Effects of Text Difficulty and Readers on Predicting Reading Comprehension from Eye Movements

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***Abstract*—The task of predicting reader state from readers' eye gaze is not trivial. Whilst eye movements have long been shown to reflect the reading process, the task of predicting quantified measures of reading comprehension has been attempted with unsatisfactory results. We conducted an experiment to collect eye gaze data from participants as they read texts with differing degrees of difficulty. Participants were sourced as being either first or second English language readers. We investigated the effects that reader background and text difficulty have predicting reading comprehension. The results indicate that prediction rates are similar for first and second language readers. The best combination is where the concept level is one level higher than the readability level. The optimal predictors are ELM+NN and Random Forests as they consistently produced the lowest MSEs on average. These findings are a promising step forward to predicting reading comprehension. The intention is to use such predictions in adaptive eLearning environments.**

Keywords—first language reader (L1); second language reader (L2); reading comprehension prediction; eye tracking; adaptive eLearning

I. Introduction

Online learning is now ubiquitous in tertiary education. Universities frequently offer online and / or off-campus degrees where students may have little or no face-to-face interaction with their instructors or other students. Even for university courses that deliver material traditionally, absenteeism from lectures is prevalent despite the fact it has been shown to negatively affect learning [1, 2]. As a result there is growing importance in designing effective eLearning environments. Yet eLearning for the most part is one size fits all. For the eLearning environments that provide personalization this is often done explicitly by the learner. Adaption can be provided by various methods including questionnaires [3, 4], skill level [5], motivation [6], and eye gaze [7-10].

Eye tracking has proven to be a powerful tool for investigating how humans interact with computer interfaces. With eye tracking becoming increasingly more precise and cheaper, the use of such technology in adaptive eLearning is becoming more of a reality. Eye movements can reveal much about the cognitive processes behind human behaviors. Eye movements have long been shown to reflect the reading process (see review by [11]), as they are unique in reading. Eye movements can reveal when readers encounter difficulties in reading [12] as well as text difficulty and comprehension [13]. Yet the task of predicting quantified measures of reading comprehension has been attempted with poor results [14, 15].

We investigate two factors that influence prediction performance of reading comprehension; text difficulty and first versus second language readers. To perform this investigation we conducted a study to collect eye gaze from participants as they read and completed an online tutorial and quiz. The tutorial consisted of sections of text with varying degrees of difficulty. Participants were sourced as being either first (L1) or second (L2) language English readers. We hypothesize that there will be a difference in predictive performance between L1 and L2 readers; furthermore, we predict that text difficulty will affect prediction performance. The goal is to find ways of optimizing prediction of reading comprehension.

The intended use of reading comprehension prediction from eye gaze is in the design of adaptive eLearning environments that use eye gaze to predict reading comprehension. This would allow for the omission of some assessment questions as well as to differentiate between actual understanding and accidental choice of the correct answer. We contribute to CogInfoCom research by utilizing knowledge of human cognition to develop information transfer techniques between humans and infocommunications systems that are primarily based on Internet technology and for the purpose of education. This paper is organized into the following sections: background information; user study methodology; results and analysis; implications; finishing with conclusions and further work.

II. Background

A. Eye Tracking to Analyse the Reading Process

During the process of reading the eye moves in well-studied ways that can be broadly characterized as fixations and saccades. A fixation is where the eye remains relatively still to take in visual information. A saccade is a rapid movement that transports the eye to another fixation. This behavior is due to the anatomy of the eye. At the center of the retina is a special part of the eye called the fovea. This is the part of the eye that sees in fine detail, however the foveal region is very small, being only about 0.2mm in diameter. Around the point of fixation, visual acuity extends about 2° [16]. This means that humans see very little in detail at any fixation so the eye must move around rapidly so that it can compose a more detailed view of the environment.

When reading English, fixation duration ranges anywhere between 60-500 milliseconds and is generally about 250 milliseconds [17]. Saccadic movement is between 1 and 15 characters with an average of 7-9 characters. The majority of saccades are to transport the eye forward in the text when reading English; however, a proficient reader demonstrates backward saccades to previously read words or lines about 10-15% of the time. Backward saccades are termed regressions. Short regressions can occur within words or a few words back and may be due to problems in processing the currently fixated word, overshoots in saccades, or oculomotor errors. However, longer regressions occur due to comprehension difficulties, as the reader tends to send their eyes back to the part of the text that caused the difficulty [12].

