

Can Page-Flip Predict Better Reading Comprehension? – A Preliminary Study

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Abstract: This paper explores the possibility to relate the learning log data collected on the eTextbook to the prediction of the learner's proficiency or scores of the test. The current study focuses on theories of reading comprehension involving textual and graphical information. The cognitive theory of multimedia learning requires that the reader should select, organize and integrate words and images under the three assumptions; Dual-Channel, Limited Capacity, and Active Processing. Integrated model of text and graphical comprehension assumes that dual coding applies the processing of both texts and graphics and that the processing of one mode has a strong relationship with the other to comprehend the materials better. It is natural to assume that the repetition of re-reading occurs when the reader tries to better comprehend some parts of the text, and that this should be reflected as "page-flipping" behavior, often employed in previous studies in the field of learning analytics. By employing the learning log data by digital teaching material delivery system "BookRoll", this paper considers the possibility to employ "page-flipping" behavior to predict the scores of the achievement test. A total of 10 participants were randomly selected from both upper and lower groups and subject to analyses of their learning behaviors. Although findings from the study suggest a mixed result, this paper suggests that this approach is worth perusing in the case of academic reading with graphics with the control of the structures.

Keywords: eTextbook, Reading Comprehension, Cognitive Theory of Multimedia Learning, Integrated Model of Text and Picture Comprehension, Page-Flipping History

1. Introduction

Needless to say, reading comprehension is essential to acquire a new knowledge. One of the purposes of primary education is teaching students how to read (Alexander, 2005). Recently, digital textbooks and websites contain various kinds of visual displays to support learning: diagrams, graphs, photographs, charts, maps, etc. (Mason, Tornatora, & Pluchino, 2015). In addition, free online educational videos (e.g., YouTubes, TedTalks, MOOCs, etc.) are among such multimedia textbooks that have been frequently employed in a flipped-classroom teaching model in secondly and higher education (e.g., Ono & Nakajima, 2017).

The increasing amount of data generated in digital learning contexts provides opportunities to benefit from learning analytics. A great many of researchers analyze the collected data and make sense of these data for personalized scaffolding and services to stakeholders including students, faculty/teachers and administrators. It has been pointed out that the data that can be collected during the study are not necessarily related to pedagogical or psychological constructs, with these log data resulting in less correlation to their score or proficiency prediction (Kusanagi, 2017). However, some of the previous studies have shown that the data can predict their learning process and achievement (e.g., Yamada et al., 2016).

In the context of reading comprehension, especially ESL/EFL reading, the role of multimedia on the text in comprehension has been discussed so far. Mayer's multimedia principle suggests that comprehension is better when learning from text and pictures, rather than from text alone (Mayer, 2009). In order to understand the content deeply, learners should read text, move to the page illustrating pictures, and go back to the text again to re-read, reflecting "going forward and

coming back” page- flipping behaviors. In sum, our assumption is that participants who understand the text better should have this type of repeating behavior among the pages of text and graphics.

This type of study is popular with reading comprehension research for secondary education in the field of ESL/EFL. Recently, by employing “eye-tracking” methodology, the cognitive theory of multimedia learning has come to be unraveled (e.g., Mason, Tornatora, & Pluchino, 2015). However, as far as I know, no studies have clarified the relationship between reading comprehension and page-flipping behavior. Nor have I seen a case study of academic eTextbooks in higher education. In addition, the studies so far have not paid attention to the properties of each page of the eTextbook. These are the gaps that we need to make up for and this paper tries to observe what happens when successful/unsuccessful learners read the eTextbooks.

2. Previous Studies

2.1 The Cognitive Theory of Multimedia Learning

Mayer (2009) proposed that the cognitive theory of multimedia learning involves the following three essential steps to understand verbal and graphical information: **selection**, **organization**, and **integration**.

Selection: the extraction of relevant words from the text and relevant elements from the picture

Organization: the processing of the selected material further for comprehension and retention of textual and graphical information.

Integration: the connecting of these two models with each other and with relevant prior knowledge retrieved from long-term memory to form a coherent mental representation.

The model is described in Figure 1 below.

