower, attentional dispersion is reduced, so that fewer letters are processed in each attentional fixation. To compare the current entropy decrease with the reference one, their ratio is computed; we have empirically defined a relation that yields attention dispersion for subsequent attentional fixations as a function of the entropy ratio (Figure 3, top right). The value of the adjusted attention dispersion parameter σ_A^t is computed once at the end of the first attentional fixation and then applied for all subsequent fixations until termination.

In the visuo-attentional submodel, the parameters for attention quantity Q_A and attention dispersion σ_A^t can mathematically be manipulated independently. However, the visual exploration algorithm induces a strong correlation between them. Indeed, as we have just de-

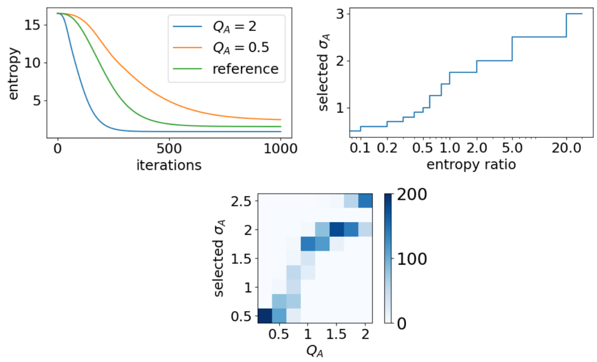

Fig. 3: Illustration of the modulation of visual attention dispersion during exploration. Top left: Evolution of the letter entropy over time. The green curve represents the reference entropy profile; the other two represent entropy evolution when the model is presented with the word “IMAGE”, for two different values of Q_A. Top right: Values of dispersion parameter σ_A^t selected by the visual exploration algorithm, as a function of the entropy gain ratio between stimulus and reference processing at the end of the first attentional fixation. Bottom: Values of dispersion parameter σ_A^t selected by the visual exploration algorithm, as a function of parameter Q_A. Color indicates how many words used each value of σ_A^t.

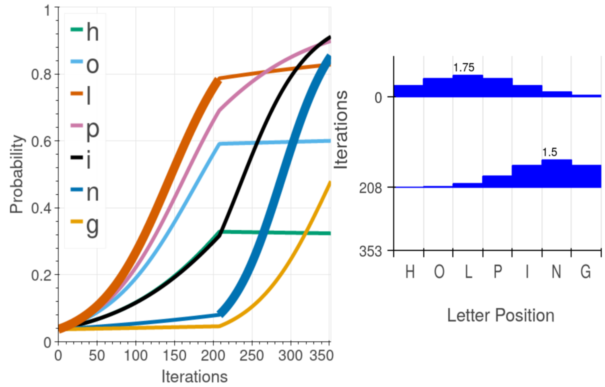

Fig. 4: Illustration of the visuo-attentional exploration algorithm on stimulus “HOLPING”. Left plot: Probability of perceived letters (y-axis) at each position, as a function of simulated time (x-axis). Each curve represents the probability value of the most likely letter hypothesis, at each position. Curves are color coded according to position (green curve for position 1, yellow curve for position 7, etc.). Curves are in thick lines when the focus of visual attention is on the position that they correspond to. Right plot: Evolution over time (y-axis) of the visuo-attentional distribution over the stimulus positions (x-axis). Letters at each positions are recalled at the bottom of the plot (“H” in position 1, etc.) Time indices indicated on the y-axis are beginnings of attentional fixations, for which the visuo-attentional distribution is the one depicted by the corresponding box plots, with its dispersion indicated by a number (e.g., between iterations 0 and 208, the focus of attention was on letter L at position 3; attention dispersion was 1.75). Box height indicates the attention allocated at each position).

scribed, attention dispersion σ_A^t is selected as a function of information accumulation speed, which is itself modulated by attention quantity Q_A. Figure 3 (bottom plot) illustrates the correlation between the two parameters on an independent experimental dataset. This dataset was composed of 200 8-letter words that were randomly extracted from the ELP database (Balota et al., 2007). As illustrated, the smaller the visual attention quantity Q_A, the smaller the adopted attentional dispersion σ_A^t. In the rest of this paper, we consider Q_A as our variable of interest, to study its effect on the predicted behavior, while σ_A^t is considered as a dependent, constrained variable.

Illustration: visuo-attentional exploration of the novel word “HOLPING”. Figure 4 illustrates the dynamics of visuo-attentional exploration (right plot) and how letter identity information evolves over time at the perceptual level (left plot), for the novel word “HOLPING” at the first exposure, with attention quantity $Q_A = 1$. At the beginning of processing (iteration 0), the distribution of visual attention is characterized by a focus aligned on the third letter of the 7-letter input word and a default value dispersion $\sigma_A^t = 1.75$. During the 208 iterations of this first attentional fixation, letter identity information gradually accumulates at the perceptual level. As can be seen on Figure 4 (left plot), during this period, identity evidence accumulates rapidly for the letter under the focus of attention and less so for other letters, as a function of their distance from the focus of attention. As a result, during the first attentional fixation, only very few letter identity information accumulates for the two final letters that are the most distant from the focus of attention.

At iteration 208, attention shifts to position 6 (i.e., on the letter N of “HOLPING”), a position that simultaneously maximizes the expected entropy gain and minimizes the motor cost associated with visual attention displacement. Given that identity evidence accumulated relatively efficiently for most letters during the first attentional fixation, visual attention dispersion is only slightly adjusted, leading to a σ_A^t value of 1.5. As can be seen on Figure 4 (left plot), the consequence of a visual attention shift at iteration 208 is twofold. First, identification of the letters at and immediately around the new attentional focus is boosted, yielding a sharp increase in identification probability for the final letters (“ING”); second, identification probability begins to decrease for the initial letters that no longer receive attention. At the end of the second attentional fixation (iteration 353), the termination criterion based on threshold T_{avg} is met, so that visual exploration and processing of the stimulus end.

