



Decoding Letters: Eye-Tracking Evidence that Bigram Frequencies Influence Reading and Naming

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Abstract

Language learning, word recognition, and reading rely on the continuous extraction of statistical regularities within a language. The current study examined how the orthographic structure of words in the English language influences letter recognition, a precursor to reading and writing. Twenty-five native English speakers named lists of letters while their eye movements and vocal responses were recorded. Letters in each list were arranged in high-probability or low-probability sequences based on the bigram frequency between two adjacent letters. Eye movement data showed that participants fixated longer on lists of letters arranged in high-probability than low-probability sequences, likely because letter pairs with higher bigram frequencies activated a larger network of words than letter pairs with lower bigram frequencies. Higher next bigram frequency was associated with longer fixations on each letter, whereas higher preceding bigram frequency, current letter frequency, and next bigram frequency were each associated with faster letter naming fluency. We conclude that statistical regularities in language build expectations for upcoming letters, with implications for reading, pattern extraction, speech perception, and language learning and processing more broadly.

Keywords Rapid automatized naming · Bigram frequency · Letter naming fluency · Eye-tracking · Letter processing

Introduction

The immensely popular game Wordle (www.nytimes.com/games/wordle/index.html) created by Josh Wardle took the Internet by storm during the COVID-19 pandemic. The objective of the game is simple: Guess the secret 5-letter word in six tries. Individual letter tiles

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turn green if the letter is in the correct location, yellow if the letter is in the word but in the incorrect location, and grey if the letter is not in the word at all. Thus, the key to victory in Wordle is two-fold: 1) knowing how often each letter of the alphabet appears in five-letter English words (i.e., letter frequency, Solso & King, 1976; see Grainger et al., 2008 for a review) and 2) understanding the rules and restrictions that govern the letter and sound combinations in the English language (i.e., phonotactics; Bauer, 2015; Gouskova, 2018). Sound sequences, such as syllable structure, consonant clusters, and vowel sequences, within each language are highly systematic. For example, in English, /bl/ is acceptable at the beginning of a syllable, but never at the end. On the contrary, /nk/ is acceptable at the end of a syllable, but never at the beginning (Pearce, 2006). Phonotactic constraints support language acquisition by defining which sound sequences are permissible (Gervain & Werker, 2008; Graf Estes et al., 2011).

In addition to letter frequency and phonotactics, positional bigram frequency is an orthotactic cue that can guide word recognition. Positional bigram frequency refers to how often two adjacent letters co-occur at any given position within a word (Jusczyk et al., 1994; Lelonekiewicz et al., 2020; Mano & Kloos, 2018; Vitevitch & Luce, 2004). Letter pairs that are less likely to occur next to each other have a low bigram frequency and typically signal a break. Low frequency bigrams typically form two separate words. For example, in the English corpus, *ty* has a higher bigram frequency (words like *adversity*, *pretty*, *duty*, and so on) than *tj*. Despite a large body of research investigating the impact of bigram frequency on word processing (e.g., Dal Ben et al., 2021; Gernsbacher, 1984; McClelland & Johnston, 1977; Muncer et al., 2014), less is known about the influence of statistical regularities on letter recognition, processing speed, and articulation. The present study examines whether positional bigram frequency in the English language impacts letter naming and processing.

Humans from a very young age extract statistical patterns and regularities from the environment to create mental representations of the world. They then apply their knowledge to facilitate attentional processes, shape representations, and predict future events in various cognitive domains, including perception (Turk-Browne, 2012), motor control (He et al., 2016 for a meta-analysis; Monroy et al., 2017), decision-making (e.g., Kool et al., 2017; Momennejad et al., 2017), memory (Gershman & Daw, 2017), and language (Erickson & Thiessen, 2015; Lupyan & Clark, 2015; Romberg & Saffran, 2010). Because speakers do not always pause between words, listeners are faced with the challenging task of determining where one word ends and the next word begins. During language acquisition, infants pay close attention to the frequency and co-occurrence of sounds within a word and across word boundaries (Saffran, 2003; see Erickson & Thiessen, 2015 and Saffran, 2020 for reviews). This is known as transitional probability. The transitional probability from one syllable to the next is generally higher for recurring speech sounds (e.g., speech sounds that exist within a word) compared to speech sounds occurring more sporadically (e.g., speech sounds spanning word boundaries). In a study by Saffran et al. (1996a), 8-month-old infants listened longer to novel than familiar syllable sequences after exposure to a continuous stream of artificial speech, indicating that they had learned the statistical regularities governing syllable transitions. This finding was replicated in adults using an artificial language (Saffran et al., 1996b) and in infants exposed to natural speech (Pelucchi et al., 2009). Moreover, recent evidence suggests that statistical learning abilities remain robust across development, with no behavioral or neural advantage observed in children relative to adults, indicating that

adults retain the capacity to efficiently extract statistical regularities from continuous input (Moreau et al., 2022).

