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Research Report

Language-universal and script-specific factors in the recognition of letters in visual crowding: The effects of lexicality, hemifield, and transitional probabilities in a right-to-left script

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ABSTRACT

Peripheral letter recognition is fundamentally limited not by the visibility of letters but by the spacing between them, i.e., 'crowding'. Crowding imposes a significant constraint on reading, however, the interplay between crowding and reading is not fully understood. Using a letter recognition task in varying display conditions, we investigated the effects of lexicality (words versus pseudowords), visual hemifield, and transitional letter probability (bigram/trigram frequency) among skilled readers ($N = 14$. and $N = 13$) in Hebrew – a script read from right to left. We observed two language-universal effects: a lexicality effect and a right hemifield (left hemisphere) advantage, as well as a strong language-specific effect – a left bigram advantage stemming from the right-to-left reading direction of Hebrew. The latter finding suggests that transitional probabilities are essential for parafoveal letter recognition. The results reveal that script-specific contextual information such as letter combination probabilities is used to accurately identify crowded letters.

1. Introduction

Visual crowding refers to our failure to identify an object when it is surrounded by other objects (Bouma, 1970; Martelli et al., 2009; Whitney & Levi, 2011). This phenomenon impacts basic features such as orientation, color, and spatial frequency (Greenwood & Parsons, 2020; Kewan-Khalayly and Yashar, 2022; Shechter & Yashar, 2021; Yashar et al., 2019), and extends to more higher-level objects such as faces and letters

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(Louie et al., 2007). Crowding is most pronounced at the visual periphery, e.g., at the parafovea (5°–8°), which plays an important role in preprocessing upcoming words during reading (Schotter et al., 2012). Thus, it sets significant constraints on the visual-orthographic processes involved in reading (Grainger et al., 2016). Crowding slows down reading speed (Pelli et al., 2007) and has been linked to reading difficulties (Joo et al., 2018) and developmental dyslexia (e.g., Bertoni et al., 2019; but see Doron et al., 2015). Thus, understanding the factors that mitigate the detrimental effect of crowding has both theoretical and practical implications.

Over the years, various factors have been shown to reduce crowding interference. These factors include mental capacities, such as visual attention (Herzog et al., 2015; Manassi et al., 2012) and perceptual learning (Hussain et al., 2012; Yashar et al., 2015), as well as stimulus-related elements like grouping (Herzog et al., 2015; Manassi et al., 2012) and object configuration (Jimenez et al., 2022). However, their practical use is limited, as they are not readily available or easily manipulated in a natural environment. Therefore, a deeper understanding of environmental regularities, also known as statistical learning (Frost et al., 2019), may be key in our ability to adapt to the natural environment. Yet, whether environmental statistics and context can help mitigate crowding interference remains unknown. We address this issue in the context of letter recognition.

Regarding higher-order contextual factors in reading, there is well-replicated evidence, at least in alphabetic scripts, that gazed-centered letter recognition is better when it appears within the context of a (familiar) word compared to isolation (word superiority effect) or a pseudoword (lexicality effect). These phenomena have been explained by the orthographic context of the word (e.g., McClelland & Rumelhart, 1981; Reicher, 1969). That is, the orthographic context (i.e., a familiar word) supplies more information compared to the no-context condition (i.e., isolated letter), hence makes the letter within a word more predictable and more resistant to interference than a letter presented alone (Reicher, 1969). McClelland and Rumelhart (1981) explained this finding by their interactive-activation model which postulates that visual word perception incorporates simultaneously processing of "bottom-up" and "top-down" input. Thus, in the case of a familiar letter string, facilitatory activation will be generated from the feature level to the letter level and from the letter to the word level, concurrently with activation from the word level to the letter level.

An alternative to the parallel activation model has been proposed by Pelli et al. (2003), who postulate that recognition involves feedforward connections in a hierarchical and sequential process. This begins with feature perception, progresses to letter identification, and culminates in interpreting combinations of letters. According to this model, words are unreadable unless each of their letters is separately identifiable. Despite their differences, both models emphasize the importance of orthographic processing, which involves the extraction of the identity and position of letters within a string (Grainger et al., 2016).

The involvement of orthographic processes in parafoveal processing in reading (e.g., Bouma, 1971, 1973; also see Schotter et al., 2012) is supported by studies that demonstrate a reduction in parafoveal crowding interference on letter recognition when the target letter is embedded in a real word compared to a pseudoword, the well-known lexicality effect (Bouma & Legein, 1977; Martelli et al., 2005). For instance, Martelli et al. (2005) examined word recognition, specifically focusing on familiarity and crowding effects, in three conditions: isolated letters, letters embedded within a three-letter string consisting of a real word (e.g., ace) or a pseudoword (e.g., aca). Along with replicating the word superiority effect in central vision, they found an opposite pattern in the visual periphery, with surrounding letters causing hindrance in performance due to crowding. Nonetheless, performance improved when letters were embedded in a real word as opposed to pseudowords – thus confirming the "lexicality" effect at both the fovea and parafovea (Martelli et al., 2005).

However, lexicality is only part of the story as words and pseudowords not only differ in their lexical properties, but also sub-lexically in terms of the probabilities of the word-internal sequence of letters (n-grams). In a given orthography, the probability of a specific letter can be determined by the preceding and following letters within the text. For example, in English, the letter *c* frequently precedes the word-final letter *e* (e.g., *ace, once, ice*, etc.), but *c* rarely precedes a word-final *a*. Consequently, certain bigrams (strings of two letters) and trigrams (strings of three letters) have higher probabilities than others (independently of their lexical status), with their frequency in the orthography dictating this probability. In reading research, investigators have explored the role of transitional probability by examining the impact of statistical learning on reading skills and deficits (see Frost et al., 2019). However, no studies have yet directly investigated the influence of transitional probability on letter recognition in print. Here, we address this issue by investigating the independent effects of lexicality (words versus pseudowords) and bigram and trigram frequencies on letter recognition at the parafovea in a crowded display of letters.

