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Analyzing Learning Patterns Based on Log Data from Digital Textbooks

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ABSTRACT

The analysis of learning behaviors from the log data of digital textbooks is beneficial for improving education systems. The focus of discussion in any analysis of learning behaviors is often on discovering the relationships between learning behavior and learning performance. However, little attention has been paid to investigating and analyzing learning patterns or rules among learning style of index (LSI), cognitive style of index (CSI), and the logs of digital textbooks. In this study, the authors proposed a method to analyze learning patterns or rules of reading digital textbooks. The analysis method used association analysis with the Apriori algorithm. The analysis was conducted using logs of digital textbooks and questionnaires to investigate students' learning and cognitive styles. From the detected meaningful association rules, this study found three student types: poorly motivated, efficient, and diligent. The authors believe that consideration of these student types can contribute to the improvement of learning and teaching

KEYWORDS

Association Rule, Cognitive Style, Digital Textbooks Reading Log, Learning Analytics, Learning Style

INTRODUCTION

With the development of e-publishing technologies and standards, it is easy to obtain digital books, such as "living books," "talking books," and "CD-ROM books," from the Internet (Yin et al., 2015). Digital books have become a potentially effective pedagogic tool (Hezroni, 2004; Reinking, 1997; Snyder, 2002), indicated by the fact that digital book reading has increased significantly in the United States (Lee et al., 2012). Consequently, traditional textbooks are being increasingly replaced by digital textbooks (Ren, Uosaki, Kumamoto, Liu, & Yin, 2017).

Many researchers have been paying attention to the development of digital books to support teaching, learning, and scholarship. By using digital books, large bodies of log data can be accumulated, the analysis of which can be used to perform learning analytics.

Learning analytics can be used in making suggestions to policy makers, instructors, and learners (Baker & Inventado, 2014; Hwang, Hsu, Lai, & Hsueh, 2017). Therefore, learning analytics have become an important issue in education (Hwang, Chu, & Yin, 2017) that have entailed important changes in educational research.

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The objective of learning analytics is to provide helpful information to optimize or improve learning designs, learning outcomes, and learning environments based on the analysis results (Greller & Drachsler, 2012; Hwang, Chu, & Yin, 2017).

In the analysis of learning behaviors in this study, we used a digital textbook system to collect students' learning logs. Learning log is defined as a digital record of what learners have learned in a formal and an informal setting (Ogata, Hou, Uosaki, Mouri, & Liu., 2014; Mouri, Ogata, & Uosaki, 2015). The system was used in a commercial law course for undergraduate students, which was conducted in entirety in English: The students were assigned readings in English, and the teacher spoke in English. We also used questionnaires to collect data on students' learning styles and cognitive styles.

Using these data, we applied the association analysis method with the Apriori algorithm to analyze students' learning patterns or rules. One of the advantages of analyzing the learning patterns or rules is the preemptive prediction of students' final grade and progresses in the future. As a result, teachers can improve their teaching strategies and support students' learning behaviors. From the analysis, this study found three meaningful student types by considering the detected association rules.

LITERATURE REVIEW

Previous Studies of Data Collection

Data collection is the first step in learning analysis (Yin, Hirokawa, et al., 2013; Yin, Sung, et al., 2013). Yin et al. (2016) performed a review of previous research to survey the methods of data collection. Based on the data collection source, previous studies of data collection can be classified into three types: Questionnaire-Based Data Collection (QDC), Manual Data Collection (MDC), and Automatic Data Collection (ADC) (Yin et al., 2014; Yin et al., 2017).

- **QDC**. In this method, data are collected by using a predesigned questionnaire. The questionnaire is a tool to elicit specific responses from the participants of the survey, and it is a data-gathering method used to collect and analyze the feedback of a group of people from a target population.
- **MDC**. In this method, a manual data collection system is open to users of the system to consciously provide data about their learning behaviors. Users may save data that they consider useful through the system by themselves. For example, if a student encounters interesting images that he or she wants to share with his or her friends, then he or she can capture images from an authentic and shareable environment.
- **ADC**. In this method, students' log data for learning behaviors are automatically recorded while reading e-documents. For example, Yin et al. (2015) analyzed learning behavior to identify students' learning style using data from the automatically recorded reading logs of the students' digital textbooks. By using the same digital textbook log data, Shimada, Okubo, Yin, and Ogata (2017) summarized lecture slides to enhance preview efficiency and improve students' understanding of the content, and Mouri and Yin (2017) found some patterns for improving learning materials.