1) Eye movements and Reading Comphrension

Eye movements can be used to understand the ongoing cognitive processes that occur during reading [17]. Comprehension of text can have significant effects on eye movements [13]. A number of studies have shown there are many variables based upon comprehension functions that can influence eye movements during reading. These variables include: semantic relationships, anaphora and co-reference, lexical ambiguity, phonological ambiguity, discourse factors, stylistic conventions, and syntactic disambiguation (see review by [11]). These variables have different effects on eye movement, causing them to deviate from the default reading process. For example, syntactically ambiguous sentences induce regressions to resolve the comprehension problems [12]. Eye movements have been shown to reflect global text difficulty as well as inconsistencies within text [13]. More difficult text causes more fixations, more regressions, and longer fixation duration time. Eye movement has also been shown to indicate reading comprehension and reading skill [14, 18].

B. Providing Adaptivity in eLearning

The use of eye tracking to make eLearning adaptive is not new. The advantage of using eye tracking is that eye movements are an implicit behavior and can reveal underlying cognitive behavior [17]. Eye gaze patterns can be used to detect what kind of task the participant is performing [19] or whether a person is reading or not [20] as well as if they are reading or skimming [21]. More recently, eye gaze has been used to investigate parts of text that readers are failing to comprehend [22]. Results from this investigation indicate that eye gaze features such as number and duration of fixations can be used to identify reading incomprehension. A classic example of the use of eye tracking in eLearning is AdeLE (Adaptive e-Learning with Eye-Tracking). The AdeLE project sets out a structure for how an adaptive eLearning environment could be constructed using eye tracking data such as blink rate and how open the eye lid is [7].

Eye tracking has been shown to be an effective way of identifying learner style. Learner style is a common way of adapting learning material to suit different students [3, 4]. Eye tracking has been shown to be a potential way of identifying visual and verbal learners [8]. Eye movements in areas of interest on the page were related to measures of learner style in that investigation. Similar uses of eye tracking have been used to investigate learning behaviors between novice and advanced students when learning SQL [23]. Indeed more advanced students looked at the database schema more that novices. Studies such as this are useful for identifying such difference in order to provide more help for novice students.

One aspect that has about learning that is frequently investigated is engagement. Eye tracking has been used to identify aspects of a student's emotional state, such as stress and arousal, and adapt the material based on the identified state. An example of this is e5Learning (enhanced exploitation of eyes for effective eLearning) which uses eye gaze metrics such as fixation statistics and pupil diameter to identify the students emotional state [10]. Gaze Tutor uses eye gaze to determine the user's level of stimulation to alter the environment to stimulate the user [9]. An interesting approach to identifying students engagement comes from the use of type-2 fuzzy logic based system [24]. This novel method gauges degree of engagement to adapt the learning environment. Results show that using the system to adapt material there is significant improvement in average scores compared to other methods of adaption and no adaption.

Eye tracking is also used to analyze reading in eLearning environments. One example is iDict, a reading aid designed to help readers of a foreign language that uses eye gaze to predict when a reader is having comprehension difficulties [25]. If the user hesitates whilst reading a word then a translation of the word is provided along with a dictionary meaning. Similarly, the Reading Assistant [26] uses eye gaze to predict failure to recognize a word. The Reading Assistant then provides an auditory pronunciation of the word to aid reading. Adaption of reading material has been shown to be beneficial to young students [27]. Adaptive eBooks involves detection of reading difficulty, currently based on measures such as out load reading speed, and dynamically simplifying the text for the students. The system is designed for year 4 students and an initial study shows that such modifications can improve reading performance. However, the authors note that the reading problem detection currently used is in the system not sufficient and should be replaced, noting also that eye tracking would be a good solution.

A gap still remaining is whether reading comprehension can be quantifiably predicted from eye gaze data. Whilst there has been progress on the matter, it has been shown to be difficult to predict quantified reading comprehension measures [14, 15] .

III. User Study Methodology

A. Participants and Design

The eye gaze of 70 participants (47 male, 23 female) was recorded. Participants had an average age of 25 years with standard deviation of 9 year (age range of 18 to 60 years).