Previous studies have suggested a domain-specific neural mechanism for reading, located in the left hemisphere (Dehaene, 2005; Ossowski & Behrmann, 2015). According to the neuronal recycling hypothesis, this lateralization to the left hemisphere explains the findings of higher accuracy in the right hemifield in reading tasks in multiple scripts (e.g., White et al., 2020), including Hebrew (Ibrahim & Eviatar, 2009). Here, we further examined the assumed left hemisphere advantage by focusing on letter recognition under varied crowded conditions.

Our study also addresses concerns that research based on English and Western European alphabets may not necessarily allow generalizations regarding universal reading and language processing phenomena (e.g., Huettig & Ferreira, 2022; Share, 2008, 2021). Here, we conducted our investigation in Hebrew, a non-European language written in a non-alphabetic right-to-left script. We predict two language universal effects. First, we expect a right hemifield advantage due to left hemisphere language and reading circuits. Second, we anticipate a lexicality effect similar to that found in English. Crucially, if the lexicality effect in Hebrew can be largely explained by sublexical transitional probabilities, we predict that bigram frequencies will account for a significant portion of performance variation. Furthermore, language specific factors, mainly the right-to-left reading direction of Hebrew that extends the reading span more to the left (Pollatsek et al., 1981), may be reflected by any difference between the effect of the right bigram frequency and the left bigram frequency.

2. Experiment 1

Participants performed a letter recognition task in which the target letter was located at the parafovea (5° eccentricity) and appeared alone (uncrowded conditions) or flanked (crowded conditions) by two adjacent letters. In the crowded conditions, the target letter was always in the middle of the letter string, generating either a real three letter word or a pseudoword. Here, we examined the interaction between crowding and lexicality by controlling for both variation in visual acuity and bigram and trigram frequencies across the crowded conditions.

2.1. *Method*

In all experiments, we report how we determined our sample size, all data exclusions, all inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all manipulations, and all measures in the study.

2.1.1. *Participants*

Based on previous crowding studies (Shechter & Yashar, 2021; Yashar et al., 2019), we estimated that a sample size of 12 participants was required for detecting the crowding effect with 95% power and a significance level of .05. Data were collected from four more participants in anticipation of possible attrition or equipment failure. Two participants were excluded from the analyses owing to performance beyond 3 standard deviations above the mean in at least one experimental condition. This left a total of 14 participants (8 females; age: $M = 28.07$, $SD = 9.44$). Participants received course credits or a monetary payment of 40 ILS (around $12). All participants were native Hebrew speakers with no reported past or present attention deficits, learning disabilities or epilepsy, and with normal or corrected-to-normal vision. Each participant signed a written informed consent form before the experiment. The experimental procedure was approved by the University Committee on Activities Involving Human Subjects at The University of Haifa (No. 473/21).

2.1.2. *Apparatus*

Stimuli were programmed in Matlab software (The MathWorks, Inc., Natick, MA) with the Psychophysics Toolbox extensions (Kleiner et al., 2007) and displayed, using an iMac computer, on a gamma-corrected monitor (ViewPixx 22.5-in with 1920 × 1080 resolution and 120 Hz refresh rate). We monitored eye movements (from a viewing distance of 57 cm) using an Eyelink 1000 Plus (SR Research, Ottawa, ON, Canada) to control for fixation breaks. Participants responded by using the computer mouse.

2.1.3. *Procedure*

Fig. 1 illustrates a trial sequence in Experiment 1. All stimuli were white (235 cd/m^2) on a gray background (65 cd/m^2) and with a contrast of 56%. Each trial began with the presentation of the fixation display (a cross subtending .5° at the center of the screen) for a random duration lasting 750 msec. Following observers' fixation for 300 msec, a pre-mask display was presented for 250 msec. The pre-mask display consisted of the fixation mark along with a string of three Xs on the horizonal meridian, randomly selected to be either in the right or the left hemifields (5° eccentricity and with a ±1.59° vertical offset from the horizontal meridian). The target display appeared for 500 msec. The target display consisted of the fixation mark and a target; a Hebrew letter centered at 5° eccentricity (in the same hemifield as the pre-mask) and with a ±1.59° vertical offset from the horizontal meridian. The target could either appear in isolation (uncrowded display) or be flanked by two other Hebrew letters. The flanking letters appeared on the horizontal meridian (radial crowding display), one flanking letter on each side of the target. This arrangement created a Hebrew trigram, which could either be a word or a pseudoword. The pre-mask and the following target stimulus were centered at the same location and with similar dimensions, thereby reducing location uncertainty. The spacing between the edges of two adjacent letters in the pre-mask and target displays was set to be .1 of the letters' width, which was determined by an adaptive procedure (see Design). This ratio is within the limit of crowding interference (Pelli et al., 2016).

Following the target display, a blank screen was presented for 200 msec, followed by a response display; an array of all 22 Hebrew letters. Observers were required to report the target letter by pointing and clicking on a letter using the mouse cursor. Following an observer's response, a blank inter-trial interval (ITI) appeared for 200 msec. In each trial, we monitored eye fixation using an eye tracker (see "Apparatus"). Trials in which fixations was broken (>2° from fixation mark) were terminated and rerun at the end of the block.

2.1.4. *Stimuli*

Target stimuli. There were 160 unique target stimuli. We used Arial font of all 22 Hebrew non-final letters א-ת)), to generate all target stimuli. No word-final letters were included (ך,ם,ן,ף,ץ). In the crowded display conditions, we used three types of 3-letter strings (trigrams); a trigram word (word) (e.g., סדר), and two types of pseudowords: a trigram pseudoword 1 (pseudoword 1) in which we swapped the first letter and the last letter of each word (e.g., רדס), and trigram pseudoword 2 (pseudoword 2), in which we replaced the central letter of each word with another letter (e.g., סצר).