In the present work, we used QDC and ADC methods to collect data. Three kinds of data were used to analyze students' learning patterns. The first was log data from digital textbooks (ADC). The second was students' learning style data collected through the Index of Learning Styles questionnaire. Felder and Soloman (2001) developed this questionnaire to assess preferences on four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global) of a learning style model. The third was students' cognitive style data, collected with the Cognitive Style Index questionnaire. Allinson and Hayes (1996) developed this questionnaire, which is widely used to measure cognitive styles in the field of education.

Digital Textbooks

In the past decade, various studies have been conducted to investigate the effectiveness of learning with digital textbooks. For example, Shepperd, Grace, and Koch (2008) compared the efficacy of digital textbooks and traditional textbooks and indicated that students rated the usability of digital textbooks positively. Rockinson-Szapkiw, Courduff, Carter, and Bennett (2013) compared the learning effectiveness of digital textbooks and traditional textbooks and found that digital textbooks are as effective for learning as traditional textbooks.

In contrast to traditional textbooks, digital textbooks can offer digital listening, reading, and vocabulary practice. Therefore, it is necessary to consider the design of digital textbooks for offering effective learning. Gu, Wu, and Xu (2015) reported the importance regarding the design of digital textbooks and suggested that well-designed digital textbooks positively enhance learning.

Therefore, many researchers concur that digital textbooks have become a potentially effective pedagogic tool to support teaching, learning, and scholarship (Hezroni, 2004; Reinking, 1997; Snyder, 2002).

A large body of log data can be accumulated using digital textbook systems for the purpose of monitoring students' activities. However, there are few studies analyzing the relationships between learners' learning style, cognitive style, and the log data from digital textbooks. We believe that analyzing such relationships can help in providing different forms of effective learning support in accordance with their learning and cognitive styles.

Association Analysis

This study employed association analysis using the Apriori algorithm. This method is designed to extract association rules from a database containing transactions, such as collections of items bought by customers or details of website frequentation. In educational technology fields, researchers focus on this method of analysis to mine regularities among some parameters of educational big data.

For example, Behrouz, Gerd, and William (2004) found association rules by grouping students who were enrolled in an online education system based on parameters such as GPA (Grade Point Average), age, and gender. In their study, if there were students with GPA scores between 3.0 and 3.5, the system can give them the probability of whether they can pass a course that they will attend based on the detected association rules.

Mouri and colleagues (Mouri, Ogata, & Uosaki, 2016; Mouri, Okubo, Shimada, & Ogata, 2016) used association analysis to mine useful rules or patterns from learning logs accumulated in a ubiquitous learning system. By providing them advice based on the detected association rules, students' learning activities in informal settings can be improved. However, little attention has been paid to analyzing data such as Learning Style Index (LSI) and Cognitive Style Index (CSI) to find the association rules between learning styles and digital textbook logs. By analyzing the relations between learning styles and digital textbook logs, there is a possibility that we can identify important association rules to predict future learners' grade based on their learning styles and digital textbook logs. Therefore, this study focuses on analyzing logs collected in a digital textbook system in combination with results from the learning-style or cognitive-style questionnaires.