Participants' eye gaze was tracked as they read and completed a tutorial on the topic of Digital Images. The tutorial was taken from a first year computer science course on Web Development and Design offered at the Australian National University (ANU). The tutorial was composed of 9 texts of approximately 240 words in length. Given that there are 70 participants and 9 texts there is a total of 630 eye gaze sets for the prediction analysis. Due to problems in collected data 12 of these eye gaze sets had to be removed resulting in 618 eye gaze data sets for the prediction analysis.

After each text, 2 comprehension questions were asked, each scored out of 1. Each text has a readability level in one of three classes, easy, medium or hard. The readability levels are calculated using Flesch Kincaid Grade level and are described in Table I. Each increase in readability level is approximately 3 years of education.

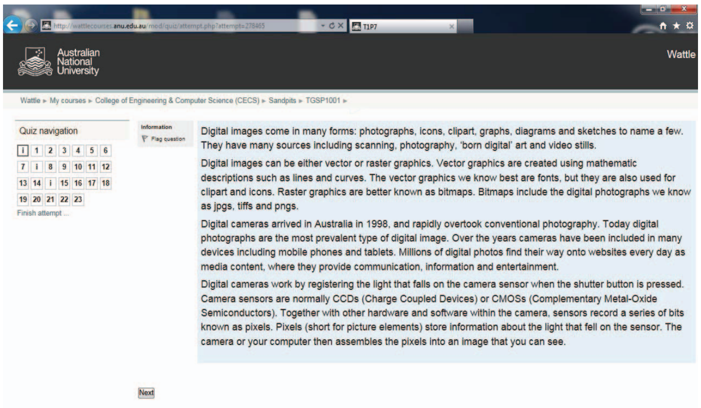
TABLE I. READABILITY GROUPS

Readability Grade	**Readability Level**		
	Easy	***Medium***	***Hard***
Flesch Kincaid Grade Level	11.3 SD 1.0	14.8 SD 0.9	18.4 SD 0.8

B. Materials and Procedure

The tutorial quiz was accessible via the online learning environment used at ANU, called Wattle (a Moodle variant). The study was displayed on a 1280x1024 pixel Dell monitor.

Fig. 1. Example of text shown in Wattle eLearning Environment



Eye gaze data was recorded at 60Hz using Seeing Machines FaceLAB 5 infrared cameras mounted at the base of the monitor. The study involved a 9-point calibration prior to data collection for each participant. As the data recorded is a series of gaze points, EyeWorks Analyze was used to pre-process the data to give fixation points. The parameters used for this were a minimum duration of 60 milliseconds and a threshold of 5 pixels.

C. Data Pre-processing

The raw eye gaze data consists of x,y-coordinates of where the participants eye was looking. Fixation and saccade identification was performed on the eye gaze data. From this data many other eye movement measures are derived. For each piece of text the following eye movement measures are calculated:

1) Inputs : Eye movements measures

a) Normalised Number of fixations: The sum of fixations recorded for each page is divided by the number of words on the page. The number of fixations can be affected by reading behavior, text difficulty, and reading skill [11].

b) Maximum fixation duration (seconds): The maximum duration of the longest fixation recorded for a tutorial page. Longer fixations can be an indicator of difficulties in processing particular words or due to linguistic and/or comprehension difficulties [11].

c) Average fixation duration (seconds): The sum of the duration of all fixations is divided by the total number of fixations. This measure has been used to predict reading comprehension [18].

d) Normalised total fixation duration (seconds): The sum of all fixations divided by the number of words in the text. This measure is useful in global text processing analysis [28] because this measures immediate as well as delayed effects of comprehension.

e) Regression ratio: The number of regressions divided by the total number of saccades on a paragraph. There is evidence that when reading more difficult text more regressions are observed [13].

f) Percentage of fixations and duration in text area and out of text area: The number of fixations as well as the duration of fixation recorded in the text area divided by the total number of fixations. The text area is shown in light blue in Fig. 1. Additionally, the inverses were calculated as inputs, that is the number of fixations and fixations duration out of the text area.

g) Number of distractions: A count of the number of times the readers eyes exited the text area to look at another part of the page.

h) Reading analysis: Using our combination of two reading detection algorithms [20, 21], the percentage of saccades classified as being part of reading (read ratio), skimming (skim ratio), and scanning/searching (scan ratio).