To select the words, we asked 42 university students to respond to an online questionnaire containing 100 Hebrew roots. The Hebrew roots usually consist of three letters which convey the lexical identity of the word (Deutsch et al., 2000). Using a five-point Likert-type scale, respondents were asked to evaluate, "How many times have you seen the following root in its printed form?": not at all (1), several times (2), dozens of times (3), hundreds of times (4), and thousands of times (5). The mean frequency rating was then calculated for each item. For choosing the target words, we used a cut-off score of 2.24.

We checked the familiarity of the trigrams in each trigram condition (trigram-word, pseudoword 1, pseudoword 2) by calculating the printed frequency of each item (e.g., סדר). In addition, for each trigram we calculated the frequency of each bigram component (right bigram e.g., סד and left bigram e.g., דר). To calculate frequencies of trigrams and bigrams, we used the heTenTen 2021 corpus via Sketch Engine (Kilgarriff et al.,

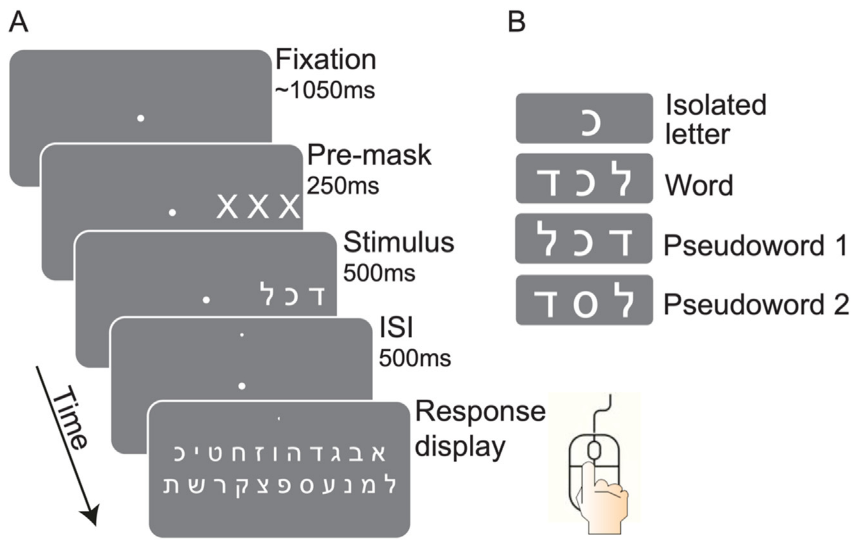

Fig. 1 – Example trial sequence in Experiment 1. Each trial began with a fixation display that persisted until the observer maintained fixation for at least 300 msec. Participants saw a single letter (isolated (uncrowded) letter) or a Hebrew trigram (crowded conditions). We asked participants to report the target letter by using the mouse cursor.

2004), a corpus which includes 2.7 billion Hebrew words extracted from the internet.[1]

Table 1 depicts the mean and median of trigram and bigram frequencies for each trigram type. Statistical comparisons using independent samples *t*-tests revealed significant differences between the trigram-word condition and each of the two non-word trigrams types [trigram-word versus trigram-swapped: $t(44.398) = 4.12$, $p < .001$; trigram-word versus trigram-replaced: $t(41.68) = 4.69$, $p < .001$]. Importantly, there was no significant difference between the two types of non-word trigrams (swapped versus replaced, $p > .12$), suggesting that the two types of non-words had the same level of familiarity. Notably, there were non-significant differences across trigram types at the bigram level ($p > .33$), suggesting that the three types of trigrams only differed at the wholistic level (whole trigram) but not at the level of sub-lexical (bigram) components. Furthermore, paired-samples *t*-tests revealed no significant differences between the right and left bigrams within each word condition, $t(39) = -1.73$; $p = .09$, the Pseudoword 1 condition, $t(39) = -1.22$; $p = .23$, and the Pseudoword 2 condition, $t(39) = -1.55$; $p = .13$.

2.1.5. *Design*

For each of the four display conditions, we measured font size (font width in °) threshold level (82% correct) by using the QUEST (Watson & Pelli, 1983) adaptive staircase procedure. There were 40 staircase trials in each display condition (160 trials in total). Each trial presented one of the 160 unique letter(s) stimuli (one trial per unique stimulus). We interleaved the trials of all staircases. The order of the display conditions and stimuli was random. Note that varying letter size also varies letter center-to-center spacing. However, because center-to-center spacing, rather than size, determines crowding (Martelli et al., 2009) there are two main benefits of using this method in a staircase procedure. First, it enables the measurement of very small critical spacings without presenting overlapping letters. Second, it enables measurements of acuity (uncrowded letter font size) and critical spacing (trigram font size) using the same scale (font size), and, thereby, controls for variation in visual acuity. This is particularly important as visual acuity can explain variation in letter recognition and reading independently of crowding (Kurzawski et al., 2021), which varies across individuals (Kurzawski et al., 2023). Each experiment began with ten practice trials with letter strings which were not used during the experiment.

2.2. *Analysis*

First, we conducted a repeated measures analysis of variance (ANOVA) on accuracy and RT for the four display conditions (uncrowded letter, word, pseudoword 1, pseudoword 2). Next, we ran a two-way ANOVA with two repeated factors: visual lateralization (right versus left hemifields) and trigram type (word, pseudoword 1, pseudoword 2) on accuracy. Then, for each ANOVA, we analyzed the Bayes Factors based on the Bayesian model selection approach (Masson, 2011). Using simple transformations of the sums of squares values from each ANOVA, we calculated the Bayes factor for the alternative hypotheses (H1), which is the ratio of H1 given the data D and the evidence for the null hypotheses (H0) given the data, $BF_{10} = \frac{P(H1|D)}{P(H0|D)}$.