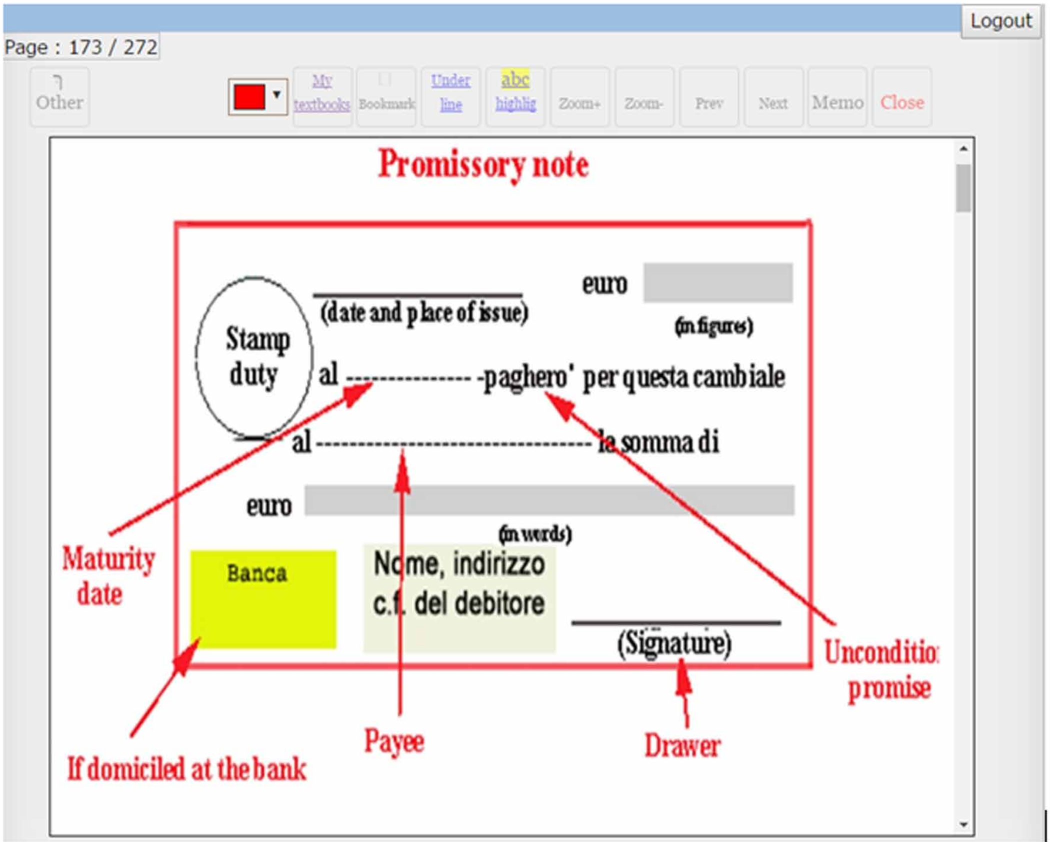
SYSTEM

The Architecture and Interface of the Digital Textbook System

The server side runs on CentOS, and it is programmed using Java and Mysql. The client side is working on a web browser using HTML5 and javascript. The users can register and read digital textbooks anytime and anywhere.

A web-based digital textbook system using the e-pub format was developed for use in this research. This digital textbook system was developed to collect data from classes. The system is

Figure 1. Student interface of DITeL



named Digital textbook for Improving Teaching and Learning (DITeL). The DITeL system can be used not only on personal computers, but also on smart phones. Specifically, this digital system can be used anywhere and anytime. Teachers and students can use the DITeL system and read a digital textbook on mobile devices such as iPads, iPhones, and Android. In addition, their learning logs were collected to analyze their learning behaviors to improve the DITeL system.

Figure 1 and Figure 2 show the interface for students and teachers, respectively. By using this online digital textbook reading system, we can collect data like "turning to next/previous page," "memo," "zoom in/out," and "adding marker." All of these actions are stored to the database. These data were used to analyze learning behaviors.

Turning to next/previous page. Students can read the teaching content repeatedly; they can go to the next page by clicking the "Next" button, and backtrack to the previous page by clicking the "Prev" button.

