Predicting Reading Performance based on Eye Movement Analysis with Hidden Markov Models

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Abstract*—Reading is an essential medium for learning, but it is challenging to measure learners' cognitive processes during reading. Eye-tracking, as an approach in multimodal learning analytics (MmLA), can provide fine-grained data that reflect cognitive processes during reading. In this study, we investigated whether eye movements could predict passage reading performance in addition to language proficiency and cognitive abilities. In particular, we assessed learners' eye movement pattern and consistency through a novel method, Eye Movement analysis with Hidden Markov Models (EMHMM), in addition to traditional eye movement measures. We found that longer saccade length predicted faster reading speed. Also, higher English proficiency predicted faster reading speed through the mediation of longer saccade length. In contrast, reading comprehension accuracy was best predicted by a more consistent eye fixation at the beginning of reading engagement, which may result from a better developed visual routine due to higher reading expertise. These findings have important implications for ways to assess and facilitate learners' reading through eye movement measures and to examine factors influencing reading performance. The methods adopted could further the development of MmLA and serve as an empirical example of understanding learners' cognitive processes through collecting and modeling critical learner-centered metrics in novel modalities.

***Keywords*—reading performance, eye movements, EMHMM, prediction**

I. Introduction

Reading is a standard medium for learning and instruction. Learners' individual factors contributing to reading performance have been investigated extensively. Language proficiency has been found to be one of the strongest predictors of reading performance, especially for English as Second Language (ESL) learners [1]. Learners who had larger vocabulary size, indicating higher language proficiency, performed better in reading comprehension [2]. Language proficiency also accounts for reading speed. People with a large vocabulary size were found to read text faster while maintaining good comprehension [3].

To deepen our understanding of learners' behaviors, cognition and affect, learning analytics researchers have started to exploit learners' data in multiple modalities [4]. Besides modalities commonly available in traditional and online learning systems such as test scores or clickstreams [5], data streams that can be automatically recorded through specialized devices during learning have drawn researchers' attention [4]. Eye movement data provide a continuous record of reading behavior and reflect cognitive processes during reading [6]. It has been found that language proficiency moderates eye movements. For example, Brunfaut and McCray found that more proficient readers have shorter total and single-word fixation time [7]. In general, people fixated longer when the texts become more difficult and when the word is less frequent or less predictable [8]. Thus, longer fixation time and more fixations indicate greater cognitive efforts required or engaged during reading [9].

Eye movement consistency, which refers to the consistency of readers' eye movements across words, sentences, or passages, may also contribute to reading comprehension outcomes. More specifically, people had improved recognition performance of a stimulus if it was presented repeatedly at a certain visual field location due to perceptual learning [10]. Consequently, readers had the best word reading performance when their fixation was directed to locations upon which they most often fixated during reading [11]. This leads to our speculation that eye movement consistency may be associated with better-developed reading skills. Indeed, in sentence reading, adults have more consistent eye movements in viewing words with varied lengths than children [12], indicating that eye movement consistency may be linked with expert-level reading processes.

The above findings suggest that readers' eye movement pattern and consistency may both be good indicators for reading performance. This study thus aims to examine empirical evidence on the following two research questions (RQs):

RQ1. Can learners' eye movement pattern and consistency could predict reading performance, in addition to language proficiency and cognitive abilities?

RQ2. Can eye movements mediate the effect of language proficiency on reading performance?

Previous studies on reading typically only used summary statistics of eye movements to measure eye movement behavior, such as fixation duration, saccade length and regression frequency [6]. The advancement of machine learning enables us to extract high-level information and insights from eye movement data which can be meaningful to both learners and educators. We used a novel machine learning method, Eye Movement analysis with Hidden Markov Models (EMHMM)

2161-377X/22/$31.00 ©2022 IEEE
DOI 10.1109/ICALT55010.2022.00058

[13] to provide quantitative measures of participant's eye movement pattern and consistency, taking both spatial (eye fixation locations) and temporal (the order of fixation locations) dimensions of eye movements into account simultaneously.

This study introduces the EMHMM method into the literature of learning analytics. Together with summary statistics of local eye movement measures (e.g., saccade length and fixation duration), we use EMHMM method to recognize global eye movement patterns and examine whether and how they help predict reading performances, in addition to learners' language proficiency and cognitive abilities.