Previous research has shown that familiarity influences word segmentation (see Krogh et al., 2013 for a review). For example, Onnis and Thiessen (2013) showed that native-language word order regularities influenced how English speakers and Korean speakers segmented speech at the phrase level. Specifically, each group segmented speech in ways that aligned with the statistical structure of their native language, demonstrating that prior linguistic experience shapes how continuous input is parsed. However, most research has focused on spoken language, where statistical regularities support the segmentation of syllables, words, and phrases. Comparatively little is known about whether analogous statistical regularities in written language influence processing at the level of individual letters. This question is particularly relevant because fluent reading requires the rapid identification of letters within larger orthographic sequences (Arciuli & Simpson, 2012).

Although orthotactic regularities are typically studied in the context of visual word recognition, they may also influence more basic stages of orthographic processing. Through extensive reading experience, readers acquire probabilistic knowledge about the co-occurrence of letters, allowing them to generate expectations about upcoming visual input. During serial letter naming, these expectations may facilitate the encoding of letter sequences, guide the allocation of visual attention, and reduce processing demands. Positional bigram frequency is expected to facilitate individual letter processing because frequently co-occurring letter pairs are encountered repeatedly during reading, leading to stronger orthographic representations through statistical learning. As a result, high-frequency letter combinations should be recognized more efficiently than low-frequency combinations, thereby reducing the processing demands associated with identifying and encoding successive letters. During rapid letter naming, this facilitation may manifest as shorter letter fixation durations, reflecting more efficient orthographic processing, which in turn should support faster naming latencies. Conversely, low-frequency bigrams may require greater visual inspection and orthographic processing, resulting in longer or more frequent fixations and slower naming.

One task that has been used to examine letter naming fluency is the Rapid Automatized Naming (RAN) task (Denckla & Rudel, 1974). The RAN task measures the time needed to name a series of familiar stimuli (e.g., letters, digits, colors, or objects) as quickly and as accurately as possible. The RAN task serves as an index of automaticity (e.g., Kail & Hall, 1994; Wolf & Bowers, 1999), phonological awareness (e.g., de Jong & van der Leij, 1999; Torgesen et al., 1994), and orthographic processing (Georgiou et al., 2016). Performance on this task is strongly associated with reading development because it relies on cognitive processes critical for reading, including the rapid integration of visual symbols with their phonological representations and efficient serial processing of orthographic units (Georgiou et al., 2016; Kail & Hall, 1994). These processes are foundational to early reading development, supporting the transition from effortful, serial letter-by-letter processing to more automatic word recognition. In the case of orthographically inconsistent languages, these processes are particularly important because decoding letters is less transparent and readers rely more heavily on rapid lexical access and integration processes (Araújo et al., 2015; Ziegler et al., 2010). In addition, it is often used as a screening tool for children who are at risk of reading difficulties (Graziani et al., 2025; Norton & Wolf, 2012; Peterson & Pennington, 2012), as previous work has shown that it is a strong predictor of reading comprehen-

sion in both children and adults (see Borokhovski et al., 2018; Kirby et al., 2010; McWeeny et al., 2022 for systematic reviews and meta-analyses).

To our knowledge, only one study to date has examined the impact of statistical learning, as measured by bigram frequency, on letter naming fluency in adults using the RAN task. In a study by Borokhovski (2018), adults were faster to name letters in sequences composed of high frequency bigrams than letters in sequences composed of low frequency bigrams, suggesting that more familiar orthographic combinations are processed more efficiently. Borokhovski interpreted their findings as reflecting greater automatization for familiar orthographic patterns, whereas unfamiliar sequences (i.e., low frequency bigrams) may require additional processing time.

The Current Study

The current study examined how the orthographic structure of words in the English language influences letter processing in adults. Participants were presented with visually displayed letter sequences arranged into lists that varied systematically in orthotactic probability. Specifically, high-probability lists consisted of letters forming frequent bigrams in English, whereas low-probability lists consisted of letters forming less frequent bigram combinations. Thus, the manipulation contrasted familiar, highly predictable orthographic patterns with less familiar, low-probability letter sequences.

Based on prior work in adults, one hypothesis is that high-probability sequences facilitate processing, leading to faster naming and more efficient articulation, consistent with findings from Borokhovski (2018), who reported faster naming for high-frequency bigram sequences and interpreted this effect in terms of increased automatization for familiar orthographic patterns. In contrast, infant studies on statistical learning suggest a different possibility. Jusczyk et al. (1994) found that infants showed increased attention to high-probability phonemic sequences, which has been interpreted as reflecting sensitivity to regularities that support early language acquisition. If a similar sensitivity extends to visual orthography in adults, high-probability sequences might also attract greater attentional engagement, potentially leading to longer fixation times due to increased allocation of attention or integration demands.

To address these competing predictions, the present study combined behavioral measures of naming and articulation with eye-tracking. Eye-tracking was selected because it provides a sensitive, continuous, and temporally precise index of visual attention (Conklin et al., 2018; Eckstein et al., 2017). Specifically, fixation durations and gaze patterns offer a direct window into early perceptual and lexical processing, making eye-tracking well suited for assessing the influence of orthotactic structure on online letter processing. Voice recordings were used in parallel to obtain an overt measure of letter recognition and production speed (i.e., naming latency; Chacon et al., 2024). Unlike eye movements, vocal onset times capture the culmination of processing leading to articulation. Together, these methods provide a more comprehensive characterization of letter processing by distinguishing between early attentional processes (eye-tracking) and later production-related processes (voice recordings).