At the end of processing, lexical membership evaluation assessed the stimulus word as being a novel word, so that a new lexical representation was created. This lexical representation corresponds to knowledge accumulated on letter identity during processing. For the novel word "HOLPING", the new memory trace will be relatively complete, providing some identity information on all the letters of the input string. However, none of the input letters were perfectly identified at the first exposure (none reached Dirac probability) and some letters were better identified than others, thus leading the possibility to improve lexical knowledge for this item during subsequent exposures. To evaluate simulations, two measures characterizing processing at the first exposure are considered: a measure of processing time (in this example with the novel word "HOLPING", 353 iterations) and a measure of the number of attentional fixations during this processing time (here, 2).

3. Method

3.1. Material

Seven hundred words were selected from the model's lexical database to serve as stimuli for the current study. The words varied in length from 4 to 10 letters. We used the `Gurobi` problem solver (Gurobi Optimization LLC, Beaverton, Oregon, USA; Gurobi Optimization, LLC 2021), to select one hundred words, for each length, so that they were matched in frequency and belonged to the Noun grammatical category. The selected words were of medium frequency, varying between 3.6 and 3.7 occurrences per million words (the average frequency of the whole lexicon was 3.63 occurrences per million words). To exclude any potential additional effect of neighborhood, all target word neighbors (i.e., all the words that differed from target words by a single letter) were excluded from the lexicon, thus resulting in a set of stimuli without orthographic neighbors. This removed 1,983 words from the 79,673 (2.5%) words of the lexicon. Removing the orthographic neighbors allowed studying the length effect while excluding confounding factors. Indeed, short words typically have many more orthographic neighbors than long words, so that the number of neighbors cannot be equated for sets of words that strongly differ in length.

For the current experiment, this set of 700 words was used twice. They were considered once as known words – thus belonging to the model's lexical word knowledge – and once as novel words, in which case they were removed from the model's lexical database. This was done to ensure a perfect matching between the characteristics of stimuli, independently of their status as known words or novel words; this also ensures that stimuli considered as novel words are realistic, in the sense that, for instance, they are orthographically legal. The list of stimuli can be found in Appendix A.

3.2. Procedure

The model was used to simulate the visuo-attentional exploration of the 700 stimuli, twice each, as each was once considered a known word and once as a novel word, for a total of 1,400 simulations. This was repeated for seven possible values of attention quantity Q_A (0.5, 0.75, 1, 1.25, 1.5, 1.75 and 2). In each simulation, the same stimulus was presented five times to the model: at each of these exposures, we simulated the visual-attentional exploration of the stimulus, and the subsequent updating of an existing orthographic trace, or the creation of a new one.

From each simulated exposure, we measured two variables of interest. First, a measure of Processing Time (PT) was computed as the number of iterations occurring before the termination criterion was met. Second, we measured the Number of Attentional Fixations (NAF) performed by the model in the same time interval. The length effect was quantified by the slope between performance on the two measures of interest for the shortest and the longest items, item length being estimated in number of letters (4 versus 10 letters).

3.3. Statistical analyses

The simulated Processing Times were analyzed using generalized linear models (*glm* function; R Core Team 2020) with a Gamma family and an inverse link. To select the most appropriate link function, we tested several possibilities ("identity", "inverse" and "log") and analyzed the results of the subsequent models: we chose the model that minimized both the resulting AIC (Akaike Information Criterion; Akaike, 1973) and the Fisher Scoring (number of iterations required for the model to converge). To analyze the NAF, we followed the suggestion of Harris et al. (2012) and used a generalized Poisson regression (*vglm* function; R Core Team 2020), as the data were underdispersed (`dispersiontest` function; R Core Team 2020). All statistical models and simulated results are provided as Supplementary Material[1]

First, we used two models to compare PT and NAF for words and novel words at the first exposure, in which Attention Quantity (7 Q_A values), Item Type (novel

[1]Open access availability for Supplementary Material files: `https://osf.io/g8cbf/`.

word vs. known word) and Item Length (from 4 to 10 letters) were included as fixed factors. For the sake of clarity, results are first presented while focusing on the lexicality effect, then, on the length effect.

Second, we used two models to analyze PT and NAF across exposures, but for the novel words only, with Attention Quantity (Q_A), Item Length and Exposure Number (from 1 to 5) as fixed factors. The results are first presented while focusing on the interaction between Q_A and the number of exposures, in which case PT and NAF are expressed per letter, then focusing on the length effect for the two variables of interest (PT and NAF).

4. Simulation results

For the known words, the process of orthographic learning was always successful, for all Item Lengths and Attention Quantity Q_A values. For novel words, orthographic learning sometimes failed. This occurred when a novel word was erroneously categorized as a known word, so that the orthographic trace of the most activated known word (typically an orthographically similar word) was updated. Erroneous learning further occurred when a previously encountered novel word was once more categorized as novel during a subsequent exposure, so that a new, extraneous trace was created and the orthographic trace previously created for this same novel word was not updated.

The success rates for novel word learning are provided in Table 1 for the different Q_A values and lengths. While all the shorter novel words (from 4 to 6 letters) were successfully learned regardless of Q_A, learning errors were observed for longer items. As shown in Table 1, the success learning rate increased as the Attention Quantity Q_A increased. For each Q_A value, stimuli that generated learning errors were excluded from all further analyses.

The effect of Q_A on stimuli processing is described in the next two sections. We first focus on processing at the first exposure to describe how Attention Quantity affects PT and the NAF depending on Item Type (novel words vs. known words) and Item Length (from 4 to 10 letters). Given the high level of performance of the model for known words from the first exposure, in the second section, we focus on novel word processing alone to describe how the Item Length effect evolves across the five exposures depending on Attention Quantity. Note that all the results reported in the following sections were derived from the same data set using a single statistical model for each measure. They are presented in different sections for the sake of clarity.