II. Eye Movement analysis with Hidden Markov Models (EMHMM)

EMHMM is a data-driven approach that summarizes each individual learner's eye movements using a hidden Markov model (HMM), a machine learning method for modelling time-series data. More specifically, a learner's eye movements are summarized using an HMM in terms of individualized regions of interest (ROIs) and transition probabilities among these ROIs. A sequence of ROIs visited by the learner is represented by a hidden state sequence, which develops according to a Markov process where the current hidden state depends on the previous hidden state. As only the fixations but not the ROIs are observable, the ROI sequence is hidden and has to be inferred from the fixation sequence. The ROIs are modeled by Gaussian emissions, which represents the fixation distributions in the ROIs. A variational Bayesian approach [14] was adopted to estimate an HMM such that the optimal number of ROIs can be automatically determined. As HMMs summarize probability distributions of time-series data, the similarities among probability distributions can be used to cluster individual HMMs into groups through the variational hierarchical expectation maximization algorithm [15] to discover representative HMMs/ eye movement patterns. The similarity between individual eye movement patterns and representative patterns can be measured quantitatively using data log-likelihoods of the individual HMMs given the representative HMMs. This log-likelihood measure can then be used to quantitatively examine individual differences in eye movement patterns in visual processing.

Eye movement consistency of an individual learner can be assessed using the entropy of his/her HMM. Entropy is a measure of predictability of a dataset or measure, with lower entropy indicating higher predictability and thus higher consistency of a set of data or measures [16]. Therefore, lower entropy of an HMM indicates the corresponding learner has a higher eye movement consistency.

EMHMM has been applied in modeling eye movements in viewing different visual inputs. For example, it discovered eyes-focused and nose-focused patterns in face processing [17], distributed and centralized patterns in video viewing [18], and explorative and focused patterns in scene perception [19]. However, it has not yet been applied to passage reading. Here EMHMM provides additional measures that enabled us to evaluate the role of eye movements more comprehensively.

III. Research Design

To fulfill the goal of this study, a reading comprehension experiment was conducted to collect reading performance measures, learners' eye movement, language proficiency and cognitive abilities which were then analyzed through EMHMM, prediction modeling and mediator analysis.

A. Materials and Apparatus

Nine English academic passages were selected from the Graduate Record Examinations (GRE) reading samples; the content was regarded to be at a typical university learning level [20]. They were emotionally neutral and with a low arousal level, and varied in topics: archaeology, astronomy, biology, history, science, literature, and sociology. All passages had a similar number of words (M = 218; SD = 9.84). Participants' comprehension performance of each passage was assessed by two multiple-choice questions (MCQs), with one text/fact-based question and one inference-based question [20]. Online LexTale [21] was adopted to measure participants' English proficiency.

A monitor (19 inches) with 1280 x 1024 pixels resolution was placed at a viewing distance of 56 cm from a chinrest. The horizontal visual angle of each character was around 0.3°, which simulated a normal reading situation [22]. An Eyelink1000 eye tracker with a default setting for cognitive research was used. A keyboard was used to record learners' responses.

B. Procedure

We recruited 50[1] participants (25 males and 25 females) at a university, with a mean age of 22.5 (SD = 3.88). All of them were non-native English speakers and reported normal or corrected to normal vision and no learning impairment.

Before starting the experiment, participants signed informed consent forms, took LexTale test in which they decided whether a presented string of text was an existing word or not. In the experiment, they completed a passage reading task with the movement of their dominant eye tracked. They then completed four cognitive tasks, including two-back task [23], the flanker test [24], multitasking test [25], and the Tower of London (ToL) test[26], which measure working memory capacity, inhibitory control capacity, multitasking and executive planning abilities respectively.

The passage reading task consisted of three blocks, with three passages varied in difficulty level in each block. Block and passage order were randomized across participants. Standard calibration and drift correction procedures were performed to ensure the quality of eye tracking. In each trial, participants read the passages and answered two MCQs with unlimited time to simulate a typical learning context instead of examinations.

C. Data Analysis

We used the novel method EMHMM with co-clustering [19] to analyze eye movement data since it allowed us to examine individual differences in eye movement patterns during reading across passages which were shown in different word/sentence layouts. As there were 9 passages in this experiment, each participant had 9 HMMs, with each corresponding to a passage.

[1] One participant was excluded from eye movement analysis due to technical problem, and thus N = 49 in this study. According to a power analysis for regression, assuming a large effect size ($f^2 = .35$) with 6 tested predictors, $\alpha = .05$, $\beta = .2$, the sample size required was 49.