2) Output : Reading comprehension score

The outcome variables are in the form of the participants' reading comprehension scores. After each piece of text the participant was asked two comprehension questions. The minimum score is 0 and the maximum that could be obtained is 2 however there was part marks that could be obtained for each of the questions depending on the answer provided so that reading comprehension scores are continuous from 0 to 2.

IV. RESULTS: READING COMPREHENSION PREDICTIONS

In this investigation we consider two factors that influence prediction performance of reading comprehension, text difficulty and the difference between L1 and L2 readers. The results section is divided into three subsections that analyze the reader types separately and then combined. In each subsection we investigate the effects of text difficulty. In all of the analyses five prediction methods are trialed; regression trees, boosted regression trees, random forests, artificial neural networks trained using backpropagation (FFNN) as well as the extreme learning machine (ELM-NN) algorithm. The activation function used for the ELM+NN training is Hard-limit. The backprogation neural networks were trained using the Levenberg Mardqaurt method and a topology of [16 8 4] was used as this has proven to be an effective topology for prediction reading comprehension from eye gaze using neural networks [29]. All analyses were performed using Matlab R2013b.

A. Prediction of reading comprehension for L1 readers only

The half of the data set that was collected from L1 readers is used to predict reading comprehension using the predictions methods. Mean MSEs from 5-fold cross validation are shown in Table II.

TABLE II. MSE FROM PREDICTOR FOR L1 READERS

Text Properties		**ELM-NN**	**FFNN**	**RegTree**	**Boosted RegTree**	**Random Forest**
Readability	***Concept***					
Easy	Basic	0.39	*0.33*	0.41	0.64	0.34
Easy	Interm.	*0.23*	0.26	0.34	0.70	*0.23*
Easy	Adv.	0.39	0.49	0.45	0.72	*0.33*
Mod.	Basic	0.48	0.75	0.68	0.66	*0.42*
Mod.	Interm.	0.36	0.55	0.69	0.66	*0.34*
Mod.	Adv.	*0.18*	0.44	0.24	0.67	*0.18*
Difficult	Basic	*0.34*	0.54	0.72	0.54	0.37
Difficult	Interm.	*0.44*	0.63	0.78	0.71	0.48
Difficult	Adv.	0.46	*0.42*	0.78	0.83	0.45

The italicized are the lowest MSEs for each combination of text properties. The results show that the lowest MSEs come from the combinations where the concept level is one level higher than the readability. More specifically when the readability is *Easy* and the concept is *Intermediate* the MSE is on average 0.23 using both ELM-NN and Random Forest predictors, and when the readability is *Moderate* and the concept is *Advanced* the MSE is on average 0.18 using both ELM-NN and Random Forest predictors again. This highlights another key finding that both ELM-NN and Random Forest predictors tend to generate the lowest MSE values.

B. Prediction of reading comprehension for L2 readers only

The half of the data set that was collected from L2 readers is used to predict reading comprehension using the predictions methods. Mean MSEs from 5-fold cross validation are shown in Table III.

TABLE III. MSE FROM PREDICTOR FOR L2 READERS

Text Properties		**ELM-NN**	**FFNN**	**RegTree**	**Boosted RegTree**	**Random Forest**
Readability	***Concept***					
1	1	0.49	0.67	0.52	0.62	*0.44*
1	2	0.83	0.75	0.75	0.75	*0.43*
1	3	0.78	0.64	0.48	0.76	*0.32*
2	1	0.93	0.72	0.76	0.82	*0.62*
2	2	0.57	0.40	0.63	0.70	*0.51*
2	3	*0.26*	0.52	0.48	0.66	0.29
3	1	*0.29*	0.35	0.54	0.65	0.34
3	2	0.67	0.68	0.86	0.70	*0.58*
3	3	0.98	0.59	0.74	0.73	*0.40*

The italicized are the lowest MSEs for each combination of text properties. The MSEs predicted for the L2 data set are higher on average than from the L1 data set indicating that it is harder to make predictions from the L2 data set. In this case, primarily the Random Forest predictor produces the lowest MSEs on average. Again the lowest average MSE of 0.26 is recorded from where the readability is *Moderate* and the concept is *Advanced.*

C. Prediction of reading comprehension for both reader types combined

The full data set that was collected is used to predict reading comprehension using the predictions methods. Mean MSEs from 10-fold cross validation are shown in Table IV. Note that in this case 10-fold cross validation is used as the data set is much larger.