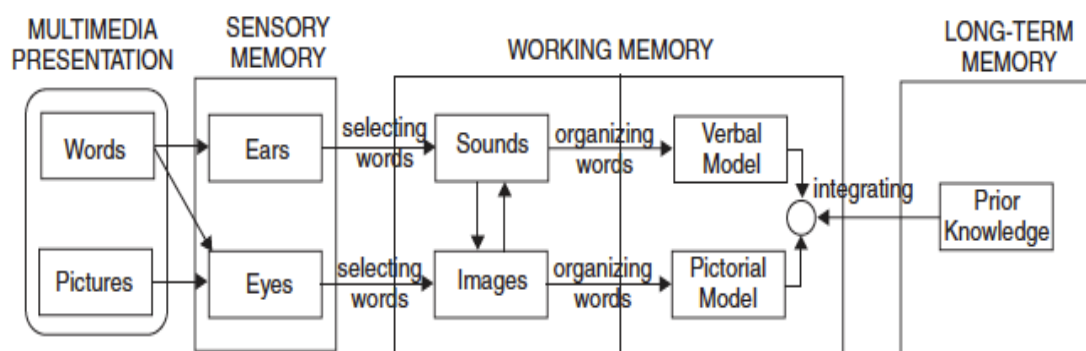


Figure 1. Cognitive theory of multimedia learning (Mayer, 2009, p. 61).

With this model in mind, Mayer (2009, p. 63) further posits the three assumptions: Dual Channel, Limited Capacity, and Active Processing. Dual Channel assumes that humans possess separate channels for processing visual and auditory information. Limited Capacity is proposed to state that humans are limited in the amount of information that they can process in each channel at one time. Active processing states that humans engage in active learning by attending to relevant incoming information, organizing selected information into coherent mental representations, and integrating mental representations with other knowledge. From the theories and assumptions above, we can conclude that we need to spend time in processing selection, organization, and integration from the multimedia textbook. Note that this study does not employ the eTextbook with recorded voice or sound. In other words, we are concentrating only on the information input from eyes.

2.2 The Integrated Model of Text and Picture Comprehension

The model assumes that dual coding applies to the processing of both texts and images, and the different principles of representation complement each other (Schnotz, 2014; Schnotz & Bannert, 2003). Dual coding theory assumes that dual coding of information provides better recognition and recall performance because if one code is forgotten the other code may still be accessible in memory. Thus, these theories predict that successful readers would take the following three steps: (i) Read the whole text to get a central concept; (ii) Examine the picture using the information obtained in (i), shifting from one to the other; and (iii) Relate the two types of representations and verbalize the integrated representation. The point here is that the successful readers would shift from text to pictures again and again in steps (ii) and (iii). If the text and the picture are given on different pages, they will have to flip the pages again and again, resulting in activated learning behavior of page-flipping.

2.3 Page-Flipping History

Horikoshi, Yamazaki and Tamura (2015) examined whether the index of page-flip history during learning is relevant to learning styles. The result was that a feature that learners glance all materials during a certain time period, was significantly relevant to “Global” learning style, where students glance at all the materials at first and then go local. In this case, it is highly expected that the learner will repeat the above steps for deeper understanding the details about the text. However, this study does not say anything about the prediction about the score since their focus is on the predicting learning styles. In addition, the properties of the pages have not been considered, either.

2.4 Learning Environment and Data to be Collected



Figure 2. Interface of BookRoll.

This paper employs the learning log data “Data1” by digital teaching material delivery system “BookRoll” (Flanagan & Ogata, 2017; Ogata et al., 2015), provided for ICCE2018 Learning Analytics Workshop. Actually, the system collects data of BOOKMARK, MARKER, and MEMO as well as PAGES. This study, however, picks up PAGES data for the purpose of counting up the frequency of coming back. The screenshot of the interface is given in Figure 2.

3. Method

3.1 Participants

The dataset contains 50 participants of university students. The eTextbook looks like a PDF file of the lecture slides. The dataset also contains the final score data ($n = 53$, $M = 78.0$, $SD = 25.1$, $MAX = 100$, $MIN = 0.0$). As many as 20 participants got 100 points, while 10 participants were within 0-50 points. Therefore, on the basis of the final score data, we picked up five participants randomly from the top 20 participants as Upper group and other five from the lowest 10 participants as Lower group.