2.3. *Results*

Fig. 2A presents the averaged font width threshold (in visual °) for each display condition. We found a significant main effect

[1] The frequency counts here include any letter string of any length that contain the trigram, ranging from a single string including only the target trigram through to long multi-morphemic strings that contain the target string whether or not the target trigram constitutes an integral morpheme or not. By analogy consider the English words <cat> and <scathing> both of which contain the trigram <cat>. This explains the non-zero frequency of the pseudowords.

Table 1 – Trigram and bigram frequencies. The mean and median of trigram and bigram frequencies of the trigrams used in Experiment 1. Original frequencies were multiplied by one million. There were 40 different trigrams in each type.

Trigram type	Trigram frequency			Right Bigram frequency			Left Bigram frequency		
	M	*Mdn*	*SD*	*M*	*Mdn*	*SD*	*M*	*Mdn*	*SD*
Trigram-word	217.92	125.96	265.05	2695.11	1864.12	2626.13	3691	2899.22	2817.83
Pseudoword 1	39.32	3.40	69.90	2205.41	1616.45	1973.34	3000.62	2095.45	3390.27
Pseudoword 2	18.22	.34	49.16	2330.08	1172.05	3950.52	3473.39	2353.28	4433.03

of display condition, $F(3, 39) = 14.51$, MSE $= 27.72$, $p < .001$, $\eta_p = .73$, $BF_{10} > 100$, indicating decisive evidence for a main effect of display condition. As predicted, the smallest font width was observed in the uncrowded letter condition. Further analyses yielded a trigram type effect with smaller font size for the word trigram compared with the pseudoword conditions: pseudoword 1, $t(13) = -2.53$, $p = .025$; and pseudoword 2, $t(13) = -3.63$, $p = .003$. No difference was observed between the pseudoword conditions, $t(13) = .74$, $p = .47$. These results confirm that observers identify a Hebrew letter more accurately when it embedded in a familiar word trigram compared to unfamiliar (pseudoword) trigram. To take into consideration individual differences in acuity and crowding effects, we calculated the ratio between the crowded/uncrowded thresholds. Similar patterns were observed, confirming the magnitude of the effect of lexicality (Fig. 2B and C).

Reaction times (RT) analyses revealed no significant effect of display condition, $F(3, 39) = 1.20$, MSE $= .03$, $p = .32$, $\eta_p = .29$, $BF_{10} = .02$, suggesting no speed-accuracy trade-off between display conditions.

An additional ANOVA analysis on the accuracy data revealed a significant main effect of visual lateralization, $F(1, 13) = 6.30$, MSE $= .06$, $p = .03$, $\eta_p = .57$, $BF_{10} = 3.6$, with higher accuracy for the right hemifield ($M = .83$, $SD = .07$) compared to the left hemifield ($M = .78$, $SD = .08$), $t(13) = -2.51$, $p = .03$.[2] The lateralization by trigram type interaction was not significant ($ps = .33$).

3. Experiment 2

Using a similar procedure as reported in Experiment 1, we further examined the effects of lexicality on crowding by focusing on the contribution of bigram and trigram frequencies to performance. In addition, we investigated the effects of visual lateralization and procedural learning.

3.1. *Method*

3.1.1. *Participants*

Fifteen native Hebrew speakers participated in this experiment. One participant was excluded due to extreme score in one experimental condition in Phase 1 (>3 SD). The final sample included 14 participants (7 females; age: $M = 26.93$, $SD = 5.59$). The recruitment protocols used were the same as those employed in Experiment 1.

3.1.2. *Apparatus*

As reported in Exp 1, except for using a different gamma-corrected monitor (21-in CRT, SGI, with 1280 × 960 resolution and 85-Hz refresh rate).

3.1.3. *Procedure*

Trial sequence was similar to that reported in Exp 1, except for two changes: fixation display appeared for a random duration lasting 500 msec, and the pre-mask display was presented for 1000 msec. Luminance values differed in respect to Experiment 1; All stimuli were white (80 cd/m^2) on a gray background (15 cd/m^2), with a contrast of 65%.

3.1.4. *Stimuli and design*

The stimuli and design were the same as in Experiment 1 except for the following changes. Experiment 2 had two phases: an initial Phase 1, and a subsequent accuracy phase.

Phase 1. Phase 1 was the same as Experiment 1, except for one change: since there was no difference between the pseudoword conditions in Experiment 1, we used one pseudoword condition (i.e., pseudoword 1). Thus, there were three display conditions: an uncrowded letter, a trigram-word and a pseudoword, that is, 120 trials in total (40 trials per condition).

Phase 2. The second phase included only the trigram-word and the pseudoword display conditions. The procedure was the same as Phase 1, except that the font size in Phase 2 was fixed to be the averaged font size of the two trigram conditions in Phase 1. We created a new set of 40 trigram-word stimuli and 40 pseudoword stimuli. Each trigram stimulus in Phase 2 was repeated three times (once every block). That is, 80 trials per block, 240 trials in total. The order of trials was random within each block.

We used the roots questionnaire data from Experiment 1 to generate a list of new trigrams-words, maintaining similar students' familiarity ratings across the experimental phases (Phase 1: $M = 3.19$, $SD = .65$; Phase 2: $M = 3.21$, $SD = .68$). Table 2 depicts the mean and median of trigram and bigram frequencies for each trigram type. Statistical comparisons using independent samples t-test revealed significant differences in the trigram condition between the word-trigram and the pseudoword, $t(41.079) = 2.465$; $p < .005$. There were no significant differences across trigram types at the bigram level ($p > .24$), suggesting that the two types of trigrams, once again, only differed at the holistic level (whole trigram) but not at the level of component bigrams. Furthermore, a paired-samples t-test indicated no significant differences between the right and left bigrams within the trigram-word condition, $t(39) = -1.36$; $p = .18$, and the pseudoword condition, $t(39) = .33$; $p = .75$.

