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Identifying Significant Indicators of Eye-movement and EEG-based Attention to Predict Reading Performance

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Abstract: It is important to extract students' reading data to predict their reading performance. This study aims to identify significant indicators of eye-movement and EEG-based attention and to test their predictive effectiveness on reading performance. Data were collected from 56 undergraduate students who read an illustrated science text about geography. Out of 21 reading indicators, 16 were found to have a significant correlation with reading performance. The multiple regression model suggested that *Whole time*, *Text-diagram*, *Test-text*, *Medium attention*, and *High attention* were significant indicators. They predicted 62.5% of the variation in students' reading performance.

Keywords: Reading performance, significant indicators, eye-movement, EEG-based attention

1. Introduction

Due to the rapid development of information and communication technologies, digital reading has become a dominant trend (Ogata et al., 2015). The analysis of reading behaviors is important to understand readers' reading processes. The analytic results contribute to the revision of learning materials, provision of learning interventions, identification of less effective learning strategies, and extraction of more effective learning strategies.

In web-based learning, students are required to read learning materials before performing related tasks. To successfully comprehend materials, students repeatedly interact with them. One class of interaction behaviors in the field of Human-Computer Interaction is eye-movement. Eye-movement provides a natural and efficient way to observe students' behaviors from gaze (Klami, 2010). According to the eye-mind hypothesis, eye tracking can identify what is attracting students' attention and subconscious behaviors (Just & Carpenter, 1980). Consequently, eye-tracking data can be applied to analyze students' areas of interest (AOIs), visual search processes, and information processing (Rayner, 2009; Sun et al., 2017). Researchers have found that eye-movement indicators, such as mean fixation duration and saccades (Jian, 2017), significantly correlate with learning performance in reading.

Furthermore, when reading learning materials, students' brains generate plenty of electrical activities, recorded as waveforms using electroencephalogram (EEG). EEG reflects the inherent features of brain waves. Brainwave frequencies are closely related to attention state (Prinzel et al., 2001; Sirca, Onorati, Mainardi, & Russo, 2015). Apparently, EEG can determine changes in attention state. EEG-based attention is regarded as a psychological process comprised of focus and concentration, which can improve cognition speed and accuracy (James, 1983). Sustained attention has close relationship with learning performance (Steinmayr, Ziegler, & Träuble, 2010).

The goal of this study is to identify significant indicators and to explore predictive effectiveness of these indicators on students' reading performance by combining eye-movement and EEG-based attention data. All the pertinent reading data concerning eye-movement and EEG-based attention were extracted to make a bivariate correlation analysis with students' reading performance. From a total of 21 potential explanatory reading indicators, 16 indicators with significant univariate relationship with reading performance were chosen for inclusion in a multiple regression analysis. *Whole time*, *Text-diagram*, *Test-text*, *Medium attention*, and *High attention* were the indicators that significantly predicted reading performance, explaining over 60% of the variation in reading performance. The results support the viewpoint that few reading indicators are able to accurately predict reading performance. Hence, the provision of reading materials that improve the level of learning attention should be of high priority during the design and practice of online reading.

2. Related Work

The surge of internet promotes the revolution and development of human learning style. As one of important symbols in the digital age, digital reading occupies a high proportion in the current learning scene, from paper to electronic, from single-media form to multimedia forms. In reading process, students produce massive interactions reflecting their engagement, which has an indelible impact on final performance (Liu, Chen, Zhang, & Rao, 2018). Hence, reading interaction data can be employed to determine the level of students' reading performance. This knowledge can help instructors to provide appropriate guidance for students in different reading states.

Eye-movement, revealing the allocation of visual attention in information search, is typically a reading interaction. Researchers have found that eye-movement data were able to estimate different levels of reading comprehension (J. Li, Ngai, Leong, & Chan, 2016; Sanches, Augereau, & Kise, 2018). Also, the associations between eye movements and reading performance were explored. For example, Everatt and Underwood (1994) found that gaze durations accounted for 9% in reading comprehension scores. S. C. Chen et al. (2014) demonstrated that eye-movement behaviors, especially the mean fixation duration and re-reading time in proportion, could successfully quantify students' performance. Similarly, Peterson et al. (2015) indicated that eye fixation and fixation sequence features were good predictors to assess learning performance. Moreover, features from eye-movement were extracted to predict reading performance by using machine learning approaches, whose results presented relatively high prediction effectiveness (Khedher & Frasson, 2016; Rajendran, Carter, & Levin, 2018). However, eye-movement data base on the external behaviors, which ignore students' internal cognitive states. By contrast, reading data based on physiological signals, such as EEG, are more reliable.