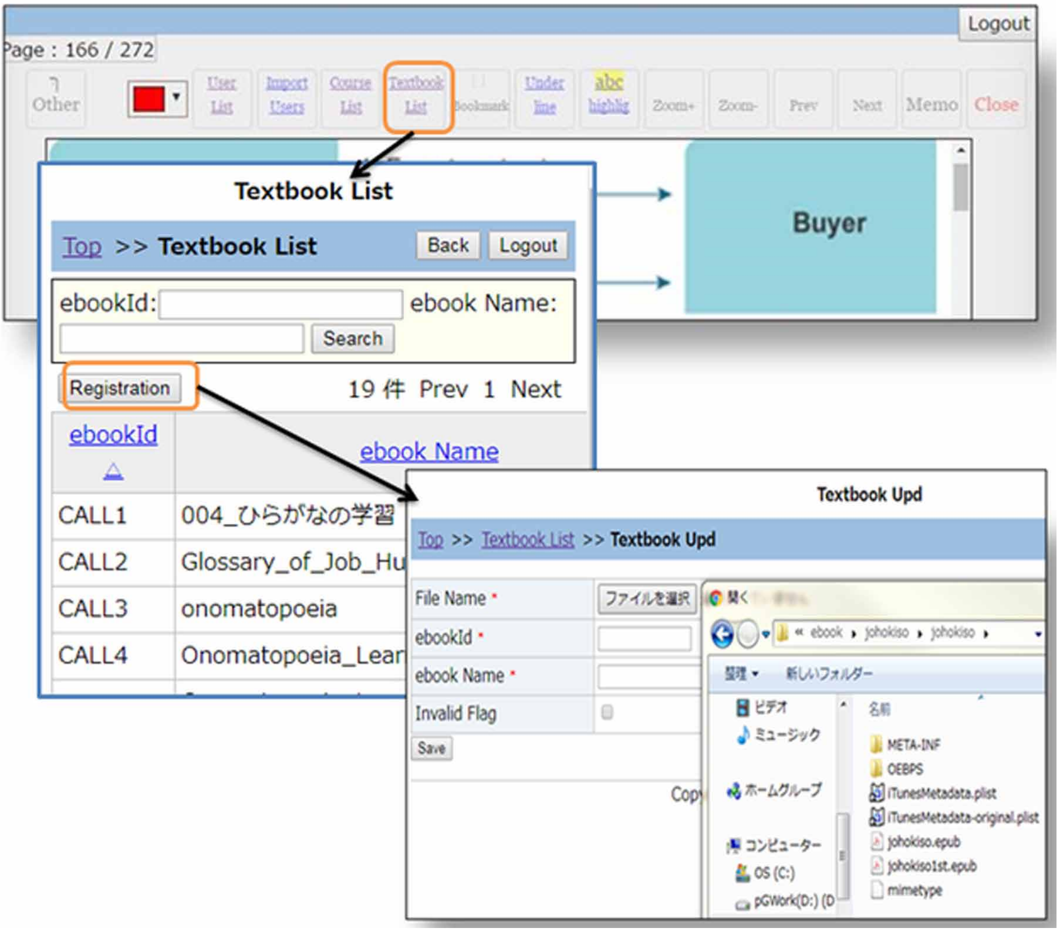
Memo. When a user wants to make a memo on the learning content, he or she clicks the "Memo" button, which shows a textbox. After the memo is written, the action name will be saved as "Memo."

Zoom in/out. The zoom in/out function can help students read the contents more clearly.

Adding marker. When a user wants to highlight some text in the learning content, he or she will click the "abc highlight" or "Underline" button, and the action name will be saved as "Highlight" or "Underline."

The teacher can register each student's name and number into the system. Before the students log into the system, the digital textbook and other relevant materials are uploaded to the system by

Figure 2. Teacher interface of DITeL



the teacher. As shown in Figure 2, when the teacher clicks the "Textbook List" button, a "Textbook List" window will appear, and when the teacher clicks the "Registration" button, a "Textbook Upd" window will appear to teacher. At the end, the teacher can select and upload the teaching materials into the system.

Each student will have an individual account to enter into the system, so that a separate record is kept for the learning activities in this course.

Log Data from the DITel System

The data were collected from the DITeL system. Table 1 shows a sample of reading action logs. One data log contains the date, time, user ID, learning content ID, page number, user action, and other data.

Participation

The DITeL system was used in a commercial law course for undergraduate students. This course was conducted wholly in English: The students were assigned English readings, and the teacher spoke in English. A total of 50,000 records were gathered from March to July 2017.

Table 1. Sample action log

Userid	Action Name	Document ID	Page Number	Action Time
Student1	Next	00000000NBU4	16	2014/10/22 8:40:55
Student1	Prev	00000000NBU4	15	2014/10/22 8:42:15
Student2	Add Marker	00000000NBU4	15	2014/10/22 8:42:16
Student3	Add Memo	00000000NBU4	15	2014/10/22 8:42:18

A total of 41 undergraduate students participated in this study. The participants were asked to read certain learning content (272 pages) via the digital textbook system. The mean age of the participants was 20 years.