TABLE IV. MSE FROM PREDICTOR FOR BOTH READERS

Text Properties		**ELM-NN**	**FFNN**	**RegTree**	**Boosted RegTree**	**Random Forest**
Readability	***Concept***					
1	1	*0.31*	0.32	0.48	0.62	*0.31*
1	2	*0.26*	0.32	0.41	0.68	0.27
1	3	*0.33*	0.55	0.60	0.77	*0.33*
2	1	0.51	0.64	0.74	0.70	0.47
2	2	0.52	0.45	0.49	0.56	0.37
2	3	*0.22*	0.29	0.38	0.68	0.23
3	1	0.40	0.59	0.48	0.53	*0.34*
3	2	0.53	0.60	0.65	0.67	*0.51*
3	3	*0.39*	0.71	0.64	0.75	0.43

The italicized are the lowest MSEs for each combination of text properties. The MSEs generated from the full data set are similar to those produced from the L1 data set. This indicates that adding the L2 data does not decrease prediction power. Once again the lowest MSEs come from the combinations where the concept level is one level higher than the readability. When the readability is *Easy* and the concept is *Intermediate* the MSE is on average 0.26 using the ELM-NN predictor, and when the readability is *Moderate* and the concept is *Advanced* the MSE is on average 0.22 using the ELM-NN predictor again. Both the ELM-NN and Random Forest predictors generated the lowest MSE values.

V. IMPLICATIONS

From previous attempts to classify eye movement measures it has been established that making predictions of reading comprehension is not a trivial task [15]. Overall the goal of this investigation was to find ways of optimizing prediction performance of reading comprehension. Two factors regarding prediction performance of reading comprehension are considered in this investigation, namely, text difficulty and L1 versus L2 readers. The results from the study indicate that there is a difference in predictive performance between L1 and L2 readers, as we hypothesized. However, this difference is not large and when the two groups are combined there is not a negative impact on prediction outcomes (Table IV). This is a somewhat surprising result given that past research has shown that while L1 and L2 readers have the same comprehension they do have different eye movements during reading, as well as taking longer to read [30]. It was therefore hypothesized that this difference would negatively impact the predictions from L1 and L2 readers combined given that they have different eye movements. The implication of this in the design of a predictor for reading comprehension in intelligent eLearning is that different predictors do not have to be created for each of the different reader types. This makes the prediction process simpler and less intrusive to the reader since explicitly asking them about their first language is not needed.

Our second hypothesis was that text difficulty affects prediction performance. We found that texts with combinations of difficulty where the concept level is one level higher than the readability produced the best prediction outcomes. In particular when readability is *Easy* and the concept is *Intermediate* and when the readability is *Moderate* and the concept is *Advanced.* The implication of this in the design of intelligent eLearning is that to obtain the best prediction results using this combination of text difficulty.

Finally, the investigation showed that the most effective predictor of the data set are ELM+NN and Random Forests as they consistently produced the lowest MSEs on average. These predictors should be considered when constructing a predictor of reading comprehension from eye movement measures.

1) Use Case: Adaptive learning paths

The goal of reading comprehension detection is to incorporate eye tracking into eLearning environments and use this data as a form of adaption. In this way the content and the presentation of content can be altered to reflect the student's current state. The product of reading comprehension prediction is twofold; first, if students are given text to learn, instead of formatively assessing their comprehension, eye tracking could be used to assess their understanding thus reducing time, workload and potentially stress or anxiety of the students. Following on from this, predicting students' comprehension using eye tracking would allow the learning environment to adapt 1) assessment questions about the content, and 2) the content difficulty to reflect the students' current understanding levels.

If a student has read some learning materials but does not understand them altering the learning path could be used to increase understanding. This could be achieved by modifying the questions to be easier, perhaps covering more superficial understanding of the content. Text with more explanation of the content that was not understood could then be given, after which they are assessed on the original comprehension questions. This could otherwise be achieved by not asking comprehension questions at all, the text with more explanation could be provided to the student. Previous studies have shown that simplifying text can improve reading performance [27].

