Refixation Strategies in Sentential Word Reading: An Exploration by Linked Linear Mixed Models

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Abstract

The current study undertakes refixation patterns on words in sentential reading. Utilizing a Linked Linear Mixed Model approach, the analysis focused on words with a single fixation and the first fixation from words with a double fixation. The model findings revealed a relationship between refixation probability and fixation locations, with initial fixations tending to occur closer to the beginning of a word in instances of higher refixation likelihood. Incorporating predicted and residual values of the fixation location models into the fixation duration models resulted in congruence in the observed fixation locations, durations, and residual values. Finally, the models revealed differences between progressive and regressive second fixations.

Keywords: Linked Linear Mixed Models; reading; refixation; inverted optimal viewing position.

Introduction

The study of eye movements in attentive reading has been developed as a progressive research domain for the past several decades. The duration of fixations and their location (as identified by saccades) have led to a major research question in reading research: where and when to move the eyes. This question has been investigated by linear mixed model analyses, an extension of simple linear models allowing random and fixed effects, and computational models of oculomotor control. The computational models have exhibited high performance in predicting first-pass fixations, especially for words with short and medium length and low frequency (E-Z Reader by Reichle et al., 1998; Reichle et al., 2006; 2009; SWIFT by Engbert et al., 2002; 2005; Richter et al., 2006; Schad & Engbert, 2012; Risse et al., 2014; Glenmore by Reilly & Radach, 2003, 2006). Nevertheless, the models revealed divergent results for long words (Richter et al., 2006) and high-frequency words (Reichle & Sheridan, 2015; Reichle et al., 2003, 2006). They also performed differently in predicting the Inverted Optimal Viewing Position (IOVP) effect (Reilly & Radach, 2006).

The current study focuses on analyzing the IOVP effect in the context of refixation mechanisms. The effect is usually described in contrast to the Optimal Viewing Position (OVP) effect proposed by Rayner (1979). Briefly, the OVP effect states that a fixation landing around the center of a word tends to be shorter than a fixation on the edges of the word when presented without a text context (i.e., in isolation). The IOVP effect is the reversed OVP effect. It states that a fixation landing around the center of a word tends to be *longer* than a fixation on the edges of the word if they are embedded in the text. Accordingly, the effect is observed in sentences and larger text. A working explanation for the IOVP effect is that a fixation on the edge of a word is an undershoot or overshoot fixation (i.e., saccadic error assumption; Vitu et al., 2001). The IOVP effect is a robust phenomenon reported for numerous languages (Vitu et al., 2001; Kliegl et al., 2006 for German; Yan et al., 2014 for Uighur; and Hyönä, Yan, Vainio, 2018 for Finnish; Özkan et al., 2021 for Turkish). Oculomotor control models of reading, such as E-Z Reader and SWIFT, incorporate this assumption. These models effectively reproduce the IOVP effect in their simulations.

More recently, Hohenstein et al. (2017) proposed Linked Linear Mixed Models (LLMM) to study the relationship between the duration and location of fixations on words. They studied the IOVP effect and saccadic error assumption using the Potsdam Sentence Corpus (PSC, German; Kliegl et al., 2004) with three LMMs: a model of relative fixation locations and two models of fixation durations for words with a single fixation. The fixation location model included factors such as launch site distance, previous word skipping, and characteristics of the previous and the fixated word. The first single fixation duration model included canonical variables, such as characteristics of the fixated word and that of its neighbors, and a second-order orthogonal polynomial for the fixation location (to capture IOVP curvature). The second model included the same variables regarding word characteristics. However, instead of the observed fixation locations, the model included second-order orthogonal polynomials for the predicted and residual values of the fixation location model in three steps (i.e., predicted values, residual values, and both; the study reported the last step).