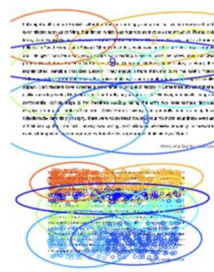
For each HMM, the optimal number of ROIs was determined using the variational Bayesian method [14] which required a preset range. We chose to set 1- 9 ROIs to capture potential ROIs in 3 vertical (top, center, bottom) and 3 horizontal (left, center, right) locations. As the 9 passages had different visual layouts due to varying word lengths and paragraph separation, the HMMs on different passages were not directly comparable. Thus, co-clustering was used to separate participants into two groups, A and B, such that those in the same group had similar eye movement pattern to one another across the 9 passages. For each passage, the algorithm used one HMM to summarize the eye movement patterns of the participants in each group, resulting in 9 representative HMMs per group. The number of ROIs in each representative HMM was set to be the median number of ROIs in the individual HMMs. We clustered participants into two groups so that each participant's eye movement pattern could be quantified using data log-likelihood along the two contrasting representative pattern groups. The data log-likelihoods towards the two representative pattern groups, A and B, were averaged across 9 passages. Following previous studies [17] in measuring participants' eye movement pattern along the dimension of the two contrasting representative pattern groups, we defined A-B scale as $(L_A - L_B) / (|L_A| + |L_B|)$, where L_A and L_B represent the log-likelihood of the participant's eye movement data being classified as Pattern Group A and Pattern Group B respectively. A more positive A-B scale indicates higher similarity to Pattern Group A. Independent sample t-tests were performed to verify whether participants in the two pattern groups (A and B) differ in averaged fixation duration, averaged saccade length, horizontal/vertical saccade proportion. The overall entropy of all fixations, marginal entropy of the first and the second fixation were assessed. Marginal entropy of the first fixation measures how people plan their gaze from the central fixation cross towards the stimulus, and the marginal entropy of the second fixation measures how people plan their fixation after initial stimulus processing. The entropy measures were calculated from individual HMMs for each stimulus (i.e., text passage) respectively and averaged across 9 passages for each participant. In general, early measures, such as entropies of the first and second fixations, are considered to reflect automatic processing and initial lexical access, while overall measures, such as overall eye movement pattern and overall entropy, reflect more strategic processing and lexical integration (c.f., [27]).

Stepwise multiple linear regression was performed to predict reading comprehension accuracy (ACC) and reading time using features including eye movement pattern and consistency measures, English proficiency, and cognitive ability measures. The tested predictors included A-B scale for eye movement pattern, overall entropy, marginal entropy of the first fixation and the second fixation, averaged fixation duration and averaged saccade length. English proficiency and cognitive ability measures were controlled variables testing whether eye movement measures can better predict reading performance than these usual predictors found in existing studies. Pearson's correlation analysis was performed between A-B scale and LexTale/reading time. Mediation analysis was conducted to test the hypothesis that English proficiency predicts reading time through the mediation of eye movement pattern.

IV. Results

A. Eye Movement Patterns

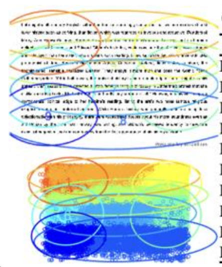
Using EMHMM with co-clustering, we discovered two representative viewing pattern groups during passage reading among all participants with 9 (resulting median number of ROIs) ROIs as shown in Fig. 1. Comparing the two pattern groups, the pattern shown in Fig. 1A, referred to as Pattern Group A, had the shape of ROIs vertically longer and horizontally shorter than those in pattern group B (Fig. 1B), suggesting more vertical than horizontal eye movements in general. In contrast, in Pattern Group B, the shape of ROIs was shorter in the vertical direction and longer in the horizontal direction. Five participants were clustered into group A and 44 were clustered into group B. The two pattern groups were significantly different according to KL divergence estimation [19]: $F(1,47) = 41.63$, $p < .001$, $\eta^2 = .03$. To confirm our speculation, we found that participants using Pattern Group A had a larger proportion of vertical saccades than those using Pattern Group B, $t(47) = 2.131$, $p = .038$, whereas Pattern Group B involved more horizontal saccades.



A.

Group A Pattern (5 participants)

	To 1	To 2	To 3	To 4	To 5	To 6	To 7	To 8	To 9
Priors	.52	.11	.02	.06	.04	.05	.06	.10	.04
From 1	.83	.16	.00	.01	.00	.00	.00	.00	.00
From 2	.08	.88	.03	.00	.00	.00	.00	.00	.01
From 3	.16	.01	.72	.11	.00	.00	.00	.00	.00
From 4	.00	.00	.02	.77	.12	.02	.04	.01	.01
From 5	.01	.01	.00	.00	.79	.18	.00	.00	.01
From 6	.00	.00	.00	.16	.00	.80	.02	.00	.00
From 7	.01	.00	.00	.01	.00	.00	.81	.16	.00
From 8	.01	.00	.00	.00	.00	.01	.09	.88	.00
From 9	.02	.00	.00	.00	.00	.01	.00	.02	.94



B.