4.1. Processing of known words and novel words at the first exposure

The effect of Q_A on PT and NAF for the two types of items at the first exposure is illustrated in Figure 5. Keep in mind that stimuli are of variable length, and thus induce very different PT and NAF. For the coherence of the figure, and since we are not focusing on the length effect for now, both PT and NAF were normalized by word length. Novel words were processed slower than known words ($\beta = -5.6\text{e}{-4}, t = -14.70, p < .001$). Regardless of Item Type, average PT decreased when Attention Quantity increased ($\beta = 6.5\text{e}{-4}, t = 59.60, p < .001$), varying from 188 iterations per letter on average for $Q_A = 0.5$ to 59 iterations per letter on average for $Q_A = 2$. More importantly, the Attention Quantity (Q_A) by Item Type interaction was significant ($\beta = -1.1\text{e}{-4}, t = -8.80, p < .001$), showing that PT decreased more for novel words than for known words as the Attention Quantity increased. Average PT varied from 261 iterations per letter for $Q_A = 0.5$ to 70 iterations per letter for $Q_A = 2$ for the novel words and from 127 to 47 iterations per letter for the known words. As a result, the difference in PT between known words and novel words, that is the lexicality effect on PT, decreased when more attention quantity was available for processing.

Similar effects characterized NAF performance. The Attention Quantity (Q_A) by Item Type interaction was significant ($\beta = -0.078, z = -3.24, p = .001$). Post-hoc analysis showed that Attention Quantity (Q_A) affected NAF for the novel words ($\beta = -0.095, z = -6.47, p < .001$) but not for the known words ($\beta = -0.016, z = -0.86, p = .392$). With respect to novel words, average NAF varied from 1.17 NAF per letter for $Q_A = 0.5$ to 0.44 NAF per letter for $Q_A = 2$. With respect to known words, average NAF varied from 0.52 NAF per letter for $Q_A = 0.5$ to 0.33 NAF per letter for $Q_A = 2$. Thus, the lexicality effect on NAF was modulated by Attention Quantity, so that the difference in NAF between known and novel words decreased when Attention Quantity (Q_A) increased. Otherwise, the main Item Type effect was significant; more attentional fixations were observed on novel words than on known words ($\beta = 0.28, z = 2.87, p = .004$).

At the first exposure, the effect of Q_A on PT and NAF for the two types of items depending on Item Length is illustrated in Figure 6. This figure illustrates the same data as the previous one, and corresponds to the same statistical analyses. However, the graphical representation here focuses on the impact of Item Length on the two measures of PT and NAF. With respect to PT, the Item Length effect was modulated by Attention

Table 1: Successful learning rate, in the learning simulation, for novel words (successful learning rate is 1.0 for words).

Q_A \ Length	4L	5L	6L	7L	8L	9L	10L
0.5	1.0	1.0	1.0	0.88	0.81	0.68	0.56
0.75	1.0	1.0	1.0	0.97	0.95	0.80	0.73
1	1.0	1.0	1.0	0.96	0.96	0.83	0.71
1.25	1.0	1.0	1.0	0.97	0.97	0.85	0.80
1.5	1.0	1.0	1.0	0.97	0.99	0.85	0.85
1.75	1.0	1.0	1.0	0.97	0.99	0.91	0.88
2	1.0	1.0	1.0	0.98	0.98	0.93	0.89

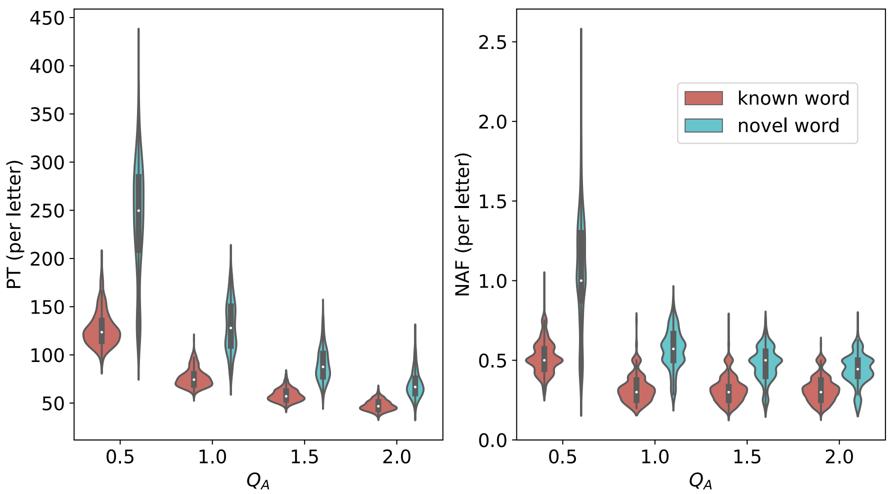

Fig. 5: Processing Time (PT, left) and Number of Attentional Fixations (NAF, right) per letter (*y*-axes), depending of Item Type (known words, in light blue, or novel words, in dark blue), as a function of visual Attention Quantity (Q_A values, *x*-axes). For each measure, a "violin plot" depicts the distribution of obtained values, with wider portions indicating higher density of values. The central dot represents the median of the distribution of values.

Quantity (Q_A): it was larger when Attention Quantity was smaller ($\beta = -4.5\text{e}{-5}, t = -33.91, p < .001$). There was no larger Item Length effect on PTs for the novel words than for the known words, as shown by the non significant Item Type by Item Length interaction ($\beta = -2.8\text{e}{-6}, t = -0.61, p = .545$). This is due to the range of explored Q_A values, in which large values yield a floor effect on Processing Times; the interaction is significant when considering only small Q_A values (e.g., when $Q_A < 1$). However, the Attention Quantity by Item Type by Item Length double interaction was significant ($\beta = 6.92\text{e}{-6}, t = -4.55, p =< .001$), showing that the Length effect on PT was larger for novel words than for words when Attention Quantity (Q_A) was smaller. Otherwise, the main Item Length effect on PTs was significant (varying from 431 iterations for 4-letter items to 975 iterations for 10-letter items; $\beta = -7.0\text{e}{-5}, t = -16.81, p < .001$).