[2] Analyzing the lateralization effect without the left-handed subjects (n = 2) enlarged the effect size from .05 to .07.

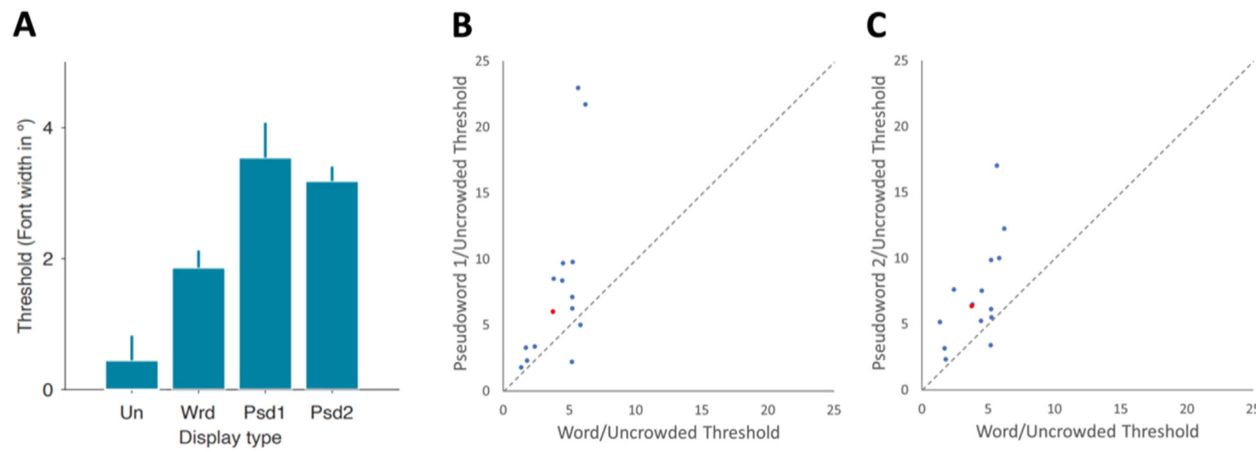

Fig. 2 – Crowding thresholds and ratio between conditions in Experiment 1. (A) Averaged font width threshold (in visual °) for each display condition based on a threshold criterion of 82% correct responses. Error bars represent standard errors of the mean. (B, C) Ratio of thresholds represented by geometric means. Each point represents a subject, the red point represents the average across observers.

3.2. *Analysis*

Threshold. We conducted a repeated measures ANOVA with three levels of display type (uncrowded letter, trigram-word, and pseudoword) on font-size thresholds and RT. To examine the effect of visual lateralization, we also ran a two-way ANOVA on accuracy with visual lateralization (right versus left hemifields) and trigram type (word versus pseudoword) as repeated factors.

Accuracy phase. We conducted a three-way ANOVA with three repeated factors: block (block 1, 2 and 3), trigram type (word versus pseudoword) and visual lateralization (right versus left hemifields) on accuracy and RT.

In both phases we report the Bayes Factors using transformations of the sums of squares from each ANOVA (as reported in Exp 1).

Bigram and trigram frequencies. Next, we analyzed the contribution of bigram and trigram frequencies to performance by fitting a binominal logistic regression to the accuracy data of each participant. The model predicts response accuracy in each trial (correct versus incorrect) based on five parameters: familiarity (word versus pseudoword), right bigram frequency, left bigram frequency and trigram frequency.

The logistic model estimates the probability of correctly reporting the target later (1 for correct versus 0 for incorrect) using the following equation:

$$p_c = \frac{1}{1 + e^{-z}}$$

Where z is a linear combination:

$$z = \beta_0 + \beta_{Hemifield} \times H + \beta_{lexical} \times L + \beta_{Trigram} \times T + \beta_{RightBigram} \times RB + \beta_{LeftBigram} \times LB$$

Here, β_0 (intercept) represents the baseline for each participant, while $\beta_{Hemifield}$, $\beta_{Lexical}$, $\beta_{Trigram}$ $\beta_{RightBigram}$ and $\beta_{LeftBigram}$ are the weights for the factors hemifield (H, left or right), lexical condition (L, either word or pseudoword), trigram frequency (T), left bigram frequency (LB), and right bigram frequency (RB), respectively. Lexical condition is nominal, whereas trigram and bigram frequencies are continuous probability values. To compare the weight of each factor, we normalized each factor by dividing its values by their respective standard deviations. To assess the contribution of each factor, we compared the mean weights of the individual fits to zero.

3.3. *Results*

3.3.1. *Phase 1*

Threshold. There was a significant effect of display type, $F(2, 26) = 24.33$, MSE = 31.47, $p < .001$, $\eta_p = .81$, $BF_{10} > 100$. As predicted, the smallest font size was observed in the uncrowded letter condition ($M = .53$, $SD = .08$). Further analyses

Table 2 – Trigram and bigram frequencies. The mean and median of trigram and bigram frequencies in written Hebrew of the trigrams used in Phase 2 of Experiment 2. Original frequencies were multiplied by one million. There were 40 different trigrams in each type.