The confidentiality of the participants was protected by hiding their personal information during the research process; moreover, they knew that their participation was voluntary and that they could withdraw from the study at any time.

ANALYSIS METHOD

The association analysis was conducted using the "arules" package (2017) of the R language and transaction data based on digital textbook logs, LSI, and CSI questionnaires. Table 2 shows the ranking that was established from the individual students' reading times based on the total time of the page flipping logs. The mean and median were 5,407 and 5,402 respectively for the rank A group, 3,553 and 3,586 respectively for the rank B group, and 1,849 and 1,808 respectively for the rank C group. The reading time was categorized into three ranks: A (the top 33%), B (the middle 33%) and C (the bottom 34%). The students were classified into these three types accordingly. Table 3 shows the parts of transaction data. Based on Felder and Soloman (2001), the four dimensions of LSI were divided into LSI1 (Active or Reflective), LSI2 (Sensing or Intuitive), LSI3 (Visual or Verbal), and LSI4 (Sequential or Global). Based on Allinson et al. (1996), the ranges of CSI scores were classified into three cognitive styles, namely Analytic, Adaptive, and Intuitive ((Table 2).

The analysis detected 5623 association rules (Figure 3). The horizontal axis represents the support value, and the vertical axis represents the confidence value. Support is an indication of how frequently the detected rules appear in the database; thus, support is the relative frequency of transactions that contain X and Y (X and Y are item sets). Confidence is an indication of how often the rule has been found to be true. This study decided the two regions (1) and (2) through expert human judgment with the detected association rules.

Region (1) includes the association rules whose support is less than 0.1, and its confidence is less than 0.6. The experts were not able to find important association rules such as the relations among learning styles, digital textbook logs, and learning achievements if the support value is less than 0.1 and the confidence value is less than 0.6. Therefore, we do not consider the association rules of region (1).

Table 2. The ranking of reading time

Rank	Criteria	Sum of reading time (seconds)	Mean (seconds)	Median (seconds)
A	Top 33%	91,919	5,407	5,042
B	Middle 33%	53,303	3,553	3,586
C	Bottom 34%	29,590	1,849	1,808

Table 3. The parts of transaction data

ID	OP	Pre-test	Post-test	Reading time	LSI1	LSI2	LSI3	LSI4	CSI
1	NEXT	80	90	A	Active	Sensing	Visual	Sequential	Analytic
2	NEXT	80	90	A	Active	Sensing	Verbal	Sequential	Adaptive
3	PREV	70	80	B	Reflective	Intuitive	Visual	Global	Intuitive
4	NEXT	80	90	A	Reflective	Intuitive	Verbal	Global	Intuitive

Region (2) includes the association rules whose support is greater than 0.1, and its confidence is greater than 0.6. The number of detected association rules in this region was 712. This study analyzed the relationships among the test scores, reading times, LSI, and CSI based on the association rules with detected high support and confidence values.

RESULT

First, to determine the relationships among CSI and other parameters, we detected association rules if the Right-Hand-Side (RHS) represents the Analytic type of CSI. Table 4 shows the association rules containing one or two factors in the Left-Hand-Side (LHS) and RHS with the Analytic type of CSI. The color of each cell represents the confidence value if the support value is greater than 0.1. For example, (1) in Table 4 indicates one association rule if LHS is “LSI1 = Reflective” and “LSI2 = Sensing” and RHS is “CSI = Analytic,” and the confidence value is 0.626.