As shown on Figure 6, the Length effect on NAF was greater for novel words than for known words ($\beta = 0.093, z = 7.42, p < .001$), and greater for the lower values of Attention Quantity ($\beta = -6.6\text{e}{-3}, z = -2.65, p = .008$). However, neither the Attention Quantity by Length interaction nor the Attention Quantity by Length by Item Type double interaction were significant ($\beta = -4.3\text{e}{-3}, z = -1.37, p < .170$). The main effect of Length was significant ($\beta = 0.10, z = 10.43, p < .001$), varying from 2.18 NAF for 4-letter items to 4.52 for 10-letter items.

4.2. *Evolution of the processing of novel words across exposures*

Figure 7 illustrates the effect of both Q_A and the Number of Exposures on novel words' PT and NAF. As shown on Figure 7 (left), PT decreased across Exposures ($\beta = 9.5\text{e}{-5}, t = 11.0, p < .001$), varying from

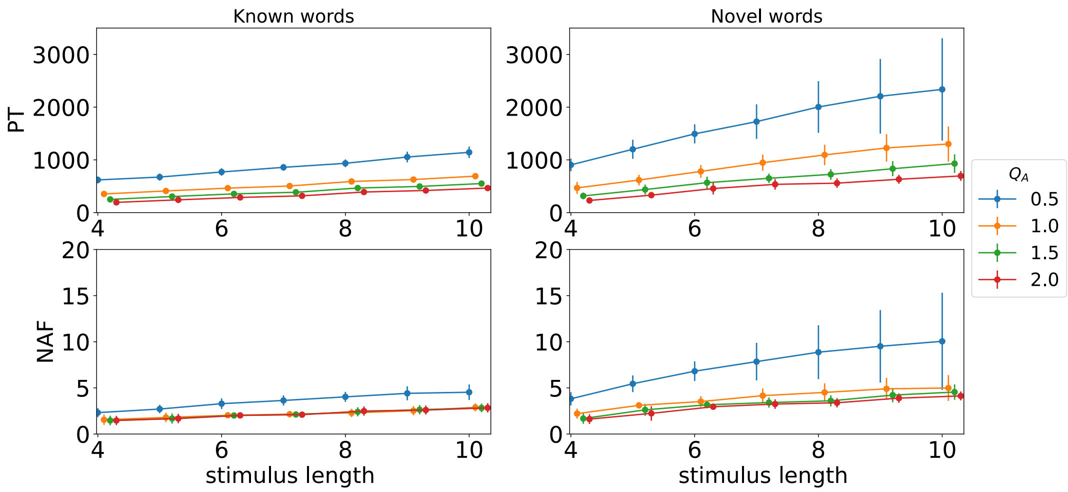

Fig. 6: Measures of visuo-attentional exploration (PT, top row and NAF, bottom row, on *y*-axes), at the first exposure, for known (left column) and novel words (right column), as a function of stimulus length (*x*-axes) and Attention Quantity Q_A (colored curves, from blue ($Q_A = 0.5$) to pink ($Q_A = 2.0$)). Error bars represent the data's standard deviation. The curves are slightly shifted horizontally from each other to ensure that the error bars are readable in the presence of overlap.

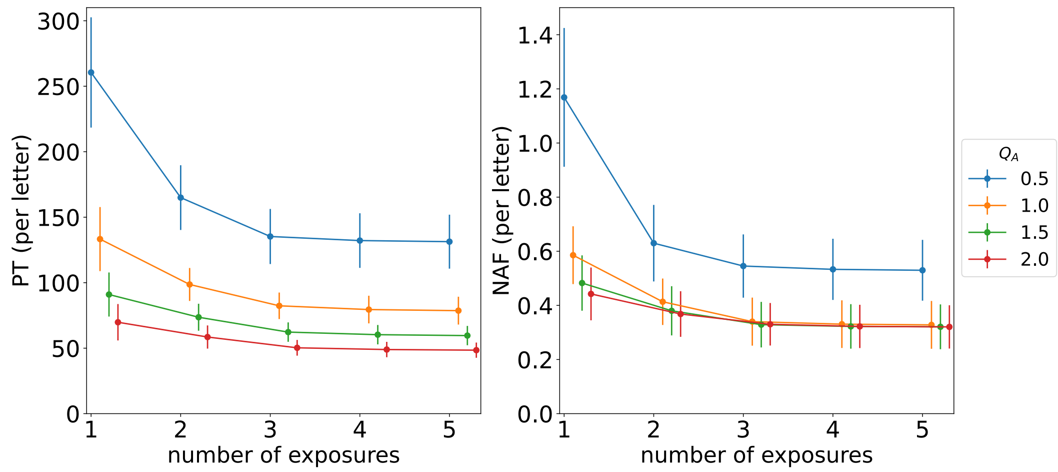

Fig. 7: Measures of visuo-attentional exploration (left, PT, in number of iterations per letter; right, NAF, in number of attentional fixations per letter; on *y*-axes) across exposures (*x*-axes) for novel words. Error bars represent the data's standard deviation. Curves are slightly shifted horizontally from each other to ensure that the error bars are readable in the presence of overlap. Each curve refers to a given visual Attention Quantity (Q_A), from 0.5 (blue) to 2.0 (pink).