Trigram type	Trigram frequency			Right Bigram frequency			Left Bigram frequency		
	M	*Mdn*	*SD*	*M*	*Mdn*	*SD*	*M*	*Mdn*	*SD*
Word	490.69	186.59	1057.94	4826.95	3380.76	5426.20	6371.12	3593.04	9614.80
Pseudoword	72.81	5.75	172.79	4650.92	2647.99	6260.59	4313.40	2436.24	5112.76

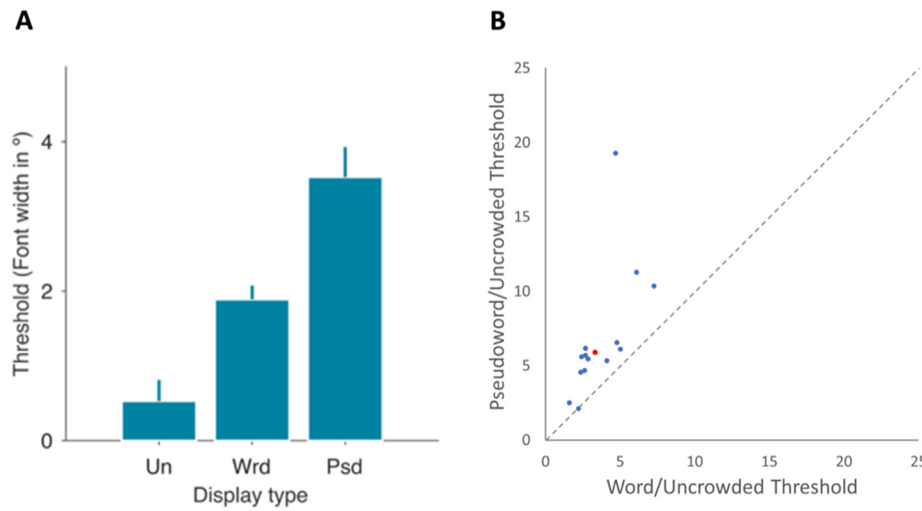

Fig. 3 – Description of displayed conditions in Phase 1 of "Experiment 2". (A) Mean font-width threshold for each display type in Experiment 2. Un: Uncrowded, Wrd: Word, Psd: Pseudoword. Error bars represent within subject standard errors of the mean (Moray 2006). (B) Ratio of thresholds represented by geometric means. Each point represents a subject, the red point represents the averaged ratio across observers.

yielded a word familiarity effect with larger font size for the pseudoword ($M = 3.52$, $SD = 2.04$) compared with the word ($M = 1.89$, $SD = .75$), $t(13) = 3.56$, $p = .004$. Fig. 3 shows the averaged font size for each display type and ratio between conditions.

RT. RT analyses revealed no significant effect of display condition, $F(2, 26) = 1.57$, MSE = .02, $p = .23$ $\eta_p = .33$, $BF_{10} = .17$, indicating no speed-accuracy trade-off.

There was a significant main effect of visual lateralization, $F(1, 13) = 13.78$, MSE = .16, $p = .003$, $\eta_p = .72$, $BF_{10} = 30.38$, with higher accuracy for the right hemifield ($M = .84$, $SD = .05$) compared to the left hemifield ($M = .74$, $SD = .08$), $t(13) = -3.65$, $p = .003$.[3] The lateralization by trigram type interaction was not significant ($ps = .53$).

3.3.2. *Phase 2*

Accuracy. Fig. 4 presents mean proportion correct as a function of lexicality (word versus pseudoword) and visual lateralization (left versus right hemifields) in Phase 2. The ANOVA on the accuracy data in phase 2 revealed no significant main effect of learning, $F(2, 26) = .91$, MSE = .00, $p = .42$, $\eta_p = .25$, $BF_{10} = .09$, indicating that observers did not learn the repeated trigrams across the blocks of the accuracy-phase trials (block 1: $M = .79$, $SD = .41$; block 2: $M = .79$, $SD = .41$; block 3: $M = .80$, $SD = .40$). There was a main effect of lexicality, $F(1, 13) = 59.07$, MSE = .11, $p < .001$, $\eta_p = .91$, $BF_{10} > 100$, with higher accuracy for words ($M = .82$, $SD = .06$) than for pseudowords ($M = .77$, $SD = .07$), $t(13) = -7.01$, $p < .001$. There was also a significant main effect of visual lateralization, $F(1, 13) = 5.58$, MSE = .17, $p = .03$, $\eta_p = .55$, $BF_{10} = 2.84$, with higher accuracy for the right hemifield ($M = .83$, $SD = .06$) compared to the left hemifield ($M = .76$, $SD = .10$), $t(13) = -2.33$, $p = .04$.[4] All possible interactions were non-significant ($ps > .15$).

RT. RT analyses revealed a significant main effect for learning, $F(2, 26) = 3.87$, MSE = .26, $p = .03$, $\eta_p = .48$, $BF_{10} = 1.14$, with faster RT as a function of block order (first block: $M = 1.10$, $SD = .14$; second block: $M = 1.05$, $SD = .17$); third block: $M = .99$, $SD = .14$). This effect on RT indicated procedural learning relating to response production rather than perceptual learning. There were no significant main effects of familiarity or visual lateralization, and no significant interaction ($ps > .36$), indicating no speed-accuracy tradeoff.

Bigram and trigram frequencies. One subject was removed from the analysis due to extreme fitted parameter values (>3 SD). Fig. 4B depicts mean β weights for each variable of the logistic regression. *T*-tests with each weight compared to zero revealed a significant difference for the trigram frequency, $t(12) = 2.33$, $p = .04$, Cohen's D = .65, and for the left bigram frequency β, $t(12) = 5.79$, $p < .001$, Cohen's D = 1.61. There was also a significant effect for the Baseline, $t(12) = 3.58$, $p = .004$, Cohen's D = .99. No other variable was significantly different from zero (all $ps > .07$). Taken together, these findings reveal that transitional probabilities, rather than hemifield and lexicality, provide a reliable prediction of performance. Specifically, participants rely on the leftmost letter of each trigram to identify the middle letter. To confirm that the small effect of trigram frequency was due to the pseudoword condition, we performed separate analyses on the pseudoword and word conditions. In both conditions the left bigram frequency β was significant, $t(12) = 4.05$, $p = .002$, Cohen's D = 1.12, and $t(12) = 1.42$, $p = .015$, Cohen's D = .67, respectively. For trigram frequency β, there was a significant effect in word trials but not in pseudoword trials, $t(12) = 2.19$, $p = .049$, Cohen's D = .61, and $t(12) = 1.42$, $p = .210$, Cohen's D = 18.13, respectively.