The rationale for using LLMM is to test a hypothesis: Using a fixation location model's predicted and residual components as the fixation location component of a fixation duration model would reveal the saccadic error patterns. Specifically, by representing the saccadic error, the residual of the fixation location model would have a significant, negative IOVP curvature, which is assumed to be the result of saccadic error. On the other hand, the relationship between fixation duration and predicted values would show the pattern observed when words are presented in isolation (i.e., OVP

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effect). Hohenstein et al. (2017) found a small but significant positive quadratic component, a more pronounced linear component of predicted values, and a significant negative quadratic component of residual values aligned with their expectations. Our goal in the present study is to investigate refixation patterns using the same rationale described in the following section.

The Present Study

Agglutinating languages, such as Turkish, provide an appropriate testbed to study refixation patterns, as they usually have long words. Turkish is a language read left to right, uses the Latin alphabet with specific Turkish characters, and has a shallow orthography. The present study uses a target-word dataset of eye movements in reading, namely the TURead dataset (Acartürk et al., 2023), to investigate the IOVP effect and refixation mechanisms. The TURead dataset comprises eye movement recordings during Turkish text reading silently and aloud (only silent reading instances included in the current study).

The current study focuses on words with two fixations (henceforth, double fixation words) compared to words with a single fixation. The comparison would provide insight into understanding the extent of the saccadic error explanation of IOVP: Is it entirely the result of the saccadic error of the oculomotor system, or is there a strategy component? We explored the findings of Hohenstein et al. (2017) with two sets of models: (i) Single fixation cases and (ii) double fixation cases. We constructed three models for each set: a model for fixation locations and two for fixation durations. In the fixation location LMMs, we modeled single fixation locations (i.e., single fixation cases; the words when they received a single fixation) and first fixation locations in double fixation cases. We modeled single fixation durations and first fixation durations (in double-fixation cases) for the fixation duration models. We also assumed that fixation count probabilities like skipping and multiple fixation probabilities imply different mechanisms. The assumption posits that when readers tend to skip certain words, any fixations on these words are likely to occur on the right half, indicative of an undershoot in the saccadic movement. Conversely, when there is a high probability of multiple fixations on a word, with these fixations predominantly occurring on the first half of the word, it suggests a strategic approach to reading rather than simply being attributable to saccadic errors.

Fixation probabilities were calculated over all instances in the dataset, including skipping cases. There were high correlations between skipping probabilities and multiple fixation probabilities: single fixation cases: $r(7598) = -0.73$, $p < .001$; double fixation cases ($r(4605) = -0.57$, $p < .001$. Including both in LLMs would result in a multicollinearity problem. Due to our focus on refixation strategies in the current study, we have included multiple fixation probabilities in the fixation location models. We also incorporated the interaction between the multiple fixation probability and the length of the word *n* into the models. The interaction term was a control for word length's impact on the probability of multiple fixations.

We preserved the model structures of the original study for single fixation duration models (Hohenstein et al., 2017). We developed two versions of the linked model: one using the base model's predicted and residual values and one with our version. We reported the latter. The details of the model that uses the base fixation location model's outputs are provided as an online supplement[1].

In cases of double fixation, we anticipated that in instances where the second fixation is regressive, we would predict shorter first fixation durations if the first fixation was located toward the end of the word. This pattern is particularly expected among residual values. On the contrary, among progressive second fixations, we expected to observe a positive relationship between the first fixation location and first fixation duration among predicted values, implying a strategy for a refixation. Therefore, we have included the saccade direction and its interaction with the first fixation location values in our first fixation duration models for double fixation data.

Method

We use the silent reading data published in the TURead dataset of eye movements in reading (Acartürk et al., 2023). In the TURead dataset, a large set of oral reading and silent reading eye-movement metrics and several lexical and prelexical word characteristics are provided in two sets: (1) for all words and (2) for the target words of the texts (except for the predictability data which was available only for target words and their neighboring words in the target word set). In the present study, we selected the target word set to have analyses comparable to those of previous studies. Below is the basic information about the dataset.

Participants

The dataset included eye movement recordings of 196 participants (M = 22.72, SD = 2.64 years old; 93 females) with their written consent. All included participants were native, monolingual Turkish speakers. The sessions had two parts, each lasting approximately 45 minutes.