128 iterations per letter on average at the first exposure to 74 iterations per letter at the fifth exposure. The Attention Quantity (Q_A) by Exposure interaction was significant ($\beta = 4.6\text{e}{-5}, t = 17.10, p < .001$), showing that the decrease in PT across exposures was stronger when visual Attention Quantity (Q_A) was more limited. Processing Times varied from 261 iterations per letter to 130 iterations per letter across the five exposures for $Q_A = 0.5$, from 70 iterations per letter to 48 iterations per letter for $Q_A = 2$. For all Q_A values, Processing Time stabilized after a few exposures, but the PT value at stabilization was higher for the lower values of Q_A, suggesting less efficient orthographic learning when the visuo-attentional quantity allocated to processing was more limited. For the lower Q_A values ($Q_A < 1$), PT after five exposures remained higher than PT at the first

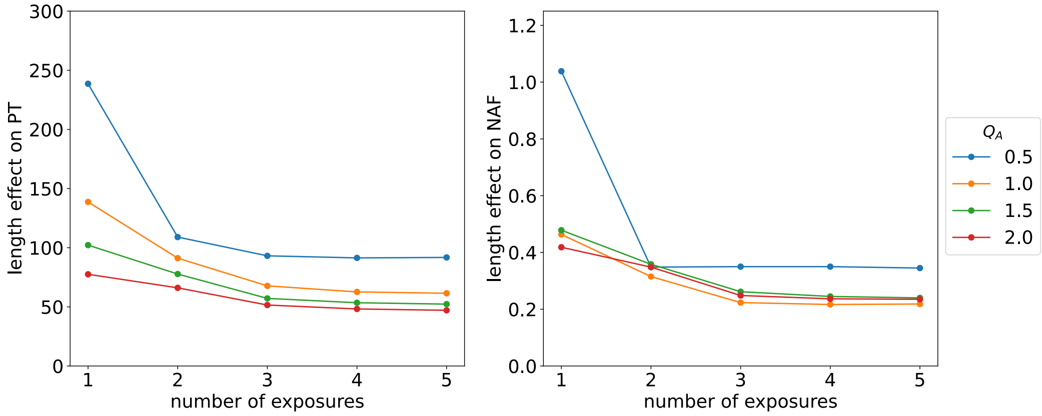

Fig. 8: Evolution of the length effect on PT (left, in number of additional iterations per additional letter) and NAF (right, on number of additional attentional fixations per additional letter), on y-axes, as a function of exposures (x-axes). Each curve refers to a given visual Attention Quantity (Q_A), from 0.5 (blue) to 2.0 (pink).

exposure for the higher Q_A values.

Different patterns characterized NAF performance. As shown on Figure 7 (right), neither the main effect of Exposure nor the Attention Quantity (Q_A) by Exposure interaction were significant ($\beta = -0.031, z = -1.37, p = .172$ and $\beta = 1.4\text{e}{-3}, z = 0.25, p = .801$ respectively).

The plots on Figure 8 illustrate the evolution of length effects on novel words' PT and NAF across Exposures depending on Attention Quantity. As shown on Figure 8 (left), the Exposure by Length interaction was significant ($\beta = 1.1\text{e}{-5}, t = 9.76, p < .001$), showing that the difference in PT between the shortest and the longest words was reduced across exposures. This reduction was further modulated by visual Attention Quantity (Q_A), as shown by the significant Attention Quantity by Length by Exposure double interaction ($\beta = -4.3\text{e}{-6}, t = -13.11, p < .001$). The length effect on PTs diminishes faster across exposures when Attention Quantity was lower.

The same pattern was observed regarding NAF (see Figure 8, right). Both the Exposure by Length interaction ($\beta = -0.031, z = -10.10, p < .001$) and the Attention Quantity by Exposure by Length double interaction ($\beta = 3.6\text{e}{-3}, z = 4.95, p < .001$) were significant. The NAF was far more important for the longest than the shortest words at the first (6.24 vs. 2.23 for the 10- and 4-letter words respectively) than at the fifth exposure (3.08 vs. 1.72) and the NAF difference between the longest and the shortest words decreased faster across Exposures when (Q_A) was lower.

5. Discussion

In the present paper, computational modeling was used to examine the role of visual attention in the transition from more serial to more parallel letter-string processing. We used the BRAID-Learn model, a model of orthographic processing that includes word recognition and orthographic learning mechanisms, as an experimental substitute.

Simulations showed that lexicality and length effects on PT and NAF decreased when larger visual attention quantity was available for processing. Orthographic learning was less successful when visual attention quantity was smaller and the input novel word longer. The evolution patterns of orthographic processing across exposures were also affected by visual attention quantity. Repeated exposure to the same novel word resulted in a larger decrease of PT and NAF when the quantity of visual attention was smaller. In the same way, smaller visual attention quantity yielded a larger decrease of the length effect on PT and NAF with repeated exposure to the same novel word. Overall, the model predicts that variations in visual attention quantity would significantly affect letter string processing and orthographic learning.

The advantage of computational modeling is to offer the opportunity to examine the effect of a single parameter manipulation, here visual attention quantity Q_A, on orthographic processing while controlling for all the other effects, either inherent to the system (like visual acuity or lateral interference) or to the input stimuli (like frequency or lexical neighborhood). However, isolating a single mechanism in this manner is easier in a computational model than in behavioral studies. Furthermore, the amount of visual attention available for processing is not easy to measure in humans, even though estimating it in reference to the Theory of Visual Attention has been attempted (Bogon et al., 2014; Bundesen, 1990).

Therefore, to evaluate the plausibility and relevance of the model's predictions, we will concentrate on the orthographic processing mechanisms that are responsible for the simulated lexicality and length effects, first without considering the effect of Q_A variations. Second, provided a close relationship between the model's general predictions and behavioral findings, we will discuss to what extent the evolution of the lexicality and length effects on PT and NAF depending on visual attention quantity provides insights on the serial-to-more-parallel transition and is compatible with available behavioral evidence.

5.1. Lexicality and word length effects irrespective of Q_A

We focused on the two effects of lexicality and word length, as markers of serial processing. The lexicality effect in the model directly follows from top-down influence of word knowledge that speeds up letter identification at the perceptual level and facilitates processing for the input letter strings that match an orthographic representation. The length effect in the model follows from the fact that the same amount of visual attention spreads over the input letter string whatever its length, so that less attention is allocated to each letter in longer stimuli. As a result, letter identity information accumulates less efficiently at the perceptual level for longer than for shorter stimuli, which increases PT and NAF during visuo-attentional exploration of the input string. However, partial identity information accumulated at the perceptual level through visuo-attentional exploration can be compensated by top-down lexical information, so that known words suffer lesser length effects than novel words, that have no orthographic representation (at the first exposure). These simulated length and lexicality effects, and their interaction, are coherent with many behavioral findings from studies on eye movements, word recognition and reading (Barton et al., 2014). In particular, longer fixation duration and a higher number of fixations are reported in longer than shorter words (Hautala et al., 2011; Joseph et al., 2009; Kliegl et al., 2004; Loberg et al., 2019; McDonald, 2006; Rayner, 1998). Readers spend more times fixating novel words (Chaffin et al., 2001; Williams and Morris, 2004) and show a larger length effect on these items than on known words (Lowell et al., 2014).