Table 1
Participants in This Study

ID	Action Frequency	Score
L01	89	50
L02	1301	50
L03	341	50
L04	618	40
L05	425	40
U01	1950	100
U02	376	100
U03	207	100
U04	2368	100
U05	208	100

Note. L = Lower; U = Upper.

3.2 Reading Materials

The eTextbook consists of 86 slides. Some of the slides contains pictures, words, or both. Japanese is written for some slides and English for others. Since the topic is “Social Networking”, a rather academic topic, some vocabularies might be too difficult for some lower students to follow.

3.3 Procedures

In order to examine the relationship between page-flipping behavior and test scores, the following three analyses are conducted.

Analysis (1) Visualization of frequency to observe learning behavior

Analysis (2) Cluster Analysis to divide 10 participants into clusters whether they are appropriately divided

Analysis (3) Observation of individual participant’s behavior on the time scale

3.4 Results

As to the Analysis (1), the following picture was obtained as illustrated below:

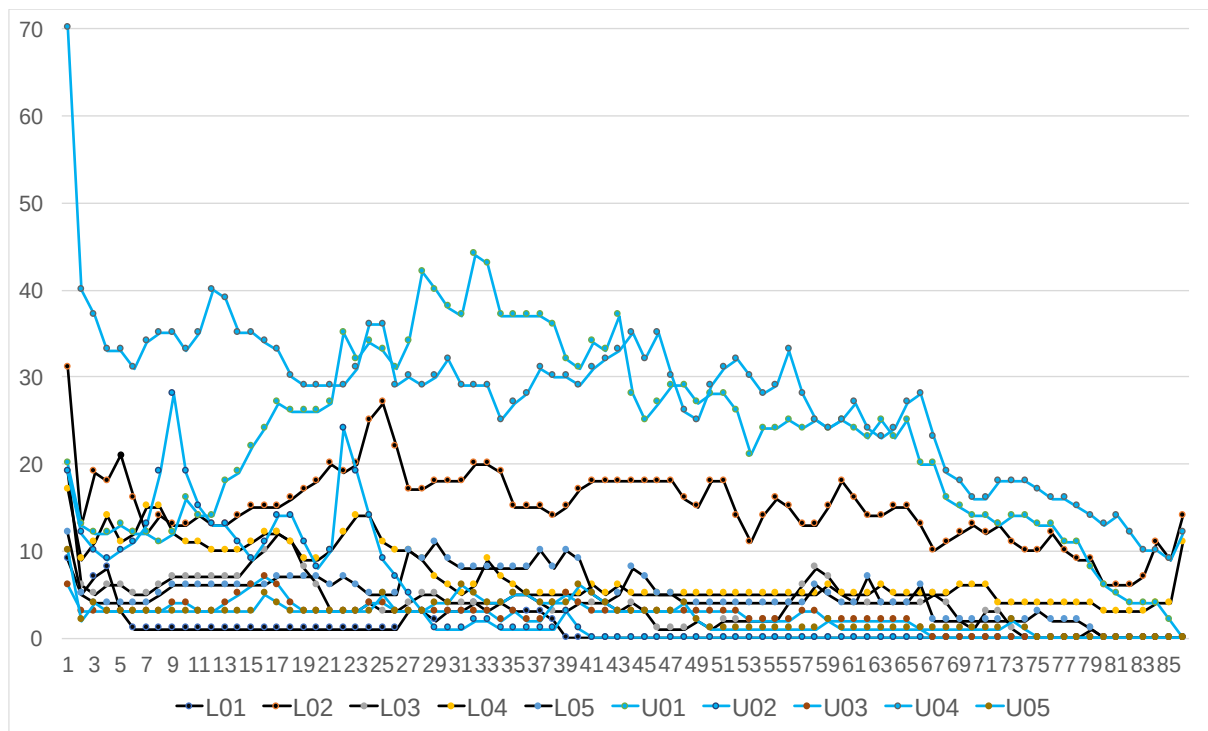


Figure 3. Screenshots of some pages.

The x-axis represents page numbers, and the y-axis represents frequency. The lines in blue are the participants of Upper group while those in black are the participants of Lower group. It is clear that the result given in Figure 3 on the basis of frequency of page-flipping history does not distinguish Upper group from Lower group.