Figure 3. The distribution of the detected association rules

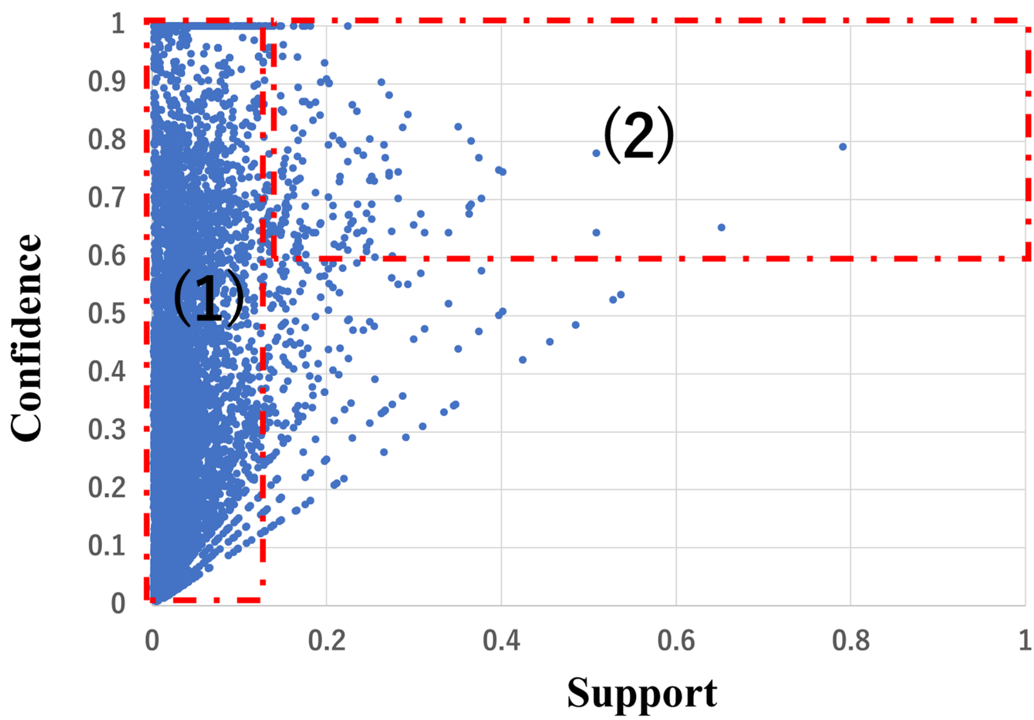


Table 4. Cross-tabulation of the CSI with analytics

	Reflective	Sensing	Visual	Sequetial	Reading time A	Pre-test 80	Post-test 90	Post-test 100
Reflective	0.616	0.626	0.62	0.719	0.91	1	0.655	0.942
Sensing	0.626	0.614	0.61		0.732	0.759	0.655	0.941
Visual	0.621	0.613		(1)	0.664	0.679	0.628	0.814
Sequential	0.719				0.67	0.731	0.82	
Reading time A	0.91	0.732	0.66	1			0.7	
Pre-test 80	1	0.759	0.68	0.731				
Post-test 90	0.655	0.655	0.63	0.82	0.7		0.655	
Post-test 100	0.942	0.941	0.81					0.814

When comparing each learning style through the pre-test and post-test sores, association rules were found when the students had a reflective type of LSI, and the pre-test score was 80, post-test score 90, and post-test score 100. These association rules had significant relationships because their confidence levels are higher than other factors such as the sensing or visual sequential type of LSI. When comparing each learning style with the reading time, association rules were found in the cases where the students have the reflective type of LSI and "reading time = A." This fact indicates that students of the reflective type with "reading time = A" fit into the analytic type of CSI.

Following the above results, this study further explored the data to find association rules in cases where the RHS represents the reflective or active types of LSI. Table 5 shows the cross-tabulation of LSI with the reflective type. The association rules between each learning style, such as sensing, visual sequential, and global, and other factors were found, but these association rules had lower confidence values.

Significant association rules among "reading time = A" and pre-test and post-test scores were found. For the association rule between pre-test score 80 and post-test score 90, the confidence value was 1. There were seven students who increased their test scores by 10 points from pre-test 80 to post-test 90. They fit into the reflective type of LSI. Table 6 shows the cross-tabulation of the LSI with the active type. For the association rule between pre-test 90 and post-test 80, there were six students who decreased their test scores by 10 points from pre-test 90 to post-test 80. They fit into the active type of LSI. Among the association rules of reading time were association rules indicating that LHS is "reading time B" or "reading time C."