In the same way, some general learning effects like the reduction of PT and NAF with repeated exposure to novel words (independently of Q_A) directly follow from the combined effects of visuo-attentional exploration and lexical feedback. At the first exposure, perceptual information on letters is only based on stimulus sensory processing, since no lexical representation is available yet for this word. From the second exposure, perceptual information benefits from the influence of the newly created orthographic representation. Improvement of the novel word orthographic representation across exposures results in an increase of lexical feedback that enhances letter identification. As a result, orthographic learning in the model is characterized by a decrease in PT and NAF, which is consistent with behavioral findings from studies on the evolution of eye movement patterns in conditions of orthographic learning (Ginestet et al., 2020; Joseph and Nation, 2018; Joseph et al., 2014; Pagan and Nation, 2019; Pellicer-Sanchez, 2016).

In our simulations, we further observed a decrease in the length effect with repeated exposure to the same novel word. This follows from the fact that better-specified orthographic representations have higher influence on letter perceptual information and that lexical feedback is particularly critical when bottom-up perceptual identity information accumulates slowly, which more likely occurs for longer than shorter words. Obviously, when the attentional fixation is directed towards initial letters, final letters do receive less attention in longer than in shorter words. As a direct consequence, perceptual information accumulates more slowly for longer words that are thus more dependent on lexical feedback. Several behavioral studies have reported a reduction of the length effect on reading latency after a few repeated exposures to novel words (Kwok and Ellis, 2014; Maloney et al., 2014; Suárez-Coalla et al., 2014). Behavioral evidence that longer words progressively tended to be read as quickly as shorter words was interpreted as a marker of orthographic learning, suggesting that more and more letters within the input string were simultaneously processed.

5.2. Modulation of lexicality and length effects by attention quantity

Our main contribution in the present paper was to evaluate the influence of visual attention quantity on orthographic processing. The model predicts that the two lexicality and length effects are modulated by visual attention quantity, thus suggesting that the total amount of visual attention available for processing further contributes to the serial-to-more-parallel processing transition. In the model, the amount of visual attention quantity deployed for processing at the first attentional fixation modulates the speed of letter identity perceptual identification and the number of letters that fall under the deployed attention. At the second fixation, visuo-attentional dispersion is modulated according to previous information accumulation speed. Fast accumulation of identity information for the higher Q_A values leads to adopt larger visual attention dispersion. A higher number of letters are then simultaneously identified at each new fixation, leading to more parallel processing. To the contrary, attentional dispersion is narrowed when identity information accumulated laboriously at the first attentional fixation. Then, only a few letters can be successfully identified at each subsequent fixation, leading to more serial processing.

Although it is difficult to directly measure the visual attention quantity in humans, the impact of perceptual processing speed and multi-letter parallel processing on behavioral performance have been investigated by reference to two theoretical frameworks, namely the Theory of Visual Attention (Bundesen, 1990; Bundesen and Habekost, 2014) and that of visual attention span (Bosse et al., 2007; Valdois, 2022; Valdois et al., 2004). Moreover, behavioral studies have established a link between perceptual processing speed and VAS, suggesting that lower VAS performance related to slower perceptual processing (Bogon et al., 2014; Dubois et al., 2010; Ginestet et al., 2020; Lobier et al., 2013). The plausibility of the model's predictions with respect to variations in visual attention quantity can therefore be questioned in the light of available behavioral evidence on how perceptual processing speed and VAS affect letter-string processing and orthographic learning.

The model predicts that individuals with smaller visual attention quantity would be more prone to rely on serial processing, thus showing higher lexicality and length effects on processing time and number of fixations while reading. The studies carried out by reference to the Theory of Visual Attention (Bundesen, 1990; Bundesen and Habekost, 2014) provide some support to this prediction. Perceptual processing speed was consistently found reduced in brain-damaged individuals showing excessive reliance on serial processing (Habekost, 2015). In particular, perceptual processing speed is markedly reduced in letter-by-letter readers who otherwise exhibit exaggerated word length effects on naming and lexical decision latencies, and eye movement measures (Barton et al., 2014; Behrmann et al., 2001). However, we lack direct evidence that word processing and the oculomotor pattern in letter-by-letter readers are related to their perceptual processing speed (or VAS). Future studies should more directly evaluate whether differences in perceptual processing speed would predict the amplitude of the length effect in letter-by-letter readers.

Lower visual attention quantity might further account for stronger reliance on serial processing in developmental dyslexia. Several studies suggest that individuals with developmental dyslexia exhibit a reduction in perceptual processing speed (Habekost, 2015; Stefanac et al., 2019; Stenneken et al., 2011) and in visual attention span (Bosse et al., 2007; Germano et al., 2014; Zoubrinetzky et al., 2014). Furthermore, it is well documented that a larger word-length effect on naming, lexical decision and oculomotor measures is a consistent finding in developmental dyslexia (De Luca et al., 2002; Martens and de Jong, 2008; Spinelli et al., 2005; Zoccolotti et al., 2005). However, once again, direct evidence that reduced processing speed or VAS affects the lexicality or length effects in developmental dyslexia is scarce. An exaggerated length effect has been described in association with reduced VAS in some case studies of developmental dyslexia (Valdois et al., 2011, 2003) and a group study has shown that the number of fixations (but not fixation duration) in text reading increased in dyslexic individuals with lower VAS (Prado et al., 2007). A more rigorous assessment of the model predictions would require to systematically evaluate whether a VAS or perceptual processing speed deficit in developmental dyslexia is associated to excessive length and lexicality effects.