Materials

The TURead dataset consists of eye movement recordings using EyeLink 1000 eye tracker system while reading 192 short texts from a combination of the BOUN Corpus (Sak et al., 2008), the METU Turkish Corpus (Say et al., 2002), the Turkish National Corpus (Aksan et al., 2012), and search engine results for the suffixed forms of infrequent target

[1] Refixation Strategies in Sentential Word Reading: An Exploration by Linked Linear Mixed Models Open Science Framework OSF Repository: https://osf.io/t3g7d/

words (as the texts were not obtained from corpora due to unavailability of some infrequent words). Each text included a target word controlled for its length and frequency. Frequency values were extracted from the BOUN web corpus. A Laplace smoothing method was applied to zero-frequency values (Brysbaert & Diependaele, 2013). The cutoff point for the high- vs. low-frequency target words was the mean of BOUN Corpus (0.75 fpm, *SD* = 35.50). Short words consisted of 4 characters of stem and 0-suffixed (4 characters), 1-suffixed (6 characters), and 2-suffixed (8 characters) variants. Long words consisted of 10 characters of stem and the suffixed variants, similar to the short words (i.e., 12 and 14 characters, respectively).

In the present study, we applied transformations to the variables following Hohenstein et al. (2017), as explained below.

Predictabilities were logit-transformed values of the raw predictions. There are two versions of the predictability data for the target words in TURead: 122 complete predictions and a randomly selected 35 predictions to enable logit transformations to be compatible with neighboring word predictabilities. That is because there are 35 predictions for the neighboring words. We selected the 35-prediction data for the target words to apply logit transformation. The following logit transformation was used to obtain Word Predictability (*WP*) values: $WP = 1/2\text{logit}(p)$ where $\text{logit}(p) = \ln(p/(1-p))$. The *p* values were calculated using the following equations (1-3).

$$p = 1/(2 \times n) \quad \text{if } p = 0 \qquad (1)$$

$$p = ((2 \times n) - 1)/(2 \times n) \quad \text{if } p = 1 \qquad (2)$$

$$p \quad \text{otherwise} \qquad (3)$$

where *p* stands for the raw predictability values, and *n* stands for the number of predictions, i.e., 35.

Relative Fixation Locations were calculated using the formula (4), which returned 0 for the center of the words, negative values for the left half of the words, and positive values for the right half.

$$R(F)FL = (FL / (WL + 1)) - ½ \qquad (4)$$

where *R(F)FL* stands for relative (first) fixation location as the number of characters from the beginning of the sentence, *FL* stands for fixation location, and *WL* stands for word length in character count.

Word Length Word lengths were the reciprocal values of the number of characters in words (i.e., 1/*WL*).

Fixation Durations were the log-transformed raw values in milliseconds, in natural logarithm.

Launch-Site Distances were the log-transformed raw values (the number of characters between the last fixation and the beginning of the target word) with base-two logarithm.

Linked Linear Mixed Models

In the current study, we explored refixation strategies following Hohenstein et al. (2017), taking their models as the base models. We explored their findings with two sets of models with target word data of the TURead dataset (Acartürk et al., 2023): (i) Single fixation cases and (ii) double fixation cases. We constructed three models for each set: a model for fixation locations and two for fixation durations. The models were constructed using the `lmer()` function with the `lme4` package (version 1.1-35.1; Bates et al., 2015) in the R environment (version 4.3.2, 64-bit build; R Core Team, 2023). The *p* values were obtained using the `lmerTest` package (version 3.1-3; Kuznetsova et al., 2017). Lines and 95% confidence bands in graphs were partial effects retrieved from LMM estimates by using the `remef` package (Hohenstein & Kliegl, 2015), and the graphs were constructed using the `ggplot2` package (version 3.4.4; Wickham, 2009).

