Analysis of Reading Behavior Based on Students' Cognitive Styles and Learning Styles

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Abstract

This study reports the results on the relationship between cognitive style and learning style to understand the reading behavior of undergraduate students using an e-book system from the standpoint of a learning analytics view. Data are recorded from 102 undergraduate students at a university in China for over 4 months. The obtained results indicate that students with an analytical cognitive style achieve the highest performance compared with the other cognitive style groups (quasi-intuitive, adaptive, and quasi-analytic) and better fit the global learning style. Further, their reading behavior is different from that of the other three cognitive style groups (quasi-intuitive, adaptive, and quasi-analytic) as they re-read the first half to better understand the complete picture, following which, they continue their reading smoothly. Personalized learning is being adopted by rapidly growing educational institutions worldwide. The results provide tangible evidence for teachers to better consider the characteristics of students to design classrooms and students to better design learning plans according to their characteristics.

Keywords: Learning analytics, Cognitive style, Reading behavior, Digital textbooks, Learning style

1 Introduction

In the last decade, rapid progress in online learning platforms has introduced new opportunities and challenges in the field of educational technology. Thus far, numerous online learning platforms have been developed for online teaching and learning; for example, massive open online courses (MOOCs), open educational resources (OER), Moodle, and e-Books systems. Learning analytics (LA) refers to the analysis and interpretation of data related to the behaviors and interactions of the learners during the learning process, and the profiles and learning contexts of the learners in which they are situated [1]. Online learning platforms facilitate the collection of a large amount of learning log data that can be used for conducting LA. The LA results can be used to optimize institutional processes and increase educational and economic benefits for learners and educators [2]. Many researchers have reported that LA can be beneficial for different roles [2-4]; for example, LA can help learners share learning experiences, help teachers master the learning statuses of students, and help administrators organize resources and evaluate teachers and students [5]. Additionally, it can help understand and improve learning processes [6].

Data collection is the first step in LA [7]. Yin et al. [5] classified data collection methods into three categories: questionnaire-based, manual, and automatic; they reported that data can be consciously collected using automatic data collection methods. Many universities have developed MOOCs and OERs to motivate students to study online [8-10]. In Japan, e-books are continually being introduced to educational institutions. Further, e-book systems are used to collect reading log data to perform LA [11]; for example, BookRoll [12] is an e-book system that can analyze the book reading logs data. In this study, we employed an e-book system called DITel, which can collect reading log data of the students [13].

Many LA studies have been conducted using reading log data collected from an e-book system. For example, Yin et al. [14] investigated the relationship between learning behavior patterns and learning achievement; Okubo et al. [15] predicted learning outcomes; Yamada et al. [4] analyzed the relationship between the markers and self-efficacy; and Shimada et al. [16] summarized lecture slides to enhance the preview efficiency of students. Although several studies have analyzed learning behavior patterns based on the log data of e-book systems, studies focusing on understanding the relationship between the learning style and the e-book learning behavior patterns are limited. Yin et al. [5] identified some potential research issues related to e-book-based LA; these issues include identifying behavioral patterns of students from learning logs and integrating LA and pedagogical theories. Several studies have indicated that teachers can make better decisions regarding supporting students and course design processes if they are aware of the types of learning strategies that students employ in their learning activities [17-18].

By contrast, the aptitude treatment interaction (ATI) theory posits that an interaction between an individual's aptitude, which refers to their inherent characteristics, and the treatment or teaching method employed exists. This theory

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suggests that the best learning outcomes can be achieved when these two factors are optimally combined [19-20]. This individual aptitude may not be readily discernible, the teaching methods adjusted or modified based on the student's learning behavior in many cases. Therefore, the relationship between students' learning behavior and their aptitudes, such as cognitive styles and learning styles, must be understood to achieve optimal integration of ATI theory.

In this study, we defined the relationship between cognitive styles and learning styles to clarify the e-book reading behavior of students. Learning styles affect the learner's performance in terms of thinking, receiving information, and understanding; therefore, the relationship between learning and cognitive styles, and the learning behavioral patterns of the students must be understood. For example, the visual learning style suggests a preference for seen or observed things, including pictures, diagrams, and demonstrations [21]. If a teacher is aware that a student employs visual learning style, the teacher can adapt teaching strategies suitable to this specific learning style, such as including pictures to aid understanding.

Herein, we collected learning log data using the e-book system DITel, and used questionnaires to collect the student learning style data. Subsequently, we analyzed these learning log data to understand the learning behavior of the students and investigated the correlations between the students' behaviors, learning styles, and performance.

2 Relevant Literature

Hamada et al. [22] employed cognitive and learning styles to understand the learning behaviors of students. Beck & Carpenter [23] reported that both word recognition and text comprehension in reading are affected by individual differences, perceptual differences, and interactions in the cognitive process of reading. Lin et al. [24] preclassified the adult participants by their cognitive styles and found a direct influence of cognitive style on reading behaviors and performance. Moreover, Dağ & Geçer [25] evaluated research conducted from 1999 to 2009 focused on both online learning and learning styles, and confirmed that the learning style in online learning affects the academic achievements of the learner. Understanding the relationships between cognitive style, learning style, and students' reading behavior contributes to online teaching and research.