EEG measurements, recording electrical activity along the scalp, are correlated with students' goal-directed attention allocation revealed by their eye movements (Gwizdka, Hosseini, Cole, & Wang, 2017). There are strong correlations between individual differences in reading rate and brain activity, and reading rate can be predicted well by measurements of brain activity (Demb, Boynton, & Heeger, 1997). From the cognitive psychology perspective, EEG instantly shows the attention level (Ghassemi, Moradi, Doust, & Abootalebi, 2009; X. Li et al., 2011). Attention has a positive correlation with learning. The higher the level of attention, the more effective the learning. Also, C. M. Chen and Huang (2014) suggested that sustained attention and reading comprehension were strongly correlated, showing that sustained attention to learning materials is the prerequisite for effective learning. All of the aforementioned studies validated the effective predictive ability of their reading indicators and identified critical variables to predict reading performance accurately. However, notably few studies have been done to examine the effects on reading performance by combining eye movements and EEG-based attention. The combination may be more effective in reading performance prediction.

3. Methods

3.1 Participants

After preprocess, this study considered data of 56 undergraduate students. 24 of them were male, 32 were female, and their age ranged from 21 to 23. Students majored in non-geography and took fundamental geography courses in middle schools, so they already possessed some prior knowledge to address the geography science problem. All participants had normal or corrected-to-normal vision.

3.2 Materials

An illustrated science text was provided for participants to read, shown in Fig. 1. The article topic was the principle of tornado, consisting of a title, text section, illustration section and test section. The text section included three paragraphs: the first briefly depicted tornadoes; the second presented the process of tornado formation during airflow motion; and the third introduced types of tornadoes. The illustration section related to Paragraph 2 of the text described the processes of airflow movement in detail. The test section included three test questions related to the article topic. Answers to the three questions were scored 0 to 6 according to their degree of correctness and completeness.