The inverse case where a student has an extremely high level of understanding, as in the case when the student has prior knowledge on a certain topic, this student may become frustrated or bored by being presented with easy content and unchallenging questions. Either the questions or the content could be altered to present these students with hard subject matter and questions that require much more thought and insight than the student with a lower level of understanding.

2) Implications for CogInfoCom

CogInfoCom is the investigation of links between cognitive science and information communication technology (ICT). The role of this is to support development and analysis of the co-evolution of infocommunications and the capabilities of the human brain [31]. The pervasive use of Internet technologies and increasing ubiquity of online learning environments means that there is an inextricable link between learning and these technologies. We contribute to CogInfoCom by investigating the inter-cognitive communication between students and online learning environments. Students learn differently now due to the existence of online learning and so our proposition is that online learning environments must evolve to take into consideration the changes in learners' needs. This is achieved through multi-modal interaction, namely eye tracking technology, between the student and the learning environment to dynamically adapt to the learners' implicit behaviours.

VI. Conclusion and Further Work

We investigated the effects that reader type and text difficulty have on predicting reading comprehension from eye movements. The overall goal is to provide insight into optimizing prediction performance for reading comprehension as it has been established as being a non-trivial task [15].

Whilst predictions from L2 readers are worse compared to L1 readers, in a combined data set there is not a significant negative impact on prediction outcomes. This implies that L1 and L2 reader can use the same predictor without negatively impacting prediction performance. Additionally, text difficulty affects prediction performance. The best combination is where the concept level is one level higher than the readability. Finally, the optimal predictors are ELM+NN and Random Forests as they consistently produced the lowest MSEs on average.

Further improvements on predictions should be explored by investigating the effectiveness of additional physiological data to see if this also increases classification results. Proposed physiological data could be in the form of pupil dilation, galvanic skin response (GSR), electrocardiogram (ECG) and electroencephalogram (EEG). Another area of investigation is breaking down the eye movement measures to different levels of granularity.

Acknowledgment

Thank you to all of the participants who took part in the study. Many thanks go to the proofreaders for your helpful comments.

References

[1] D. Romer, "Do Students Go to Class? Should They?," *The Journal of Economic Perspectives,* vol. 7, pp. 167-174, 1993.

[2] R. Woodfield, D. Jessop, and L. McMillan, "Gender differences in undergraduate attendance rates," *Studies in Higher Education,* vol. 31, pp. 1-22, 2006/02/01 2006.

[3] H. D. Surjono, "The design of adaptive e-Learning system based on student's learning styles," *International Journal of Computer Science and Information Technology (IJCSIT),* vol. 2, pp. 2350-2353, 2011.

[4] H. D. Surjono, "The Evaluation of a Moodle Based Adaptive e-Learning System," *International Journal of Information and Education Technology,* vol. 4, 2014.

[5] C.-M. Chen, "Intelligent web-based learning system with personalized learning path guidance," *Computers & Education,* vol. 51, pp. 787-814, 9// 2008.

[6] F. Kareal and J. Klema, "Adaptivity in e-learning," *A. Méndez-Vilas, A. Solano, J. Mesa and JA Mesa: Current Developments in Technology-Assisted Education,* vol. 1, pp. 260-264, 2006.

[7] C. Gütl, M. Pivec, C. Trummer, V. M. García-Barrios, F. Mödritscher, J. Pripfl*, et al.*, "Adele (adaptive e-learning with eye-tracking): Theoretical background, system architecture and application scenarios," *European Journal of open, Distance and E-learning (EURODL),* vol. 2, 2005.

[8] T. J. Mehigan, M. Barry, A. Kehoe, and I. Pitt, "Using eye tracking technology to identify visual and verbal learners," in *Multimedia and Expo (ICME), 2011 IEEE International Conference on*, 2011, pp. 1-6.

[9] S. D'Mello, A. Olney, C. Williams, and P. Hays, "Gaze tutor: A gaze-reactive intelligent tutoring system," *International Journal of Human-Computer Studies,* vol. 70, pp. 377-398, 2012.

[10] C. Calvi, M. Porta, and D. Sacchi, "e5Learning, an e-learning environment based on eye tracking," in *Advanced Learning Technologies, 2008. ICALT'08. Eighth IEEE International Conference on*, 2008, pp. 376-380.

[11] K. Rayner, "Eye movements in reading and information processing: 20 years of research," *Psychological Bulletin,* pp. 372-422, 1998.