To test whether the contribution of the left bigram frequency to performance is contingent on stimulus hemifield, we fitted a model with five parameters to each hemifield

[3] Without the left-handed subjects (n = 3) the effect size increased from .10 to .12.

[4] Without the left-handed subjects (n = 3) the effect size increased from .07 to .09.

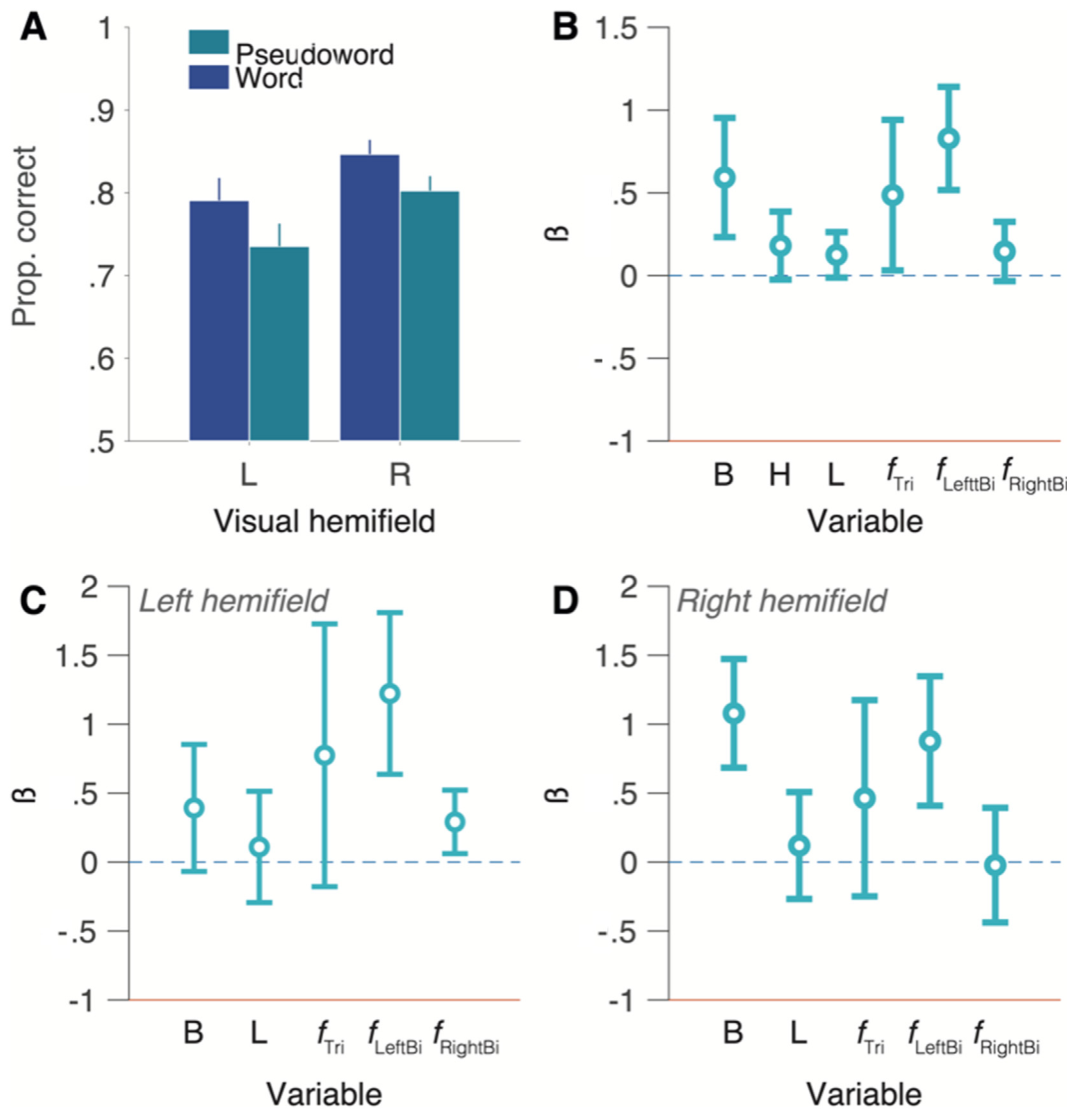

Fig. 4 – Results of Phase 2 of Experiment 2. (A) Mean proportion correct as a function of visual hemifield and lexicality. Error bars ±1 within subject SEM. (B) β weights of the logistic regression model as fitted individually to the accuracy data. The logistic regression was also fitted separately to the (C) left hemifield and (D) right hemifield. B: baseline, H: hemifield, L: Lexicality, f_{Tri}: Trigram frequency, f_{LeftBi}: Left bigram frequency, $f_{RightBi}$: Right bigram frequency. For panels B–D, error bars are 95% confidence intervals.

separately (Fig. 4C and D). The pattern of results shows that the advantage of the left bigram contribution to performance is consistent across hemifields. Note that since each variable was normalized and the model was individually fitted to the trial-by-trial data, any experiment-related differences in the frequencies between the right and left bigrams cannot explain the left bigram advantage.

4. Discussion

The current study explored universals and script-specifics regarding the recognition of letters under crowded conditions. Using a letter recognition task in varying displays and controlling for task difficulty, we investigated the effects of lexicality, visual hemifield, and transitional probability in Hebrew – a script read from right to left. Our findings reveal the critical role of transitional probabilities (bigram frequency) in parafoveal letter recognition, showing that bigram frequencies, more than lexicality (word versus pseudoword), predict performance. In addition, we confirmed two language-universal effects: a lexicality effect and a right hemifield (left hemisphere) advantage, as well as a strong language-specific effect – a left bigram advantage.