The current study tested the following two hypotheses:

1. The effect of bigram frequency was predicted to depend on whether high-probability sequences facilitate processing or capture attention. Therefore, we tested two competing hypotheses. Based on findings from the adult literature (e.g., Borokhovski, 2018) suggesting that high-probability sequences facilitate processing, we tested the prediction that high-probability sequences would yield faster naming and shorter fixation times than low-probability sequences. Alternatively, based on findings from the infant literature (e.g., Jusczyk et al., 1994) that high-probability sequences capture attention, we tested the predictions that high-probability sequences would yield longer fixation times.
2. Given that parafoveal processing facilitates word recognition (Hyönä, 2011; Rayner, 1975; Schotter et al., 2012), we predicted that orthotactic cues, such as letter frequency, preceding bigram frequency, and next bigram frequency, would systematically influence letter naming fluency and fixation times.

Methods

Participants

Twenty-five native English speakers between the ages of 18 and 35 (16 females) were recruited ($M_{age} = 22.60$, $SD_{age} = 2.65$) from a Midwestern university in the United States. A post hoc, simulation-based power analysis was conducted using the *simr* package in R (Green & MacLeod, 2016) to evaluate the sensitivity of the present design to detect the observed effect of condition. Power was estimated for the fixed effect of Condition using 1,000 simulations and a Kenward-Roger approximation for inference. The analysis indicated that the current design had estimated power of 70% (95% CI [66.8%, 72.5%]) to detect the observed effect ($\beta = -720$). Informed consent was obtained from all participants. The study was conducted in accordance with the Declaration of Helsinki and approved by the local University's Institutional Review Board. All participants had normal or corrected to normal vision and no history of a learning or language disability. One participant reported a history of a hearing impairment; further inspection of this participant's behavioral and eye-tracking data on the RAN task revealed that their performance did not deviate significantly from the group's mean and therefore the participant was not removed from the analyses.

Rapid Automatized Naming Task (RAN task; Denckla & Rudel, 1974)

Ten lists of 50 letters were created from the following letters (the number in the brackets represents the number of times they appear across all lists): a (3), b (3), c (4), d (3), e (2), f (2), g (2), h (2), i (2), j (1), k (1), l (2), m (3), n (1), o (1), p (4), r (3), s (6), t (3), u (1), and v (1). Letters in each list were arranged in high-probability or low-probability sequences based on the positional bigram frequency between two adjacent letters. See Fig. 1 for an example of a high-probability sequence (Fig. 1a) and a low-probability sequence (Fig. 1b). Positional bigram frequency refers to how often a pair of letters occurs at a specific position in a word and was calculated as the sum of log frequencies for all possible English words in the CLEARPOND database (Marian et al., 2012) that have the chosen bigram in a chosen position, divided by the sum of log frequencies for all words. The average initial, middle,

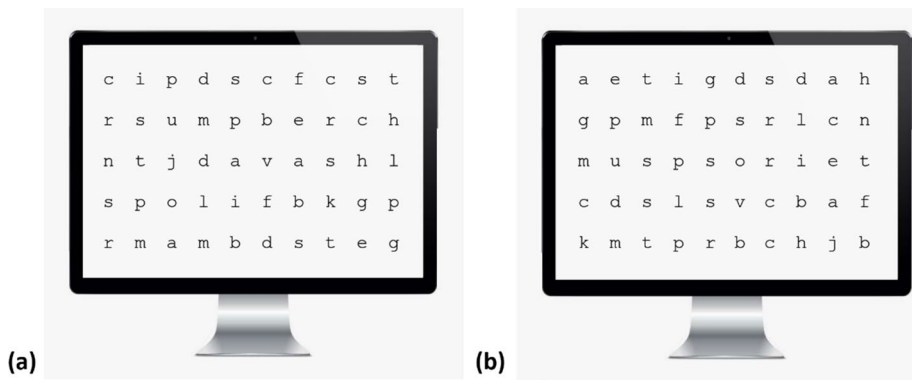


Fig. 1 Example sequences from the high-probability **a** and low-probability **b** conditions

Table 1 Positional bigram probabilities and bigram frequency for the high-probability and low-probability sequences