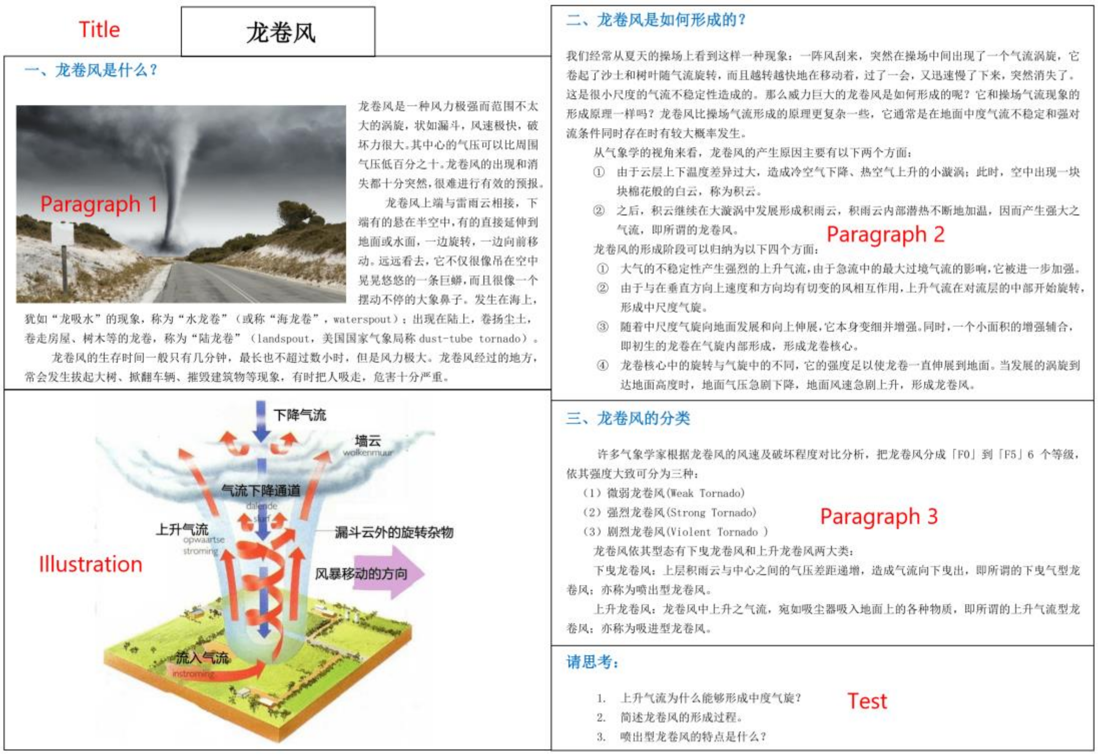

Figure 1. Six AOIs (title, paragraph 1, paragraph 2, paragraph 3, illustration and test) of the reading material. The participants in this study did not see the black frames.

3.3 *Data Source*

Data from 56 participants were recorded by the Tobii T60 eye tracker and the Neurosky mobile EEG headset. After calibration, participants were instructed to read carefully the material in less than 600s approximately. After finished reading, participants immediately completed the three questions. For these questions, the answers were scored by two independent raters who were blind to the purpose of the study. For each question, inter-rater reliability was evaluated with the Cohen's Kappa coefficient. The inter-rater reliability Kappa ranged from 0.891 to 0.975, showing fair to very good reliability. The score of each question was identified using the average score of two raters. Finally, the test grade was calculated as the sum of scores for all questions. Mean grades were 9.905 (SD = 4.126). Additionally, we first studied the whole reading material as one AOI and then divided it into three AOIs: text, diagram, and test, similar to Jian (2017). The collected features included 17 eye-movement indicators and 4 EEG-based attention indicators. EEG-based attention values, ranging from 0 to 100, were averaged to produce the attention value and categorized to three different types as Low (value under 40), Medium (value between 40 and 60), and High (value above 60). Details are shown in Table 1.

4. Results

To investigate eye-movement and EEG-based attention indicators that significantly correlated with students' reading performance, Pearson correlation analysis was performed. Then, to identify significant indicators that predicted student reading performance, inferential statistics were employed. The inferential analysis was a forward stepwise multiple regression, run on SPSS 20.0 with level of significance of .05.

The results about Pearson correlation coefficient (PCC) were presented in Table 1. There were 16 indicators (12 eye-movement indicators and 4 EEG-based attention indicators) with a statistically significant correlation ($p < 0.05$). Both *Text rate* and *Low attention* were negatively correlated with students' test grades. By contrast, others had a positive correlation. Within the significant subset of the reading indicators, 9 demonstrated a moderate effect size (PCC = 0.40-0.59). The remaining 7 indicators had a weak effect size (PCC = 0.20-0.39). Obviously, *Mean attention* (PCC = 0.536) and *High attention* (PCC = 0.592) have better effect size than all eye-movement indicators.

Although correlation coefficients are of great value in identifying the relationship of two indicators, correlation is simply a way to describe how two indicators vary together and cannot control for the other indicators that affect the dependent indicator, thereby giving false relationships. By contrast, linear regression gives coefficients when controlling for the other indicators, capturing in a better way the effect of independent indicators on dependent indicators (Lai, Sun, Wu, & Xiao, 2019; Zacharis, 2015). More importantly, a stepwise regression is a robust and valid method to find the best set of independent indicators that significantly predict student reading performance. Hence, this study employed a forward stepwise multiple regression, in which indicators that are not statistically significant in relation to the predictive power of the model are removed. From the set of significantly correlated eye-movement and EEG-based attention indicators, 16 potentially significant indicators were identified for inclusion in a multiple regression analysis. As presented in Table 2, *Whole time* ($B = -0.018$, $p < 0.01$), *Text-diagram* ($B = 0.014$, $p < 0.01$), *Test-text* ($B = 0.024$, $p < 0.01$), *Medium attention* ($B = 0.032$, $p < 0.001$), and *High attention* ($B = 0.025$, $p < 0.001$) were significant in predicting reading performance. The variance of student reading performance explained by the best fitting model was 62.5%. This showed that the 5 predictors contributed significantly to the predictive model. Moreover, the model was validated via 5-fold cross-validation with PCC, concordance correlation coefficient (CCC), mean absolute error (MAE), and root mean square error (RMSE) used as metrics for the fit. The experiments were conducted in WEKA 3.8. The experimental results showed that the regression model with a PCC of 0.621 ($p < 0.01$), CCC of 0.616, MAE of 2.969, and RMSE of 3.666, provided good prediction effectiveness. This confirmed the robustness of the model.