Group B Pattern (44 participants)

	To 1	To 2	To 3	To 4	To 5	To 6	To 7	To 8	To 9
Priors	.37	.25	.05	.06	.05	.03	.08	.08	.03
From 1	.79	.15	.01	.04	.00	.00	.01	.00	.00
From 2	.01	.92	.06	.00	.00	.00	.00	.00	.00
From 3	.15	.01	.80	.02	.01	.01	.00	.00	.00
From 4	.00	.00	.03	.93	.01	.00	.01	.00	.00
From 5	.00	.00	.00	.00	.78	.13	.01	.01	.06
From 6	.00	.00	.00	.03	.01	.74	.19	.02	.00
From 7	.00	.00	.00	.00	.07	.00	.90	.01	.00
From 8	.00	.00	.00	.00	.02	.00	.01	.94	.02
From 9	.00	.00	.00	.00	.00	.00	.02	.15	.81

Fig. 1. Example passage with readers' regions of interest and transition matrix of representative eye movement patterns during passage reading.

Participants in the two pattern groups did not differ in average fixation duration, $t(47) = -1.84$, $p = .072$, or average saccade length, $t(47) = -.16$, $p = .874$. A-B scale was negatively correlated with LexTale, $r(47) = -.36$, $p = .011$, and positively correlated with reading time, $r(47) = .47$, $p = .001$, suggesting that Pattern Group A was associated with lower English proficiency and longer reading time.

B. Predictors for Reading Performance

Stepwise multiple regression predicting reading time (Table 1) showed that saccade length was a significant predictor, $\beta = -.39$, $p < .001$, in addition to executive planning ability (measured by planning time of ToL test), $\beta = .56$, $p < .001$, $R^2 = .53$, $F(2, 46) = 28.12$, $p < .001$, with a low level of multicollinearity among entered variables (tolerance = .964). This indicated that participants with shorter saccade length and lower planning ability (reflected by longer planning time when performing the ToL test) had longer reading time.

Stepwise multiple regression predicting comprehension ACC (Table 1) showed that entropy of the second fixation, β = -.35, p = .011, was a significant predictor in addition to verbal working memory capacity (measured by 2-back task's ACC), β = .39, p = .021, R^2 = .16, F (2,46) = 5.61, p = .007, with a low level of multicollinearity among entered variables (tolerance = .981). Thus, learners with a more consistent fixation to start engaging in reading (as reflected by lower entropy of the second fixation) and better verbal working memory (as reflected by higher 2-back ACC) had better reading comprehension.

TABLE 1. STEPWISE MULTIPLE REGRESSION MODELS FOR READING PERFORMANCE INCLUDING READING TIME AND COMPREHENSION ACC (* P < 0.05; ** P < 0.01; *** P < 0.001)

	ΔR^2	β
Reading Time		
Model 1	.403***	
Planning Time of ToL		.64***
Model 2	.147***	
Planning Time of ToL		.56***
Saccade Length		-.39***
Comprehension Accuracy		
Model 1	.096*	
Entropy of the Second Fixation		-.31*
Model 2	.100*	
Entropy of the Second Fixation		-.35*
Accuracy of Verbal 2-back Test		.39*

C. Mediation Analysis

Mediation analysis showed that LexTale score affected both A-B scale, b = -.36, p =.011, and reading time, b = -.30, p = .037, significantly. When we predicted reading time with LexTale score through the mediation of A-B scale, A-B scale was a significant predictor, b = .42, p =.004, while LexTale score was not, b = -.15, p =.289. The indirect effect through A-B scale was significant, B = -58.66, 95% CI: [-133.05, -14.16], and Sobel test indicated complete mediation (z = -2.00, p = .045; Fig. 2A).

As saccade length was a better predictor of reading time than A-B scale (c.f., Table 1 model 2), we also conducted a similar mediation analysis with saccade length being the mediator and found that LexTale score affected both saccade length, b = .60, p < .001, and reading time, b = -.30, p = .037, significantly. When predicting reading time with LexTale score through the mediation of saccade length, saccade length was a significant predictor, b = -.50, p =.003, while LexTale score was not, b < .001, p = 1.000. The indirect effect through saccade length was significant, B = -116.27, 95% CI: [-204.21, -51.76], and Sobel test indicated complete mediation (z = -2.66, p = .008; Fig. 2B).