List	condition	Bigram probability			Bigram frequency
		Initial	Middle	Final	
1	High-probability	0.0060	0.0055	0.0059	0.0036
2	High-probability	0.0053	0.0036	0.0050	0.0028
3	High-probability	0.0051	0.0034	0.0048	0.0026
4	High-probability	0.0041	0.0071	0.0045	0.0037
5	High-probability	0.0045	0.0043	0.0045	0.0029
	Average	0.0050	0.0048	0.0049	0.0031
6	Low-probability	0.000029	0.0024	0.00041	0.0020
7	Low-probability	0.000045	0.0023	0.00040	0.0022
8	Low-probability	0.000151	0.0017	0.00040	0.0021
9	Low-probability	0.000040	0.0019	0.00034	0.0018
10	Low-probability	0.000083	0.0014	0.00030	0.0020
	Average	0.000070	0.0019	0.00037	0.0020

and final bigram probabilities, as well as the average bigram frequency for each list are shown in Table 1. Independent samples *t*-tests (Welch's test) revealed that the initial bigram probability, $t(4.04) = 15.01$, $p < 0.001$, Cohen's $d = 9.50$, middle bigram probability, $t(4.53) = 3.97$, $p = 0.013$, Cohen's $d = 2.51$, final bigram probability, $t(4.05) = 17.98$, $p < 0.001$, Cohen's $d = 11.37$, and bigram frequency, $t(4.78) = 4.78$, $p = 0.006$, Cohen's $d = 3.02$, were higher for the bigrams in high-probability sequence lists than the bigrams in low-probability sequence lists. The differences between conditions were largest for the initial and final bigram probabilities due to greater flexibility in constructing edge bigrams, which are determined by the first and last letter pairs, whereas middle bigrams are more constrained by the adjacent letters and their contexts.

Apparatus

Letter stimuli were presented on a 27-inch iMac with a display resolution of 2560×1440 located 60 cm away from the participant. For each participant, eye movements and vocal responses were simultaneously recorded and synchronized using Psychophysics Toolbox version 3.0.9 (Brainard, 1997; Kleiner et al., 2007) in MATLAB version 8.2 (The MathWorks Inc., Natick, MA). Eye movements were recorded monocularly from the right eye using an EyeLink1000 v.1.5.2 desk mounted eye tracker (SR Research Ltd., Ottawa, Canada) at a sampling rate of 1000 Hz. The EyeLink1000 has an average accuracy between 0.25 to 0.50 degrees of visual angle. An external microphone was used to digitally record the participant's responses.

Procedure

Participants first completed a 9-point calibration procedure with drift correction, which establishes the geometric characteristics of the participants' eyes and collects fixation samples from known positions on the screen. Participants were instructed to follow a black dot with their eyes while remaining as still as possible. Once calibration was successfully completed, participants were administered the RAN task. To start and end a trial, participants were instructed to press "Enter" on the keyboard. On each trial, participants heard a F#4 tone for 0.25 seconds and saw a grid of five rows with 10 letters in each row for a total of 50 letters. Each letter subtended 3.53 degrees horizontally in visual angle (approximately 105.63 pixels) and was presented in 18-point Courier black font on a white background. After the tone, participants named each letter into the microphone as quickly and as accurately as possible from left to right and top to bottom. Each participant completed five high-probability and five low-probability lists, which were randomly presented and counterbalanced across participants.

Data Processing and Variables of Interest

Voice recordings. The onset and offset times of each spoken letter and speech errors were manually coded by trained raters using Audacity 3.1.2 (Audacity Team, 2021). Each participant's data were coded by a single rater following a shared coding protocol. When a rater was uncertain about the letter produced in an audio recording, the recording was reviewed by the other two raters. If either of the other two raters disagreed with the initial rater, all three raters listened to the recording again and discussed the responses until 100% agreement was reached. Overall naming times were computed as the onset of the first letter produced to the offset of the last letter produced (i.e., 50th letter) on each trial. The number of incorrect responses for each trial was calculated by totaling the number of times participants made a letter substitution (e.g., saying 'c' instead of 'b'), an omission (i.e., skipped a letter), or an insertion (i.e., letter repetitions or saying new letters). The voice recordings from one participant are missing due to an equipment failure at the time of testing. As a result, this participant's data were removed from the analyses.

Eye movement recordings. Eye movement recordings were processed using the SR Research EyeLink Data Viewer software (SR Research Ltd, Mississauga, Canada). A rectangular area of interest (AOI) was manually created around each letter. Because the letters were arranged in a grid, but the display was rectangular in shape, the AOIs for the first and last letters of each row were slightly larger in width than the AOIs for the letters in the middle of each row. The AOIs for the first and last letters of each row (i.e., letters in position 1 and 10) were 281 pixels in length and 296 pixels in width, while the AOIs for the letters located in the middle of each row (i.e., letters in position 2 to 9) were 281 pixels in length and 211 pixels in width. A fixation output report for each participant was generated, including the start and end times of each fixation event, the duration of the current fixation, the number of fixations per trial, and the location of the current fixation. Eye blinks and fixations located outside of the AOIs were not included in the analyses. Similar to previous studies that used the RAN task (Hogan-Brown et al., 2014; Nayar et al., 2018), fixation events shorter than 80 ms were discarded (1.01% of the data) as they typically arise from tracking errors. The total fixation duration was defined as the total time spent fixating on all letters of a trial. The average letter fixation duration was defined as the average time spent fixating on each letter in a given trial.