However, the main prediction of the model is that differences in visual attention quantity should affect the transition from serial-to-more-parallel processing. Relevant behavioral evidence would then come from changes in reading patterns across grades and from orthographic learning studies. Only piecemeal behavioral information can be related to the model's prediction. There is evidence that VAS abilities increase across grades (van den Boer et al., 2015; van den Boer and de Jong, 2018; Bosse and Valdois, 2009; Huang et al., 2019). The large decline in word-length effect observed in typical readers as they learn to read might thus suggest a decrease in word length effect with growth in VAS skills. Unfortunately, we lack direct behavioral evidence for such a relationship across grades. However, van den Boer et al. (2013) showed that variations in VAS skills in second grade children predicted variations in length effect on their reading latencies. This finding and the consistently reported relationship between VAS and reading fluency (van den Boer and de Jong, 2018; Bosse and Valdois, 2009; Chan and Yeung, 2020; Chen et al., 2016; Lobier et al., 2013; Valdois et al., 2021b, 2019;

Zhao et al., 2018) suggest that VAS would contribute to the degree of reliance on serial processing.

To our knowledge, no study investigated the relationship between VAS (or processing speed) and the lexicality effect. Antzaka et al. (2017) examined skilled readers' pseudo-word reading in conditions of very brief presentation duration that prevented serial processing. They showed that the adult readers who played action video games and had larger VAS than non-players could successfully read more pseudo-words through parallel processing. As the two groups of players and non-players were matched on text reading fluency, their findings might suggest that larger VAS is associated to a lower lexicality effect on processing times. Behavioral studies on orthographic learning should be particularly relevant to evaluate the link between visuo-attentional resources and the shift from serial-to-more-parallel processing. Unfortunately, although available findings convincingly show incremental orthographic knowledge growth across repeated exposure to the same novel word (Joseph and Nation, 2018; Joseph et al., 2014; Pagan and Nation, 2019; Pellicer-Sanchez, 2016), neither VAS nor perceptual processing speed were simultaneously measured. A single study provided some evidence of better orthographic learning skills in the group of participants with higher VAS (Ginestet et al., 2020).

5.3. Conclusion and perspectives

The main contribution of the present modeling study is twofold. First, the model provides a sophisticated description of the dynamics of visuo-attentional exploration during printed word processing. Second, it shows how the interaction of visuo-attentional exploration and lexical knowledge contributes to the gradual strengthening of item-specific orthographic representations as learning progresses. Decrease of the lexicality and length effect across exposures suggests that the model captures some aspects of the transition from serial to more parallel processing. However, orthographic learning in the model is performed in the absence of any phonological processing. This drastically differs from previous modeling of orthographic learning through self-teaching (Pritchard et al., 2018; Ziegler et al., 2014), in which successful phonological processing was critical to acquire new orthographic knowledge and explain the transition from serial to more parallel processing.

In this respect, BRAID-Learn more directly relates to the model of automaticity in reading proposed by LaBerge and Samuels (1974). LaBerge and Samuels (1974) emphasized the role of visual attention in the processing and memorization of increasingly large orthographic units during the course of learning to read. In the same way, in BRAID-Learn, the amount of visual attention quantity influences the size (in letter number) of the processed units (from individual letters to the whole word letter-string), so that the smaller the attention quantity, the smaller the number of letters processed as a whole. However, in the absence of implemented phonological component, the predictive power of BRAID-Learn is limited. Addition of a phonological module in BRAID-Learn, or the addition of visuo-attentional processes in dual-route self-teaching models (Pritchard et al., 2018; Ziegler et al., 2014), would allow improving the models' predictions and examining the combined effects of visual attention and phonological processing on both orthographic learning and the transition from serial-to-more-parallel processing.

One could further question the relevance of our study, in which the BRAID-Learn model was equipped with an expert orthographic lexicon and tasked to learn a single novel word, to provide insights on reading acquisition. Indeed, during reading acquisition, it is unclear how the current state of the growing lexicon affects the learning of a currently encountered novel word. We surmise that our observations would generalize to this situation, since, at the first encounter, top-down lexical feedback is suppressed in the BRAID-Learn model, so that the current state of the lexicon does not affect perceptual processing and visuo-attentional exploration. However, the interaction with phonological processing, would certainly matter. Current work concerns extending BRAID-Learn in this direction, to study its capacity to gradually build up rich lexical knowledge, while starting from only minimal knowledge on word-specific orthographic representations.

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Appendix A. Stimuli

4-letter words: acme, arak, ares, barb, bess, boon, brig, cell, chin, coup, dade, deer, dill, dyne, enos, gale, gaud, gent, hemp, joss, june, kivu, lear, leek, loch, buri, cony, lura, mali, marr, mink, moth, nara, huns, oath, peru, quod, role, rook, scut, slat, soul, tarn, tofu, topi, tosh, tree, vial, womb, yeas, aide, ainu, aryl, attu, oleg, bert, body, buna, byes, caff, capn, miry, dodd, dram, edam, feat, feds, fogg, ludo, fore, gogo, gown, grot, grub, hake, hume, husk, koan, lakh, pron, menu, mort, nett, orly, oxen, pane, pomp, quay, sham, sims, skit, talc, togs, tory, vail, vats, volt, weft, wold, yule

5-letter words: arabs, aroma, aspen, babel, baker, balsa, berry, blues, cache, chump, codex, compo, crust, dicks, dildo, flank, drake, fanny, dolly, greer, harem, horne, jonah, keane, lewis, loren, macon, males, maple, oasis, ozone, pansy, penis, photo, rabbi, clasp, rotor, rover, rumba, skull, sloan, snack, syrup, tamil, teeth, toque, trier, uncle, vigil, wayne, anvil, aorta, argos, aspic, atoll, attic, aught, blood, bourn, canoe, carey, chris, cleva, della, dinar, ernie, ether, folio, foyer, gibby, gusto, heron, highs, ivory, jones, katie, kurus, levin, maine, navvy, rhode, robot, sabra, sadie, saran, scuba, sewer, shank, sioux, skiff, slush, spoof, sprig, swath, tosca, twine, walls, weiss, whorl, wilde