Table 1

Eye-movement and EEG-based attention indicators

	Attribute name	Description	PCC
Eye-movement	Whole time	Total reading time in whole article	0.498***
	Whole duration	Mean fixation duration in whole article	0.081
	Text time	Total reading time in text section	0.465***
	Text fixation	Number of fixations in text section	0.399**
	Text rate	Rate of total reading time	-0.322*
	Text duration	Mean fixation duration in text section	0.082
	Diagram time	Total reading time in diagram section	0.423**
	Diagram fixation	Number of fixations in diagram section	0.445**
	Diagram rate	Rate of total reading time	0.379**
	Diagram duration	Mean fixation duration in diagram section	0.070
	Test time	Total reading time in test section	0.320*
	Test fixation	Number of fixations in test section	0.349**
	Test rate	Rate of total reading time	0.066
	Test duration	Mean fixation duration in test section	0.112
	Text-diagram	Transitions of text to diagram	0.500***
	Test-text	Transitions of test to text	0.415**
	Test-diagram	Transitions of test to diagram	0.297*
EEG-based attention	Mean attention	Attention value in average	0.536***
	Low attention	Number of low attention value	-0.282*
	Medium attention	Number of medium attention value	0.443**
	High attention	Number of high attention value	0.592***

Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 2

Multiple regression analysis on reading performance

	B	SE	Beta	R^2
Whole time	-0.018	0.005	-0.633**	0.625
Text-diagram	0.014	0.005	0.350**	
Test-text	0.024	0.009	0.305**	
Medium attention	0.032	0.007	0.567***	
High attention	0.025	0.004	0.712***	

Note: $^{**}p < 0.01$, $^{***}p < 0.001$.

5. Conclusion

The current study was conducted to explore the significant eye-movement and EEG-based attention indicators in reading and their predictive effectiveness on reading performance to build a predictive model. Students' reading performance is highly related to their engagement level, so measures that reflected the degree of engagement are specifically employed to predict reading performance. Eye-movement and EEG-based attention data are some of the most frequently examined engagement indicators in reading. However, few studies have applied the combination of eye-movement and EEG-based attention to predict students' reading performance. In this light, this study used the combination as predictors, including 21 reading indicator variables. A bivariate correlation analysis of these indicators identified 16 of them to be significantly associated with reading performance. The multiple regression model revealed that 62.5% of the variance in students' reading performance was explained by just five indicators: *Whole time*, *Text-diagram*, *Test-text*, *Medium attention*, and *High attention*. As expected, EEG-based attention indicators (*Medium attention* and *High attention*) presented stronger effect size and significance than eye-movement indicators (*Text-diagram* and *Test-text*). This indicated that EEG-based attention indicators, displaying the level of mental effort, were stronger predictors in the construction of reading performance prediction. The findings suggested that students can have trainings about how to improve their own engagement level or search for meaningful information during reading process to foster deep understanding of the reading material that would further improve their reading performance.

There are a number of limitations that may affect the overall generalizability of this study. First, the study is based on a small sample of students at a single university. Future studies may collect a larger data set from multiple universities to build more robust model of student reading performance prediction. Second, due to the short reading material displayed on a single screen, students had no click operations. Hence, no clickstream data, which may be effective to improve the accuracy of reading performance prediction, was obtained. Future studies may present longer reading material with additional pages to collect clickstream data. Finally, deep learning approaches might be considered to construct more predictive models.

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