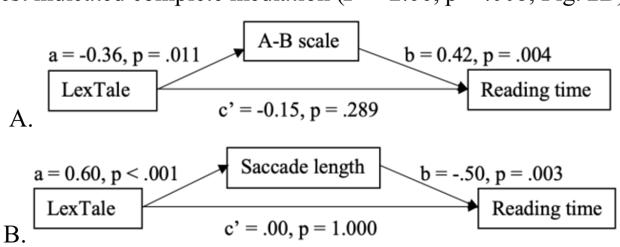


Fig. 2. The mediated models where English proficiency (LexTale score) predicts reading time through the mediation of A. eye movement pattern (A-B scale) and B. saccade length, respectively.

V. DISCUSSION

This study introduced a novel machine-learning approach, EMHMM to examine eye movement patterns and to what extent they could predict reading performance in addition to language proficiency and cognitive abilities. Through EMHMM, we discovered two representative eye movement pattern groups, and higher similarity to the pattern group with larger proportion of horizontal saccades was associated with shorter passage reading time. Considering both summary statistics of local eye movement measures as well as overall eye movement pattern and consistency measures derived using EMHMM, we found that longer saccade length best predicted faster reading speed in addition to better executive planning ability. In contrast, a more consistent second fixation predicted higher comprehension accuracy, in addition to better verbal working memory.

Previous studies suggest that higher text difficulty results in longer fixation duration, shorter saccades and more regressions [8] and that people make more and longer fixations on words requiring greater cognitive efforts [9]. Consistent with previous findings, we found that people with shorter saccade length had longer reading time. However, the two representative eye movement pattern groups discovered through EMHMM with co-clustering did not differ in fixation duration or saccade length. The main difference between the two pattern groups was in the proportion of vertical and horizontal saccades during reading. The finding that the pattern group with a larger proportion of horizontal saccades was associated with shorter reading time suggested that saccade direction may be an important indicator for reading fluency (*RQ1*). Indeed, humans generally adopt a serial reading pattern, where texts are processed sequentially (although information within each fixation may be processed in parallel) [28]. Thus, a fluent reading process should involve more horizontal than vertical reading, which supports our hypothesis that eye movement pattern predicts reading fluency. Here even though saccade length better predicted reading time than eye movement pattern generated by EMHMM, it is important to consider the overall pattern measures, which take into account both spatial and temporal aspects of fixation sequences, to achieve a more comprehensive evaluation of the role of eye movements.

In addition, from the mediation analysis (*RQ2*), we observed a complete mediation effect: English proficiency predicted passage reading time through the mediation of eye movement pattern. This suggests that the association between higher English proficiency and shorter reading time could be fully explained by the eye movement pattern involving more horizontal saccades. Thus, eye movement patterns discovered through EMHMM revealed the mechanism underlying the relationship between English proficiency and reading time. Besides, saccade length also mediated the effect of English proficiency on reading time, suggesting the importance of taking eye movement measures into account when examining the relationship between language proficiency and reading time.

In contrast to reading time, we found better comprehension accuracy was best predicted by consistency in the second fixation, in addition to verbal working memory (*RQ1*). In the reading task, participants typically made a first fixation to locate the beginning of the passage. Thus, the subsequent, second fixation typically indicated the beginning of reading engagement after initial lexical processing at the first fixation. The consistent eye fixation behavior at the second fixation may result from extensive reading experience (e.g., [12]), which can potentially lead to better word recognition through perceptual learning [10]. It could also reflect high-level reading expertise in discovering and extracting important information as a result of visual routine development [1]. Our finding supports this speculation.

VI. Conclusions and Future Work

In conclusion, this study introduces a novel machine learning method, EMHMM, to analyze individual learners' eye movement patterns during reading, which contribute to the toolbox of multimodal learning analytics. The results showed that eye movement pattern and consistency predicted passage reading performance in addition to language proficiency and general cognitive abilities. More specifically, through EMHMM we discovered that an eye movement pattern that involved a larger proportion of horizontal saccades was associated with faster reading speed. In addition, higher English proficiency predicted faster reading speed through the mediation of this eye movement pattern or longer saccade length. In contrast, a more consistent fixation behavior in the beginning of reading engagement predicted higher comprehension accuracy, as eye fixation consistency reflects high-level reading expertise or skills. Thus, eye movement pattern and consistency predicted different aspects of individual differences in reading performance. As participants in this study were English as second language learners and thus new studies are needed for investigating whether the same findings would hold for first language learners. This study fills the research gap on how eye movements could account for individual differences in reading performance with the EMHMM methods, the empirical and methodological contributions of which have important implications for assessing and/or facilitating learners' reading through eye movement analysis.

Acknowledgment

This research is supported by National Natural Science Foundation of China (No. 61703357) and the Research Grants Council of the Hong Kong S.A.R., China (No. HKU 17607018).

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