6-letter words: ablaut, anklet, arrack, beeves, borage, centum, cicala, cotman, cowmen, czechs, dalton, dowser, flagon, gigolo, hotpot, howdah, icemen, kronor, krutch, kummel, lugger, mender, noshes, office, oxcart, pignut, poppet, ranker, rioter, sacker, sateen, scrota, seekin, shensi, stamen, street, sundew, tatian, tibiae, tomtom, torrio, tumuli, xavier, yeoman, yogurt, yonder, zenith, zephyr, zinnia, zombie, andrus, beirut, bistro, bustle, cactus, cartel, catgut, chukka, cicero, delvin, dibble, doddle, duenna, dustup, emblem, escudo, family, friend, fulmar, gasmen, gooier, guizot, hangup, hannah, hippie, hopper, howell, idiocy, jasper, lemons, newton, orgasm, persia, pulsar, quincy, rapist, rogues, rotter, runnel, sayers, schulz, sidney, sinker, strang, strata, varian, volume, wicket, wilson, yokuts

7-letter words: affaire, alumnae, anthill, autarky, barnaba, blanket, blemish, brooder, buildup, clayton, colonus, waiving, corrals, country, crystal, dawdler, decoder, divider, doublet, dresser, economy, egerton, erosion, evasion, firearm, flyways, francis, gingham, gouache, goulash, grenada, hormone, imagery, inkling, longbow, macedon, maurice, nemesis, newport, newsmen, oregano, panoply, pedicel, poussin, prowess, referee, seaport, stratum, virgule, vulture, antenna, babcock, beaches, bloomer, booklet, buttock, cabbage, calypso, concept, dilemma, diploma, dorothy, forrest, garrett, gazelle, gestapo, grafton, heckler, heywood, jackson, jenkins, lincoln, liqueur, luggage, mailman, mankind, mongrel, neilson, oranges, pattern, phantom, pitcher, pitfall, pointer, pompano, pretext, privacy, provost, sangria, schmidt, siberia, slipper, snowman, stinger, surgery, syrians, tremolo, untruth, valerie, virgins,

8-letter words: besieger, bombsite, bootlace, bullhide, cajolery, causerie, clifford, decoking, division, entresol, eyetooth, families, findsome, fireclay, gallants, glumness, gripsack, icefloes, infamies, lifebelt, lifebuoy, lummoxes, majority, mastoids, medicine, orchises, overplus, parterre, prattler, property, psalmody, putsches, quirinal, raciness, raillery, rankness, rockhall, tenpence, throstle, tidemark, toadyism, tollgate, transfer, turnspit, wigmaker, wineskin, wiriness, yugoslav, zeppelin, zimbabwe, addendum, botulism, boutique, bulgaria, cambodia, cassette, causeway, churches, commando, compiler, cupboard, deathbed, detritus, eyepiece, finisher, haitians, handbook, heraldry, holiness, ideology, instance, laxative, licensee, machismo, metaphor, musician, namesake, nebraska, plastics, pretense, proposal, roadster, rushmore, seedling, sherlock, softness, specimen, speeches, stimulus, tamarind, tasmania, tendency, theology, treasury, ugliness, universe, werewolf, westwood, winfield, woodside

9-letter words: ablatives, australia, blowflies, blutwurst, bourguiba, bowerbird, bridewell, cominform, companies, contriver, costumier, crimplene, cuckoldry, deauville, exhusband, flageolet, flashcube, abasement, fortifier, identikit, lobscouse, lowlander, lowliness, luckiness, lumbermen, luridness, lustiness, mistiness, moralizer, newspaper, nunneries, oratories, orrisroot, patricide, phagocyte, phalanges, polyether, punctilio, repletion, sandshoes, scenarist, september, sixtieths, smoochers, stridence, sunniness, technique, timidness, treatment, woodlouse, agreement, attention, candidate, cerebella, charabanc, charwoman, chiseller, cicatrice, developer, diathesis, driveller, duchesses, fooleries, forcemeat, forewoman, garrulity, germicide, gushiness, hothouses, ignorance, lactation, lazaruses, leucotomy, materials, noctiluca, obscurant, omnibuses, orangeade, packhorse, panatella, papyruses, peccaries, penknives, personnel, plasterer, poltroons, stokehold, striation, sucklings, suffusion, sulkiness, sunfishes, tailboard, telltales, territory, tigresses, wesleyans, youngster, zimmerman, zoologist

10-letter words: andromache, basketball, burckhardt, burlesques, categories, coagulants, conception, concretion, conversion, coronaries, corrigenda, crustiness, delphinium, employment, evaluation, flagellant, gingersnap, graphology, hobbyhorse, horseflesh, intactness, keypunches, lordliness, maidenhood, manageress, mortuaries, newsletter, pliability, postscript, preclusion, preference, properties, propionate, psychology, quintuplet, saleswomen, savageness, scrollwork, specialist, speleology, stonemason, submission, suspension, telephotos, terramycin, thrashings, threepence, truculence, undulation, vulgarians, alpenstock, anglomania, anointment, antiheroes, apoplexies, artfulness, assumption, bestiaries, braininess, businesses, clerestory, collieries, colloquies, conclusion, conference, dishabille, eisteddfod, foundation, giantesses, glossiness, goldfishes, hibiscuses, homoeopath, horselaugh, horsewoman, husbandman, industries, instrument, intendants, inwardness, irishwoman, mainstream, minuteness, parliament, petrolatum, preferment, presbytery, psalteries, reputation, resolution, rheumatics, scantlings, subsidizer, succulence, supplanter, swordstick, throughway, waterpower, workpeople, yellowness