Note that while consistent lexicality and lateralization effects – the latter increased after excluding left-handed participants, were evident in the ANOVAs, the weights of these factors from logistic regression were not statistically significant, though they approached significance. This discrepancy might stem from the intrinsic nature of logistic regression, which often requires a larger sample size to achieve statistical power comparable to ANOVA.

4.1. Lexical and sub-lexical information and letter identification

The role of word familiarity, crowding, and their interaction in parafoveal processing in reading has been addressed in several previous studies (e.g., Bouma, 1971, 1973; Schotter et al., 2012). These investigations (e.g., Bouma & Legein, 1977; Martelli et al., 2005) showed a clear lexicality effect; that is, letter recognition within a trigram string was more accurate when the string formed a word compared to a pseudoword. While the lexicality effect has been shown to occur both in the fovea and the parafovea (Martelli et al., 2005), at least among alphabetic scripts, here, we replicated this effect in a non-alphabetic (abjadic) script. This result suggests that lexical context supports the recognition of crowded letters in any orthography and writing system.

However, the mechanisms driving the lexicality effect remain unknown. Elevated performance for words over pseudowords could signify enhanced sensory processing, potentially through reducing crowding's spatial interference or improving the sensory processing of central letters. Alternatively, it might reflect a decision-making bias where observers infer the central letter from its surrounding letters. Notably, prior research using English letters demonstrated a robust lexicality effect, even when surrounding letters didn't hint at the central letter's identity (e.g., ace, age, ape, are, axe) (Martelli et al., 2005). This suggests that in English, the effect might be rooted more in sensory processing enhancement rather than decision-making bias. To evaluate the impact of transitional probabilities it was imperative to use stimuli with varied trigram and bigram frequencies. Our findings underscore that in Hebrew, sub-lexical probabilities explain performance better than lexical information. Future research will be pivotal to determine if the effect of bigram probabilities occurs during sensory processing or during the perceptual decision-making phase.

4.2. Right hemifield advantage in Hebrew

We also found a universal lateralization effect in which the recognition of crowded letters was superior in the right hemifield compared to the left hemifield. In accordance with the neuronal recycling hypothesis, the left hemisphere advantage in Hebrew is consistent with left hemisphere language and reading specialization (Behrmann & Plaut, 2013; Dehaene, 2005; Ossowski & Behrmann, 2015) which promotes higher accuracy in the right hemifield in reading tasks (e.g., Ibrahim & Eviatar, 2009; White et al., 2020). In crowding, the right hemifield advantage has been demonstrated among native readers of alphabetic scripts (Bouma, 1973; Grainger et al., 2010; Kurzawski et al., 2023), and found to be specific to letters and not other stimulus types (Oppenheimer et al., 2023). Hence, one hypothesis is that literacy training induces more precise spatial coding in the right visual field due to the reading direction in alphabetic scripts. Our findings show that in the case of printed words, crowding is more detrimental when the crowded letter is presented in the left hemifield, regardless of script-specific factors such as reading direction. This finding falsifies this hypothesis and strongly supports the cortical lateralization view.

4.3. Bigram frequency and language-specific effect

In addition to these language-universal findings, we observed a script-specific advantage for the left bigram compared to the right bigram. This effect aligns with the left-ward bias in Hebrew readers' reading span, which stems from the right-to-left reading direction (Pollatsek et al., 1981). This outcome underscores that transitional probabilities are crucial for letter recognition. Specifically, observers appear to rely on their knowledge of letter combinations to facilitate the identification of letters, even in the presence of visual crowding. This suggests that during reading, probabilistic information about the script bolsters the efficiency of letter recognition and counters the adverse effects of crowding. Thus, our results highlight the importance of integrating bigram frequencies into models of visual word recognition in the parafovea. The observation that bigram frequencies predict performance even more than lexicality, underscores the significance of local statistical information of orthographic units over top-down activation from word-level processes.

4.4. Environmental statistics: amitigating the detrimental effect of crowding

Our findings provide insights into the visual system's processing of crowded stimuli in general and printed words in particular. Essentially, the visual system capitalizes on contextual information, such as the probabilities of stimuli co-occurrences, to accurately identify a crowded letter. This may elucidate our ability to adeptly navigate crowded visual environments. From a clinical vantage point, given that crowding is markedly pronounced in certain visual disorders like amblyopia (Bonneh et al., 2007) and possibly in a subgroup of dyslexics (Joo et al., 2018), grasping the role of statistical information in mitigating crowding could pave the way for developing innovative tools and strategies to combat heightened crowding interference.

Statement of Relevance

Our visual system often struggles to identify a target amidst surrounding items, a phenomenon known as 'crowding'. This poses significant challenges for reading, where we need to discern individual letters in tightly spaced words. Understanding the interplay between crowding and reading is key to grasping how we process visual information. Our study illuminates this interaction by examining letter recognition in Hebrew, a right-to-left script. We reveal the critical role of probabilistic information, i.e., the frequency of pairs of letters ('bigrams') in each language, in crowded letter recognition. We found universal language effects: a lexicality effect and a right hemifield (left hemisphere) advantage, and a script-specific advantage for left bigrams due to Hebrew's reading direction. These findings underscore the role of probabilistic language information in enhancing letter recognition and mitigating crowding, suggesting that such information should be considered in literacy development and incorporated into models of word recognition.

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Author contributions

Adi Shechter: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing. **Sivan Medina**: Data curation, Formal analysis, Methodology, Validation, Visualization. **David Share**: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing – review & editing. **Amit Yashar**: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing.

Data availability

Data for all experiments are publicly available on OSF at https://osf.io/643b2/.

No part of the study procedures or analyses were pre-registered prior to the research being conducted.

Open practices

The study in this article earned Open Data and Open Material badges for transparent practices. The data and material used in this study are available at https://osf.io/643b2/.

Declaration of competing interest

The authors declare that there were no relevant financial or non-financial interests or conflicts of interest with respect to the authorship or the publication of this article.

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