Table 5. Cross-tabulation of the LSI with the reflective type

	Sensing	Visual	Sequential	Global	Reading time A	Analytics	Pre-test 80	Pre-test 100	Post-test 90	Post-test 100
Sensing	0.779	0.761	0.667	0.816	0.839	0.794	0.859			
Visual	0.761	0.754	0.612	0.835	0.827	0.816	0.679	0.825		0.716
Sequential	0.667	0.612	0.654		0.654	0.739	0.731			
Global	0.816	0.835		0.856	0.811	0.823			1	
Reading time A	0.839	0.827	0.654	0.811	0.939	0.932	1	1		0.923
Analytics	0.794	0.816	0.739	0.823	0.932	0.813	1	1	1	0.829
Pre-test 80	0.859	0.679	0.731		1	1	1		1	
Pre-test 100		0.825		1	1					
Post-test 90				1		1	1			
Post-test 100		0.716			0.923	0.829				0.716

Table 7 shows the cross-tabulation of LSI with the visual type. Association rules were found indicating that LHS was associated with reflective, sensing, global, and sequential types of LSI; however, these association rules had a lower confidence value, that is, less than 0.8.

Among the association rules of CSI, it was found that the confidence value of the adaptive type was higher than that of the analytic type, while among the association rules of reading time, there were association rules whereby LHS fell into “reading time A,” “reading time B,” or “reading time C.” When comparing each reading time with high confidence values, association rules were found such that LHS fell under the reflective type of LSI with “reading time A” and that LHS fell under the sensing or global type of LSI with “reading time C.” This means that a majority of the students with the reflective type of LSI with “reading time A” or sensing or global type of LSI with “reading time C” were associated with the visual type of LSI. Among the association rules concerning the pre-test and post-test scores, a meaningful association rule was found that LHS fell under pre-test score 90 with post-test score 90. This means that students who received a pre-test score 90 and a post-test score of 90 or 100 fit into the visual type of LSI.

From these meaningful association rules, this study mainly categorized three student types: Poorly Motivated, Efficient, and Diligent (Figure 4). The diligent type meets five conditions: Pre-test score 80, Post-test score 90, “LSI = Reflective,” “CSI = Analytic,” and “Reading time A.” The efficient type fulfills five conditions: Pretest score 90 or 100, Post-test score 90, “LSI = Visual,” “CSI = Adaptive,” and “Reading time = A, B, or C.” The poorly motivated type satisfies four conditions: Pre-test score 90, Post-test score 80, “reading time B or C,” and “LSI = Active.” Based on these conditions as well as the questionnaire results for LSI and CSI, the three student types were identified.

Table 6. Cross-tabulation of the LSI with the active type

	Sensing	Pre-test 90	Post-test 80	Reading time B	Reading time C
Sensing			0.821	0.81	
Pre-test 90			0.922	0.791	
Post-test 80	0.821	0.922	0.812	0.623	0.812
Reading Time B	0.81	0.791	0.623	0.712	
Reading Time C			0.812		0.811

DISCUSSION

From the results in Figure 4, this study identified three student types. Poorly motivated type is characterized by a lower reading time of digital textbooks than other types. We considered that the active students did not prefer thinking about and reflecting on things through reading digital textbooks. Previous studies have reported that active learners learn by doing something with the information obtained. They prefer to process information by talking about it and trying it out. Therefore, when teachers identify the student type in the questionnaire stage, it is necessary to design interactive digital textbooks that students can interact with functions such as audios, videos, and so on.

The efficient type of students includes the adaptive type of CSI and the visual type of LSI. The adaptive style implies a balanced blend of intuition and analytical style. In addition, visual learners prefer visual presentations of materials. They like pictures, diagrams, graphs, and charts. In the evaluation experiments, students were able to obtain good scores in the pre-test and post-test even though we were not able to prepare rich digital textbooks with the ideal number of pictures, diagrams, and graphs. Thus, our next analysis should be more carefully planned (with well-designed digital textbooks or not).

On the other hand, a diligent type has a higher reading time of digital textbooks than other types. Reflective learners learn by thinking about information. They prefer to think things through and understand things before acting. Therefore, it is necessary to design digital textbooks that promote critical thinking.