[12] L. Frazier and K. Rayner, "Making and correcting errors during sentence comprehension: Eye movements in the analysis of structurally ambiguous sentences," *Cognitive Psychology,* vol. 14, pp. 178-210, 1982.

[13] K. Rayner, K. H. Chace, T. J. Slattery, and J. Ashby, "Eye movements as reflections of comprehension processes in reading," *Scientific Studies of Reading,* vol. 10, pp. 241-255, 2006.

[14] P. Martínez-Gómez and A. Aizawa, "Recognition of understanding level and language skill using measurements of reading behavior," in *Proceedings of the 19th international conference on Intelligent User Interfaces*, 2014, pp. 95-104.

[15] L. Copeland, T. Gedeon, and S. Mendis, "Predicting reading comprehension scores from eye movements using artificial neural networks and fuzzy output error," *Artificial Intelligence Research,* vol. 3, p. p35, 2014.

[16] K. Rayner and J. H. Bertera, "Reading without a fovea," *Science,* vol. 206, pp. 468-469, 1979.

[17] S. P. Liversedge and J. M. Findlay, "Saccadic eye movements and cognition," *Trends in cognitive sciences,* vol. 4, pp. 6-14, 2000.

[18] G. Underwood, A. Hubbard, and H. Wilkinson, "Eye fixations predict reading comprehension: The relationships between reading skill, reading speed, and visual inspection," *Language and speech,* vol. 33, pp. 69-81, 1990.

[19] S. T. Iqbal and B. P. Bailey, "Using Eye Gaze Patterns to Identify User Tasks.," *The Grace Hopper Celebration of Women in Computing 2004,* 2004.

[20] C. S. Campbell and P. P. Maglio, "A robust algorithm for reading detection," in *Proceedings of the 2001 workshop on Perceptive user interfaces*, 2001, pp. 1-7.

[21] G. Buscher, A. Dengel, and L. v. Elst, "Eye movements as implicit relevance feedback," presented at the CHI '08 Extended Abstracts on Human Factors in Computing Systems, Florence, Italy, 2008.

[22] S. Martinez-Conde, "Fixational eye movements in normal and pathological vision," *Progress in brain research,* vol. 154, pp. 151-176, 2006.

[23] Z. Liu, "Reading behavior in the digital environment: Changes in reading behavior over the past ten years," *Journal of documentation,* vol. 61, pp. 700-712, 2005.

[24] A. Paramythis and S. Loidl-Reisinger, "Adaptive learning environments and e-learning standards," in *Second European Conference on e-Learning*, 2003, pp. 369-379.

[25] A. Hyrskykari, P. Majaranta, A. Aaltonen, and K.-J. Räihä, "Design issues of iDICT: a gaze-assisted translation aid," in *Proceedings of the 2000 symposium on Eye tracking research & applications*, 2000, pp. 9-14.

[26] J. L. Sibert, M. Gokturk, and R. A. Lavine, "The reading assistant: eye gaze triggered auditory prompting for reading remediation," presented at the Proceedings of the 13th annual ACM symposium on User interface software and technology, San Diego, California, United States, 2000.

[27] A. Dingli and C. Cachia, "Adaptive eBook," in *Interactive Mobile Communication Technologies and Learning (IMCL), 2014 International Conference on*, 2014, pp. 14-19.

[28] J. Hyona, R. F. Lorch Jr, and M. Rinck, "Chapter 16 - Eye Movement Measures to Study Global Text Processing," in *The Mind's Eye*, J. Hyona, R. Radach, R. R. H. DeubelA2 - J. Hyona, and H. Deubel, Eds., ed Amsterdam: North-Holland, 2003, pp. 313-334.

[29] L. Copeland, T. Gedeon, and S. Mendis, "Fuzzy Output Error as the Performance Function for Training Artificial Neural Networks to Predict Reading Comprehension from Eye Gaze," in *The 21st International Conference on Neural Information Processing 2014*, 2014.

[30] H. Kang, "Understanding online reading through the eyes of first and second language readers: An exploratory study," *Computers & Education,* vol. 73, pp. 1-8, 2014.

[31] P. Baranyi and A. Csapo, "Definition and synergies of cognitive infocommunications," *Acta Polytechnica Hungarica,* vol. 9, pp. 67-83, 2012.