Thus, let us move to Analysis (2). Cluster analysis (Ward's Method, Euclidean Distance) was conducted as to these data. The obtained dendrogram is given below as in Figure 4.

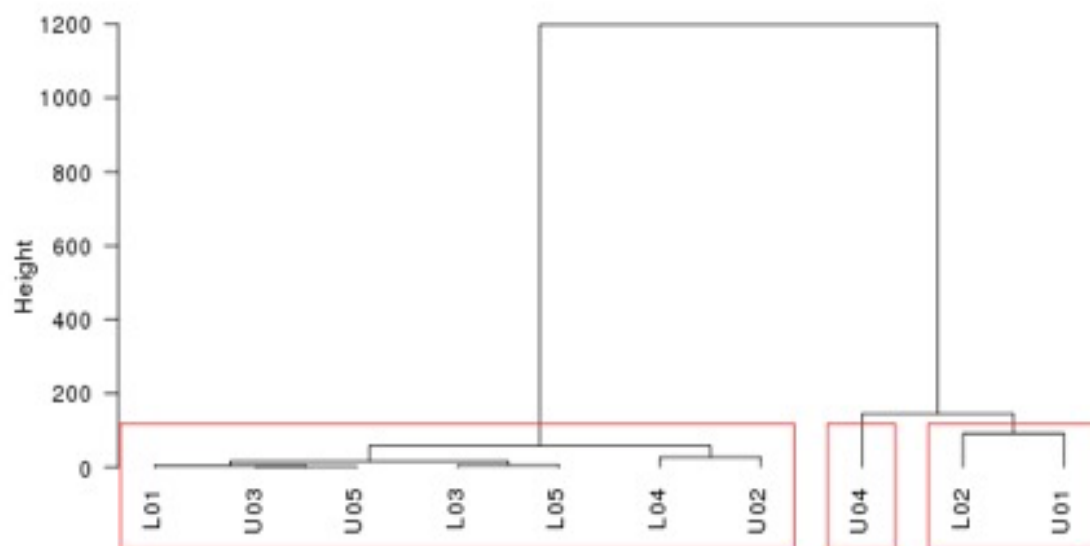


Figure 4. Dendrogram of the Cluster Analysis.

When we decide to create three clusters as illustrated in Figure 4, we can see that both Upper and Lower participant(s) are included in each cluster. This means that the clustering based on the frequency on pages does not divide participants properly, or predict test scores correctly.

To observe learning behavior on an individual level, let us move on Analysis (3); each participant's behavior of different clusters. As an example, we will see participants L04 and U02, both of whom are of the same cluster, but their scores are different.

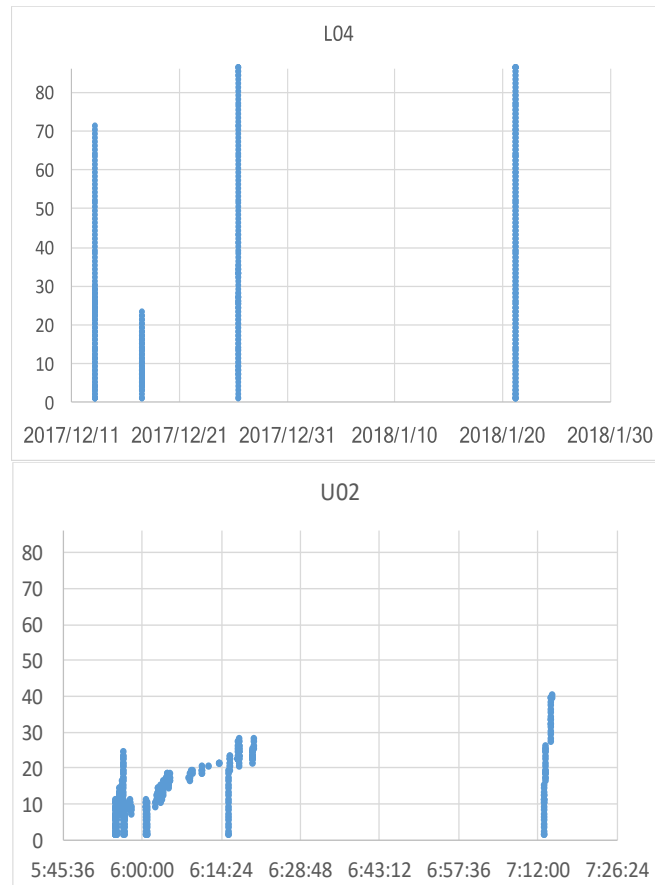


Figure 5. Reading Behaviors of L04 and U02.