Fixation-Speech Interval. The fixation-speech interval was calculated for each letter as the difference in time between the onset of the fixation (eye) and the onset of the spoken letter (voice) (Jones et al., 2008, 2013). Using a similar cleaning procedure as Nayar et al. (2018), erroneous responses and data points for two subsequent items after an error were discarded (3.02% of the data) because eye movements following an error are typically regressions, perseverations, or pauses. In addition, fixation-speech intervals less than -300 ms and greater than 3000 ms were removed from the analyses (28.38% of the data) because these values are thought to reflect either calibration issues when the fixation-speech interval is negative, regressions in cases where no error has occurred yet, or because the oculomotor system is waiting for the voice to catch up with the eye when the fixation-speech interval is too wide (Inhoff et al., 2011; Laubrock & Kliegl, 2015). For the fixation-to-speech interval measure, participants contributed on average 68.60% of trials ($SD = 8.68$), with retention rates ranging from 50.87% to 80.00%.

Statistical Analyses

Trial-level analyses. To determine the unique effect of bigram frequency on fixation and articulation measures related to RAN performance at the trial level, the eye movements and voice data were analyzed with linear mixed-effects models using the lme4 package (Bates et al., 2015) in R (R Core Team, 2020). Condition was included as a fixed effect (contrast coded as -0.5 for high-probability and 0.5 for low-probability), and Subject and Trial as random intercepts. We also added by-subject random slopes for the fixed effect in the comparison model to ensure the robustness of the effect and to better account for the hierarchical structure of the data (e.g., Barr et al., 2013). Significance levels were estimated based on the Satterthwaite approximations for degrees of freedom (Satterthwaite, 1946). Model comparisons were conducted in a stepwise manner. First, we compared a base model with list order as a covariate and random intercepts for subject and trial [$\text{lmer}(y \sim \text{order} + (1|\text{subject}) + (1|\text{trial}))$] to a model that additionally included the fixed effect of condition [$\text{lmer}(y \sim \text{condi}$

tion + order + (1|subject) + (1|trial)]]). Next, we compared the condition model with a model that further included a by-subject random slope for condition [$\text{lmer}(y \sim \text{condition} + \text{order} + (1 + \text{condition}|\text{subject}) + (1|\text{trial}))$]. For all models, y represents the outcome variable. We also determined the fit of each model by comparing the Akaike Information Criterion (AIC) of all three models. The effects were checked by running an ANOVA on the two models.

Item-level analyses. To determine the relative contribution of each orthotactic measure (i.e., letter frequency, preceding bigram frequency, and next bigram frequency) in predicting the amount of time spent fixating on each letter and the amount of time required to name each letter, we ran linear mixed-effects models using lme4 package (Bates et al., 2015) in R (R Core Team, 2020). The item-level analyses were conducted by collapsing across conditions (i.e., high- and low-probability lists). Letter frequency, preceding bigram frequency, and next bigram frequency were converted into z scores and entered as fixed effects, while Subject and Trial were entered as random intercepts. Significance levels were estimated based on the Satterthwaite approximations for degrees of freedom. The fit of each model was determined by comparing the Akaike Information Criterion (AIC) of the base model to the comparison model. The effects were checked by running an ANOVA on the two models.

The list-level and item-level analyses were designed to address complementary questions. The list-level analyses evaluated whether performance differed between the experimentally manipulated high- and low-probability conditions. Because these conditions were constructed by varying orthotactic properties, the categorical condition variable is inherently associated with the item-level orthotactic measures. Including both condition and the orthotactic predictors in the same model would therefore introduce substantial multicollinearity and obscure interpretation of their respective effects. Accordingly, the item-level analyses omitted Condition as a fixed effect and instead examined whether continuous variation in orthotactic properties predicted spoken letter duration and fixation letter duration.

Results

High- vs. Low-Probability Sequences

Means and standard deviations for the eye movements and voice recording measures are reported in Table 2. The parameter estimates for the linear mixed-effects models are presented in Table 3.

For total fixation time, adding Condition as a fixed effect to the intercept significantly improved the base model, $\chi^2(1) = 8.39$, $p = 0.0038$. In a subsequent step, adding a by-subject random slope for Condition further improved model fit, $\chi^2(2) = 6.45$, $p = 0.040$. Participants fixated longer on lists of letters arranged in high-probability sequences than lists of letters arranged in low-probability sequences, $\text{Estimate} = -736.34$, $SE = 251.93$, $t = -2.92$, $p = 0.0035$.

For average letter fixation duration, the likelihood ratio test revealed that the base model was significantly improved by adding Condition as a fixed effect, $\chi^2(1) = 5.32$, $p = 0.021$. Participants spent on average more time fixating on individual letters arranged in high-probability sequences than individual letters arranged in low-probability sequences, $\text{Estimate} = -5.35$, $SE = 2.02$, $t = -2.65$, $p = 0.008$. Adding a by-subject random slope for Condition

Table 2 Means and standard deviations (In Parentheses) for the eye movements and voice data on the rapid automatized naming task

	High-probability	Low-probability
Overall naming time (seconds)	17.11 (3.17)	16.94 (3.24)
Number of incorrect responses	1.27 (1.76)	1.06 (1.76)
Average spoken letter duration (ms)	266 (38.0)	264 (35.8)
Number of fixations	64.38 (9.13)	62.57 (8.65)
Total fixation duration (seconds)	14.67 (3.16)	13.87 (2.7)
Average letter fixation duration (ms)	228 (37)	224 (32.9)
Fixation-speech interval (ms)	513 (318)	521 (309)

ms milliseconds

Table 3 Parameter estimates of the linear mixed-effects models for total fixation duration and average letter fixation duration