Random Structure Initially, we constructed all the base models using the random structure of the models in Hohenstein et al. (2017). In their study, random slopes were the main effects for participants. Words and sentences were included in the model as intercept-only random factors. The data used in the current study included only the target word set of the TURead dataset. Since each target word appeared only once among all texts of TURead, each target word corresponded to one text. Therefore, we included only participants with slopes and words as the random factors.

Additionally, we explored the random structure of the base models to control whether our dataset allows a random structure of the base model. We applied a parsimonious mixed models approach (Bates et al., 2015). Accordingly, even if it was in the base model, a random slope was removed if it exceeded the principal component count, cumulatively accounting for 100% of the variance. Once set, the random structure stayed the same as the base model for the exploratory models.

Relative Fixation Location Models The fixation location model provided by Hohenstein et al. (2017) included the following variables as fixed effects: the skipping of word *n-1*, the length, predictability, and frequency of word *n* and word *n-1* (eight variables), and their interaction with the skipping of word n-1.

Only 4.53% of our single fixation data (361 instances out of 7961 single fixation cases) and 4.56% percent of our double fixation data (220 instances out of 4827 double fixation cases) were instances of skipped word *n-1*. Skipping the word *n-1* in our models would result in a model complexity not supported by data. On the other hand, leaving those instances in the data without including the variable in the model would ignore an essential effect on fixation locations. Therefore, instead of including it as a variable in the model, we excluded instances with a skipped word *n-1* from our datasets. Upon constructing the base model and its random structure, we included our exploratory variables (i.e., multiple fixation probability and its interaction with length of word *n*) in the models.

Fixation Duration Models Hohenstein et al. (2017) provided two models for single fixation durations: separate and linked models. The fixed effects included in the models were length, predictability, and frequency of word *n*, word *n-1*, and word *n+1* (nine variables), and Relative Fixation Location (RFL) as a second-order orthogonal polynomial.

The observed RFL with linear and quadratic components was in the "separate model." In the linked model, two RFL variables were included as second-order orthogonal polynomials: predicted RFL from the RFL model and residual of the RFL model.

We modeled the single and first fixation durations using the same method. The formula provided in equation (5) was used for the separate model of the single fixation.

$$SFD = \text{poly}(RFL_{obs}, 2) + WC + RS \tag{5}$$

where SFD stands for single fixation duration, RFL_{obs} stands for the relative fixation location included as a second-order polynomial, WC stands for word characteristics (nine variables), and RS stands for random structure.

The formula provided in equation (6) was used for the linked model.

$$SFD = \text{poly}(RFL_{pred}, 2) + \text{poly}(RFL_{res}, 2) + WC + RS \tag{6}$$

where RFL_{pred} stands for the predicted values and RFL_{res} stands for residual values obtained from the relative fixation location model, both included as second-order polynomials.

The first fixation duration models were the same regarding first fixation locations, word characteristics, and random structure. Additionally, we included the direction of the saccade to the second fixation and its interaction with the length of word *n* in the first fixation duration models.

Common LLMM Aspects Including the exploratory variables was theoretically important. Therefore, we included them in the model without testing the significance of their effect or their contribution to the model. The models were tested for the multicollinearity problem at each step by VIF calculations with the function `vif.mer()` (Lefcheck, 2012), and the final models were tested for the normality of the residuals. None of the models violated model assumptions.

Results

Below is a summary of the results. For more detailed explanations and the model estimates, please see the online supplement.[2]

[2] Refixation Strategies in Sentential Word Reading: An Exploration by Linked Linear Mixed Models Open Science Framework OSF Repository: https://osf.io/t3g7d/

Relative Fixation Locations

Single Fixations We have included multiple fixation probability and its interaction with the length of the target word in the single fixation location model. The results showed that fixations tended to be located on the first half of the word as multiple fixation probability on a word increased (b = -0.11, SE = 0.03, t = -3.51, p < .001). The result was expected regarding our assumptions about the relationship between multiple fixation probability and fixation locations: Fixations would fall in the first half of the words as a strategy for refixation. The interaction of multiple fixation probability and the length of word *n* significantly influenced relative single fixation location (b = 1.05, SE = 0.28, t = 3.77, p < .001). The influence of word length on relative fixation location tended to decrease for high multiple fixation probability cases (Figure 1).