The behaviors of L04 and U02 are similar in that they took some rest after finishing reading the text. Interestingly, U02 did not read the whole textbook, since the line stops somewhere around 40 pages. This behavior is a typical sign for a dropout without further information or contexts. However, the score is 100. This might suggest that the data is far from relevant to the performance.

However, looking at the data closely reveals that this participant (U02) re-read some pages a lot, spending some time for understanding the material. On the contrary, the first reading of L04 is pages 1-74 in less than 10 minutes. The participant did not seem to re-read sufficiently for understanding the material but repeat the linear reading again and again. Although it is not statistically clear about the line for diving the groups at all, this type of difference might be useful to divide those who read well from those who do not.

Similar thing can be said about the following two participants belonging to different clusters as to their re-reading behavior.

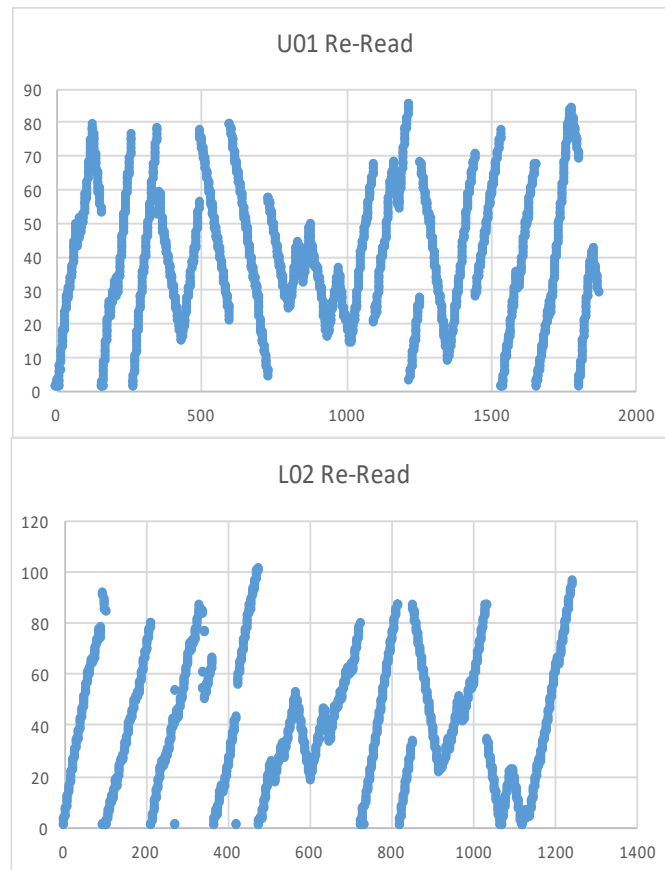


Figure 6. Re-reading Behaviors of U01 and L02.

U01 shows more “up and down” behaviors during the re-reading, signaling that they are comprehending the text in accordance with the integrated model of text and picture comprehension. L02’s behavior looks similar. However, there are fewer “up and down” behaviors on this graph. This participant is repeating, but he/she does not spend sufficient time integrating two or more slides.

These observations might lead to the possibility that the frequency of “up and down” might matter instead of total frequency of pages, and that calculating based on this new index might help us understand whether the learner sufficiently comprehend the text on eTextbook.

4. Discussion and Conclusion

This paper considered the possibility of relating page-flip behavior to reading comprehension of the text and pictures. It started with theoretical review about multimedia learning and the integrated model of text and picture comprehension. Findings from the study suggest a mixed result so far. However, the data can be related with re-reading behavior for verbal-graphic integration for better understanding. If this is true, this will connect indexes of learning analytics with pedagogical or cognitive theories, which is highly expected in the field of learning analytics (Ogata, 2017; Yamada, 2017).

The future research will involve the following tasks. The eTextbook we used in this study is purely for lecturer preparation, and it is possible for the material of reading comprehension. It is surely interesting to repeat this type of study based on the material of EFL/ESL reading under computer-assisted environment.

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