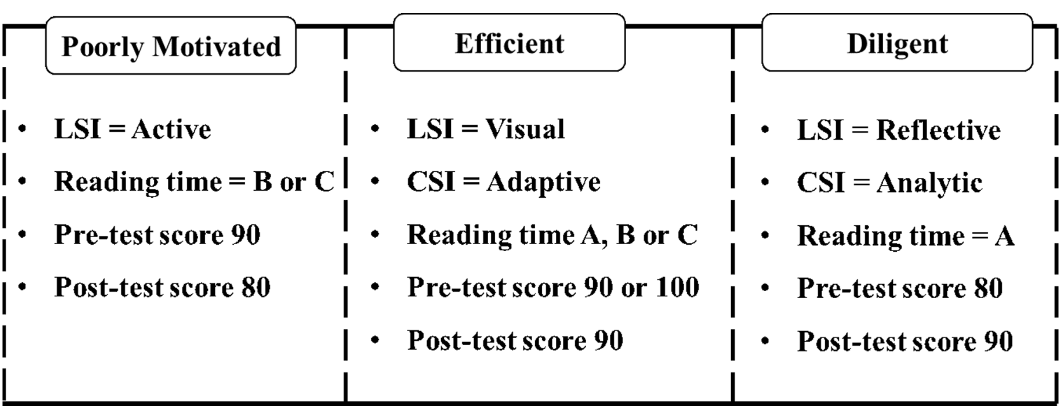
CONCLUSION

This study analyzed the learning patterns or rules using digital textbook logs with LSI and CSI questionnaires. To collect students' digital textbook logs, the DITel system was developed and used in a commercial law course for undergraduate students. The data collection period for the digital textbook logs was from March to July 2017. A total of 41 undergraduate students participated in this study. They were asked to answer the LSI and CSI questionnaires to investigate their learning and cognitive styles.

Table 7. Cross-tabulation of the LSI with the visual type

	Reflective	Sensing	Global	Sequential	Analytics	Adaptive	Reading time A	Reading time B	Reading time C	Pre-test 90	Pre-test 100	Post-test 90
Reflective	0.803	0.713	0.752	0.708	0.709	0.887	0.921	0.692			1	0.804
Sensing	0.713		0.776	0.728	0.712	0.887	0.708	0.893	0.902	0.764	1	0.763
Global	0.752	0.776	0.737		0.744	1	0.73	0.812	1	0.8144	1	0.804
Sequential	0.708	0.728		0.753	0.75		0.734	0.742				0.803
Analytics	0.709	0.712	0.744	0.75	0.805		0.81	0.892		0.766	1	0.756
Adaptive	0.887	0.887	1			0.9				0.866		0.872
Reading time A	0.921	0.708	0.73	0.734	0.81		0.831			0.715	1	0.756
Reading time B	0.692	0.893	0.812	0.742	0.892					0.811		
Reading time C		0.902	1						0.831			
Pre-test 90		0.764	0.8144		0..766	0.866	0.715	0.811		0.771		0.745
Pre-test 100	1	1	1		1		1				1	
Post-test 90	0.804	0.763	0.804	0.803	0.756	0.772	0.756			0.745		0.804

Figure 4. Three student types categorized based on the detected association rules



This study used association analysis with the Apriori algorithm. Using the analysis method, we found 5,265 association rules. Furthermore, we checked to find meaningful association rules using human judgment in accordance with the indications of support and confidence.

Based on the association rules, we found the following categories: The criteria of “CSI = Analytic” and “LSI = Reflective” on RHS and meaningful conditions detected of “Reading time A,” “Pre-test score 80,” and “Post-test score 90” categorize the diligent type. “LSI = Visual” and “CSI = Adaptive” on RHS and meaningful conditions detected of “Reading time A, B, or C,” “Pre-test score 90 or 100,” and “Post-test score 90” categorize the efficient type. Finally, “LSI = Active” on RHS and meaningful conditions detected such as “Reading time B or C,” “Pre-test score 90,” and “Post-test score 80” categorize the poorly motivated type.

In sum, the main contribution of this study is to find learning patterns or rules for enhancing education. By considering the detected learning patterns, we believe that teachers can provide support particularly to students of the poorly motivated type in advance. In the future, we will consider a dashboard development (Lkhagvasuren et al., 2016) to predict student types in accordance with their learning logs and LSI and CSI questionnaires.

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