Outcome variable		Estimate	SE	95% CI	<i>t</i>	<i>p</i>
Total fixation duration	Intercept	14,323.69	595.97	[13124.38, 15,523.87]	24.03	< .001
	Condition	-736.34	251.93	[-1267.59, -204.37]	-2.92	0.0035
		AIC	BIC	Loglik	χ^2	<i>p</i>
	Base	4260.6	4305.8	-2117.3	-	-
	Condition	4254.2	4302.9	-2113.1	8.39	0.0038
	Fixed effect and random slope	4251.8	4307.4	-2109.9	6.45	0.040
Outcome variable		Estimate	SE	95% CI	<i>t</i>	<i>p</i>
Average letter fixation duration	Intercept	225.89	7.04	[211.62, 240.14]	32.07	< .001
	Condition	-5.32	3.00	[-11.57, 0.87]	-1.77	0.076
		AIC	BIC	Loglik	χ^2	<i>p</i>
	Base	2086.4	2131.6	-1030.2	-	-
	Condition	2083.1	2131.8	-1027.6	5.32	0.021
	Fixed effect and random slope	2071.7	2127.4	-1019.9	15.39	< .001

The base model included random intercepts for Subject and Trial and List Order as a covariate. The Condition model added the fixed effect of Condition. The Fixed Effect and Random Slope model further included a by-subject random slope for Condition

further improved model fit, $\chi^2(2) = 15.39$, $p < 0.0001$. However, in this model, the effect of Condition was no longer significant, *Estimate* = -5.32, *SE* = 3.00, *t* = -1.77, $p = 0.076$.

To assess the relationship between total fixation time and average letter fixation time, we conducted a Pearson correlation. Although average fixation time reflected the mean fixation duration for individual letters, total fixation time reflected cumulative fixation time across the entire 50-letter list and therefore may have been more sensitive to list-level variation, including pauses between letters and filler words. The two measures were highly correlated,

$r(237) = .71$, 95% CI [.64, .77], $p < 0.001$, suggesting that participants who spent more time fixating on individual letters also had overall longer fixation times.

Condition as a fixed effect did not significantly improve the base model for overall naming time, $X^2(1) = 1.15$, $p = 0.28$, accuracy rates, $X^2(1) = 1.68$, $p = 0.19$, number of fixations, $X^2(1) = 2.14$, $p = 0.14$, average spoken letter duration, $X^2(1) = 3.59$, $p = 0.058$, and fixation-speech interval, $X^2(1) = 0.001$, $p = 0.97$. For these models, subsequent comparisons were not conducted because the initial addition of the fixed effect of Condition did not significantly improve model fit.

Current Letter Frequency, Preceding Bigram Frequency, and Next Bigram Frequency on Letter Fixation Duration and Spoken Letter Duration

The regression model for letter fixation duration was significantly improved by adding preceding bigram frequency, next bigram frequency, and current letter frequency to the base model [$\text{lmer}(y \sim (1|\text{subject}) + (1|\text{trial}))$], $X^2(3) = 9.17$, $p = 0.027$. Specifically, next bigram frequency increased letter fixation times relative to the intercept, $\text{Estimate} = 4.85$, $SE = 2.04$, $t = 2.38$, $p = 0.017$. Current letter frequency and preceding bigram frequency were not significant, $ps > 0.106$. Overall, orthotactic effects were limited to next bigram frequency, such that higher frequency in the upcoming context was associated with longer fixation durations.

The regression model for spoken letter duration was significantly improved by adding preceding bigram frequency, next bigram frequency, and current letter frequency to the base model [$\text{lmer}(y \sim (1|\text{subject}) + (1|\text{trial}))$], $X^2(3) = 159.04$, $p < 0.001$. Letter frequency, $\text{Estimate} = -5.19$, $SE = 0.83$, $t = -6.29$, $p < 0.001$, next bigram frequency, $\text{Estimate} = -3.85$, $SE = 0.76$, $t = -5.10$, $p < 0.001$, and preceding bigram frequency, $\text{Estimate} = -1.88$, $SE = 0.77$, $t = -2.46$, $p = 0.014$, significantly reduced letter naming times relative to the intercept. Together, these results indicate a broad facilitative influence of orthotactic probability on articulation timing. The parameter estimates for each model are presented in Table 4.