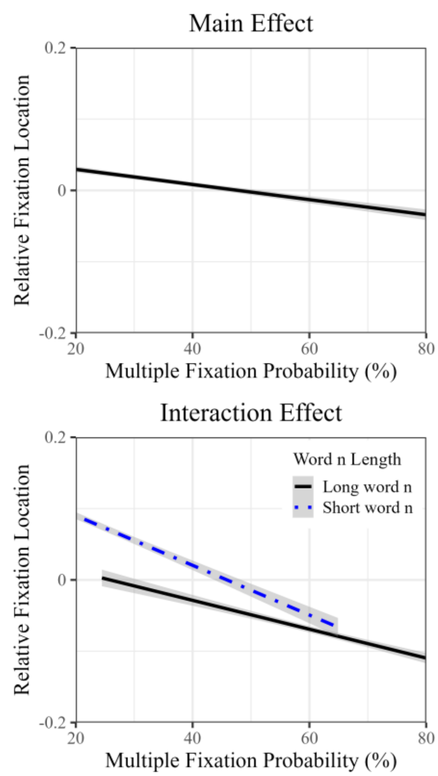

Figure 1: The effect of multiple fixation probability (top) and its interaction with word *n* length (bottom) on relative fixation location.

Double Fixations We observed a tendency of first fixation locations towards the center of the words as the multiple fixation probability of the words increased to a multiple fixation value of 0.50. They were on the left half of the word if the multiple fixation probability was over 0.50. The effect was small but significant (b = 0.14, SE = 0.04, t = 3.8, p < .001). On the other hand, when the significant effect of its interaction with the length of the word *n* was considered, we observed a tendency of first fixation locations towards the beginning of the word (b = 2.32, SE = 0.38, t = 6.1, p < .001). The result implies a dominating influence of word length on the multiple fixation probability. Figure 2 illustrates the opposing relationships between multiple fixation probability and relative first fixation location.

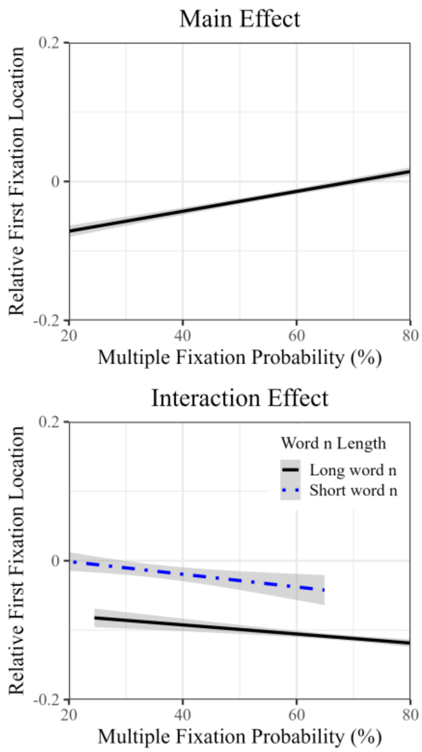

Figure 2: The effect of multiple fixation probability (top) and its interaction with word *n* length (bottom) on relative first fixation location.

Fixation Durations

Single Fixations The relationship between residual relative fixation locations (RFL) and single fixation durations was similar to that of observed fixation locations with significant linear (residual: b = 4.65, SE = 0.4, t = 11.67, p < .001; observed: b = 4.33, SE = 0.45, t = 9.56, p < .001) and negative strong quadratic components (residual: b = -4.92, SE = 0.34, t = -14.65, p < .001; observed: b = -5.79, SE = 0.34, t = -16.93, p < .001). However, we could not replicate the results of Hohenstein et al. (2017) regarding the relationship between predicted RFL and single fixation durations. Although we also observed a negative linear relationship between single fixation durations and predicted RFL values, the relationship was not significant (b = -0.05, SE = 0.62, t = -0.08, p = 0.94). Moreover, we observed a small but negative quadratic component instead of a positive one (b = -2.14, SE = 0.38, t = -5.62, p < .001). This was still the case when we modeled single fixation durations with the base model's predictions (linear: b = -0.26, SE = 0.62, t = -0.42, p = 0.67; quadratic: b = -1.88, SE = 0.38, t = -4.89, p < .001). Figure 3 illustrates the relationship between single fixation durations and observed, predicted, and residual RFL values.