Correlations Between Letter Frequency, Preceding Bigram Frequency, and Next Bigram Frequency

To examine whether preceding bigram frequency, current letter frequency, and next bigram frequency are separable, correlations between all three variables were conducted. In the high-probability condition, letter frequency was correlated with preceding bigram frequency, $r(223) = 0.42$, $p < 0.001$, 95% CI [.30, .52], and next bigram frequency, $r(223) = 0.53$, $p < 0.001$, 95% CI [.43, .62]. Preceding and next bigram frequencies were also correlated, $r(198) = 0.15$, $p = 0.036$, 95% CI [.01, .28]. A similar pattern was observed in the low-probability condition, with significant correlations between letter frequency and preceding bigram frequency, $r(223) = 0.47$, $p < 0.001$, 95% CI [.36, .56], and between letter frequency and next bigram frequency, $r(223) = 0.34$, $p < 0.001$, 95% CI [.22, .45]. Preceding and next bigram frequencies were again correlated, $r(198) = 0.19$, $p = 0.006$, 95% CI [.06, .32]. Although these predictors were significantly correlated, variance inflation factors

Table 4 Parameter estimates of the linear mixed-effects models for letter fixation duration and spoken letter duration

Outcome variable		Estimate	SE	95% CI	<i>t</i>	<i>p</i>
Letter fixation duration	Intercept	317.07	10.23	[296.26, 337.86]	31.00	< 0.0001
	Letter frequency	-0.09	2.19	[- 4.43, 4.25]	-0.04	0.966
	Preceding bigram frequency	-3.35	2.07	[- 7.44, 0.74]	-1.62	0.106
	Next bigram frequency	4.85	2.04	[0.81, 8.87]	2.38	0.017
	AIC	BIC	LogLik	χ^2	<i>p</i>	
	Base	92,971	92,999	-46,482	-	-
	Comparison	92,968	93,016	-46,477	9.17	0.027
Outcome variable		Estimate	SE	95% CI	<i>t</i>	<i>p</i>
Spoken letter duration	Intercept	263.57	6.99	[249.35, 277.79]	37.73	< 0.001
	Letter frequency	-5.19	0.83	[- 6.80, - 3.57]	-6.29	< 0.001
	Preceding bigram frequency	-1.88	0.77	[- 3.38, - 0.38]	-2.46	0.014
	Next bigram frequency	-3.85	0.76	[- 5.33, - 2.37]	-5.10	< 0.001
	AIC	BIC	Loglik	χ^2	<i>p</i>	
	Base	107,414	107,443	-53,703	-	-
	Comparison	107,261	107,311	-53,624	159.04	< 0.001

(VIF) were low (letter frequency = 1.48; next bigram frequency = 1.26; preceding bigram frequency = 1.21), indicating that multicollinearity was not a concern.

Discussion

The present study investigated whether prior knowledge of the orthographic structure of the English language influences letter processing and naming. We found that native English speakers spent overall more time fixating on lists of letters arranged in high-probability sequences than those arranged in low-probability sequences. Current letter frequency, preceding bigram frequency, and next bigram frequency each predicted letter naming fluency, such that higher bigram frequencies and current letter frequencies led to faster letter naming times. While current letter frequency and preceding bigram frequency did not predict letter fixation duration, next bigram frequency did. Higher next bigram frequencies were associated with longer letter fixation times. Such findings suggest that sensitivity to orthographic cues, including positional bigram frequency and letter frequency, can influence letter processing and may contribute to mechanisms supporting word recognition and reading.

In trial-level analyses, participants did not name letters in high-probability sequences faster than letters in low-probability sequences. No differences in overall naming times were observed between low-probability and high-probability lists. However, a closer look at the item-level analyses revealed that participants' letter naming fluency was predicted by both previous and next bigram frequencies, such that higher frequency bigrams were associated with faster letter naming times. This is consistent with the findings by Borokhovski (2018) as well as previous research demonstrating that bigram probability affects learning and memory for novel words (Frisch et al., 2000; Luce & Large, 2001; Roodenrys & Hin-

ton, 2002; Storkel et al., 2006; Thorn & Frankish, 2005). Furthermore, our findings are in line with a large body of research on the letter frequency effect. Higher frequency letters tend to be recognized faster than lower frequency letters during letter naming (Cosky, 1976; Jones & Mewhort, 2004; Kim et al., 2021; Larsen et al., 2024), visual search (Latimer, 1972; Pitchford et al., 2008), and lexical decision (Egeth & Blecker, 1971; New & Grainger, 2011). In four different experiments, New and Grainger (2011) reported negative correlations between response times and letter frequency, such that higher letter frequencies were associated with faster response times. Higher previous and next bigram frequencies may influence naming times potentially because they are easier to articulate, readily accessible, or more predictable. A notable difference between our study and Borokhovski's (2018) study is the number of letters used. While our study utilized almost the entire alphabet, Borokhovski's study administered a modified version of the RAN task that included only 3 consonants and 2 vowels (letters a, d, o, p, and s), limiting the number of possible sound combinations. Because our study included a larger set of letters, the sound combinations were less predictable and more variable, a scenario that is more representative of what is encountered in natural settings when listening to everyday speech.