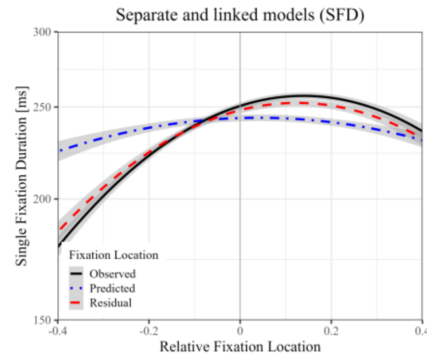

Figure 3: The effect of observed fixation locations, predicted fixation locations, and fixation location model residuals on Single Fixation Duration (SFD).

Double Fixations The first fixation durations among double fixation cases showed a strong negative quadratic relationship between the observed relative first fixation locations (RFFL), together with a significant positive linear relationship (linear: b = 4.43, SE = 1, t = 4.43, p < .001; quadratic: b = -7.91, SE = 0.81, t = -9.81, p < .001). The relationship between the first fixation durations and the residual of the RFFL model showed a similar pattern with a significant positive linear component (b = 8.34, SE = 0.64, t = 13, p < .001) and a significant negative quadratic component (b = -3.58, SE = 0.61, t = -5.85, p < .001). However, the curvature was not as strong as observed in the separate model.

Although the pattern for the relationship between the predicted RFFL components and first fixation durations of the linked model was similar to single fixation cases, the negative quadratic component of predicted RFFL was not significant (b = -0.01, SE = 0.67, t = -0.01, p = 0.99). On the other hand, the relationship between first fixation durations and the linear component of predicted RFFL was significant and positive (b = 3.66, SE = 0.74, t = 4.96, p < .001). Figure 4 illustrates the relationship between first fixation durations and observed, predicted, and residual RFFL values.

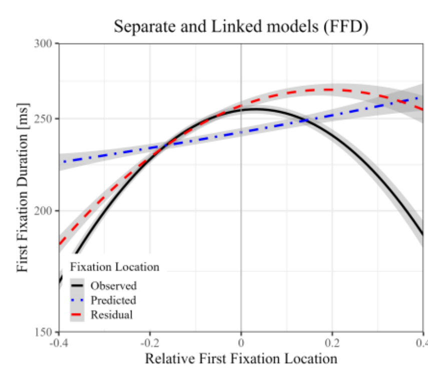

Figure 4: The effect of observed first fixation locations, predicted first fixation locations, and first fixation location model residuals on First Fixation Duration (FFD).

The direction of the saccade significantly influenced the first fixation durations among the double fixation cases in the linked model (b = -0.07, SE = 0.02, t = -3.55, p < .001). Although the direction of the effect was the same for the separate model, it was not significant (b = -0.01, SE = 0.02, t = -0.58, p = 0.56). The interactions between the saccade direction and RFFL values were significant (observed linear: b = -7.43, SE = 1.79, t = -4.15, p < .001; observed quadratic: b = 7.86, SE = 1.35, t = 5.83, p < .001; residual linear: b = -12.03, SE = 1.3, t = -9.23, p < .001; residual quadratic: b = 3.24, SE = 1.04, t = 3.12, p < .01; predicted linear: b = -2.65, SE = 1.02, t = -2.6, p < .01) except for the quadratic component of predicted RFFL values (b = -1.4, SE = 0.89, t = -1.57, p = 0.12). For both progressive and regressive second fixations, the relationship pattern between first fixation duration and observed RFFL was similar to that of residual RFFL: The quadratic component of RFFL was strong among progressive second fixation cases and was negligible among regressive second fixation cases. On the other hand, the linear component indicated a decrease in first fixation duration as observed, and residual RFFL values increased among regressive second fixation cases. The positive relationship between first fixation duration and predicted RFFL among progressive second fixation cases was lost among regressive second fixation cases. Figure 5 illustrates the relationship between the first fixation duration and predicted first fixation locations and first fixation location model residuals and the relationship between observed first fixation location and first fixation duration in the separate model.