In contrast to the behavioral data, the eye-tracking data revealed that participants spent more time fixating on letter lists arranged in high-probability sequences than on those arranged in low-probability sequences. This finding may reflect the distinct processes indexed by fixation duration, which provides a measure of the time allocated to visual inspection, attention allocation, and the integration of orthographic information during reading. One possibility is that high-probability bigrams, which occur more frequently in the language, generate greater spreading activation across associated orthographic and lexical representations. Although these sequences are more predictable, their familiarity may also activate a broader set of potential representations, increasing demands for evaluating and integrating partial orthographic information while resolving competition among activated candidates. This process may be especially relevant for scrambled letter strings, where participants must determine how familiar letter combinations fit within an unfamiliar configuration and suppress interference from familiar word forms that are incidentally activated. Thus, longer fixations for high-probability sequences may not reflect processing difficulty per se, but rather increased engagement with activated representations during early stages of orthographic processing. In contrast, behavioral measures such as naming latency and articulation duration likely reflect later stages of processing, including phonological encoding and motor planning.

A key finding of the present study is the influence of next bigram frequency on fixation time. This suggests that readers were sensitive to upcoming orthographic structure, consistent with theories that readers use anticipatory information during visual word processing (Mani & Huettig, 2014). Importantly, the absence of effects for preceding and current letter frequency indicates that this anticipatory sensitivity is not merely a consequence of processing currently available information but instead reflects forward-looking encoding of orthographic structure. In contrast, orthotactic cues exerted a broad facilitative effect on spoken letter duration across all positions (preceding, current, and next). This pattern suggests that orthotactic regularity may influence speech planning at a global level, consistent with the idea that speech production involves overlapping preparation of current and upcoming segments (Kawanoto et al., 2015). Together, these findings suggest a dissociation between perceptual encoding and production. Fixation times may reflect anticipatory sensitivity to

upcoming orthographic structure, whereas articulation appears to benefit more generally from orthotactic regularities.

Why is next bigram frequency important for both letter naming and fixation time in the RAN task? Previous studies have demonstrated that skilled adult readers extract and use limited information from upcoming letters through parafoveal processing (up to 5 degrees to the right of the fovea, e.g., Tiffin-Richards & Schroeder, 2015; see Rayner, 1998 and Schotter et al., 2012 for reviews). Parafoveal information has been found to facilitate word recognition in the direction of reading, such that lexical representations are activated from orthographic and phonological codes (e.g., Hyönä, 2011; Johnson et al., 2007; Schotter et al., 2012). Similar processes may be involved during the RAN task, such that parafoveal information (i.e., upcoming letters) are extracted to promote fluid articulation.

The absence of a list-level effect on naming fluency, despite significant item-level associations between orthographic cues and naming speed, may reflect differences in the level of analysis. Whereas the list-level analysis examined whether broad differences between high- and low-probability sequences influenced naming performance, the item-level analysis captured continuous variation in statistical properties of individual letter sequences. Thus, orthographic regularities may influence naming efficiency in a graded manner, with subtle differences in bigram and letter frequency contributing to performance that may not be detectable when collapsing items into broader categories.

In the present study, the experimental design may have constrained the interpretation of the item-level bigram frequency effects. Because item-level bigram frequency was not fully independent of the list-level probability manipulation, it is difficult to determine the extent to which the observed effects are attributable to the frequency of individual letter pairs versus the statistical structure of the list in which they appeared. Although the analyses provide evidence that item-level statistical regularities are associated with letter processing, future studies should independently manipulate item-level and list-level statistical properties to isolate their unique contributions.

Furthermore, future research should examine how phoneme bigram frequency influences the frequency of the successive segments spoken in a named letter sequence by dissociating letter frequency (e.g., orthographic bigram frequency) from patterns of speech sound frequency (e.g., combinations of phonetic segments). For example, some consonants begin with the sound associated with the letter (e.g., b, d, j, k, p, t, and v), while other consonants begin with vowels (e.g., f, l, m, n, r, and s). This variability in speech sound frequency may have interacted with orthographic bigram frequency for the letters used in the RAN task. Consonants beginning with vowels (e.g., letter l) may require additional phonological processing than consonants beginning with their associated sounds due to greater spreading activation to words that share phonological overlap (e.g., electronic, elephant, elbow, and so on). In addition, studies have shown that performance on the RAN task and phonological awareness are highly correlated (Torgesen et al., 1994; Vukovic & Siegel, 2006), such that deficits in the RAN task are often attributed to difficulties processing phonological information. Hence, future studies should include measures of phonological awareness, automaticity, working memory, and orthographic processing to examine their individual and combined roles in RAN performance.

In conclusion, the present study demonstrates that statistical regularities within language influence the processing of individual letters, highlighting the role of orthographic cues in reading. Because skilled reading depends on efficiently recognizing and integrating letter

patterns, understanding how learners extract and use these regularities may inform models of reading development and help explain variability in literacy outcomes. Given the central role of letter-sound correspondences in reading, writing, and phonological skill acquisition (Marian, 2023), these findings may also inform literacy instruction by highlighting the potential value of activities that draw learners' attention to recurring letter patterns and orthographic regularities to support letter decoding and broader reading skills.

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Data Availability The dataset analyzed for this study is available from the corresponding author upon reasonable request.

Declarations

Competing Interests The authors declare no competing interests.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments. The study was reviewed and approved by the local University's Institutional Review Board.

Informed Consent All participants provided their written informed consent to participate in this study.

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