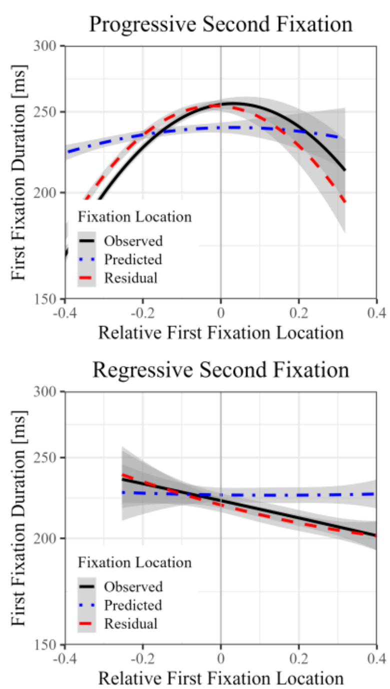

Figure 5: The effect of predicted first fixation locations and first fixation location model residuals and their interaction with saccade direction on first fixation duration and the separate model findings with observed values.

Discussion and Conclusion

In the investigation of the refixation patterns, we employed a Linked Linear Mixed Models approach to model target word data of TURead (Acartürk et al., 2023) following Hohenstein et al. (2017), which targeted the saccadic error explanation of the IOVP effect (Vitu et al., 2001). They modeled the fixation locations with oculomotor and linguistic variables. The fixation duration model included the predicted and residual values from that model as representations of saccade target selection and saccadic error. They found that the relationship between fixation duration and residual values of the fixation location model was similar to that of observed fixation locations, which complied with their expectations. Besides, they observed a mild OVP effect of predicted fixation locations on fixation durations.

To investigate whether refixations are completely saccadic errors or have a strategy aspect, we modeled single fixation and double fixation cases of the TURead dataset. Including multiple fixation probabilities revealed that as the multiple fixation probability increased, the fixations tended to fall on the right half of the words. The pattern was reversed for the first fixation locations of the double fixation cases. However, considering its interaction with the word length, the relationship was negative, implying a strong influence of word length on multiple fixation probabilities.

Our fixation duration models (i.e., single fixation and double fixation) revealed a similar pattern to those provided by Hohenstein et al. (2017) regarding residual components. In other words, we observed that with the significant and large negative quadratic components, the effect of residual values on fixation durations showed a similar pattern to the effect of observed values on fixation durations. However, we could not replicate the positive quadratic components for the models that include predicted fixation location values. Instead, we observed a small negative linear relationship that was not significant and a small but significant negative quadratic relationship between the predicted single fixation locations and durations. On the other hand, we observed a positive significant linear influence of predicted first fixation locations for the first fixation durations of double fixation cases. The slight negative quadratic component was not significant. When the direction of the saccade was considered, the pattern remained the same for progressive saccades. The negative relationship implied a corrective saccade for the regressive second fixation instances.

There were several limitations to our study. Firstly, the dataset was small and included only the target words of the TURead dataset. That might have limited the observation of refixation patterns in a text. Another limitation related to the first one was that we could not utilize the agglutinative nature of Turkish. The inclusion of suffix count into the models would increase the model complexity to the point that data did not support it, and the word lengths of the target words in the TURead dataset were a confounding factor for the suffix counts. Follow-up studies using a corpus analytical approach would overcome these limitations and provide more insight into the refixation patterns.

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