2.1 Cognitive Style

The study of cognitive style has been widely discussed in the educational field. Riding et al. [26] discussed the styles in terms of differences in their information-processing demands; they considered practical approaches for improving learning performance. Cognitive style index (CSI) is a psychometric measure designed for use by managerial and professional groups [27]. It is a self-report psychometric measure of cognitive style that specifically assesses preference-related differences in information processing according to intuition and analysis [28].

The relationship between cognitive style and reading ability was studied by Wineman [29]. He explored the relationship between reading ability and cognitive style in 270 elementary school students, and found that field-independent children had a more advanced reading ability compared with field-dependent children. Hsieh & Dwyer [30] studied reading behaviors of students in relation to their cognitive styles because these reading strategies entail different instructional structures and functions to facilitate student achievements related to various learning objectives. Chen et al. designed classroom activities considering interactions among human factors including cognitive style; their results revealed that cognitive style and learning strategy significantly affected students' learning performance and satisfaction [31]. Kuswandi & Fadhli indicated that the students with field independent cognitive style have superiority in improving early reading ability [32].

2.2 Learning Styles

Learning styles were analyzed to understand the learning characteristics of students, support student learning, and develop teaching styles [33-34]. Many educational theorists and researchers consider learning styles to be an important factor in the learning process and agree that incorporating them in education has the potential to facilitate learning for students [35]. Learning styles essentially demonstrate preferences and priorities of an individual in the learning process [36].

Felder et al. [21] defined learning styles by analyzing data from engineering students. Felder & Soloman [37] devised a tool test called the index of learning styles (ILS) that allows individuals to identify their learning styles. El-Bishouty et al. [38] designed an online class using the Felder and Silverman learning style model; they discovered that a course designed with certain learning styles in mind can improve learning of the students with those specific learning styles.

Many studies have investigated cognitive and learning styles in the educational field, and the effects of developing educational strategies for teachers and understanding the learning behavior of students have been clarified. However, research on understanding the reading behavior based on log data collected from an e-book through the analysis of the cognitive and learning styles is limited.

2.3 E-book System

DITel was developed to support the students' reading behavior and collect data in class [5]. Teachers upload lecture contents including texts and pictures, and the users read it by clicking "Prev" and "Next" buttons; further, they take notes, highlight, underline, and bookmark the page when necessary (Figure 1). All actions performed using the system are recorded in a database that contains "Log ID," "User Number," "Process Code," "Operation Date," "Device Code," "Page Number," and "Pages."

3 The Study

The study was conducted in the commercial law course, which requires reading lecture materials to preview and review. The outline of lecture materials is presented in Table 1. Essentially, 102 undergraduate students participated in this course, which consisted of ten classes scheduled once a week from March to June 2017.

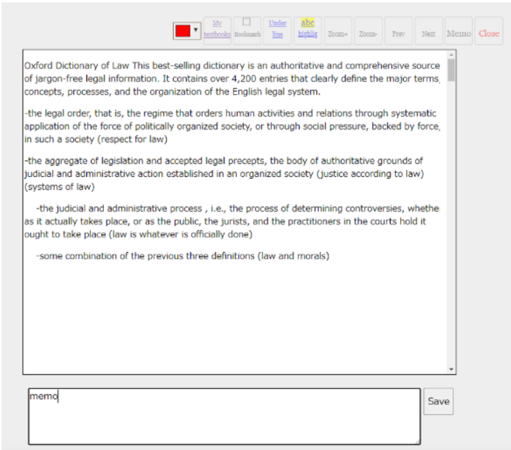

Figure 1. Screen capture of DITel system

Table 1. Contents of e-book

Chapter	Contents	Page
Cover	Commercial Law	1
Purpose	Target	2
Chapter 1	Fundamentals of Law	3-94
Chapter 2	Partnership Law	95-101
Chapter 3	The Law of Corporations	102-118
Chapter 4	Bankruptcy Law	119-141
Chapter 5	Negotiable Instrument Law	142-182
Chapter 6	Securities Law	183-218
Chapter 7	Insurance Law	219-253
Chapter 8	GATT and WTO Law	254-268
Appendix	Supplement --China	269-272

3.1 Research Purpose

This study aimed to support student learning and clarify their reading behavior by analyzing the collected log data. Previous studies have proved that cognitive style is related to students' reading ability [26], and learning styles are methods applied to assist students to be successful in school and excellent in examinations [39]. Hence, we hypothesize that the cognitive style and learning style affect the student's reading behavior, which includes reading behavior, note taking, and achievements.

3.2 Experiment Design

Initially in the first class, all the students answered a questionnaire for testing their learning style and cognitive style. The teacher explained the operation of the DITel e-book system in the first class, including how to underline, highlight, and write notes on the e-book. The students were requested to preview and review these course materials on the system using their electronic terminal (smartphones, computers, or tablets) during the semester. During the semester, the teacher carried out a test to evaluate their levels of learning and instructed all students in the same manner, without considering the learning and cognitive styles.

3.3 Data Collection

As depicted in Figure 2, we collected the data of the reading behavior of the students through the DITel e-book system and confirmed the cognitive style and learning style of the students through the results of questionnaires. These are indicated by the CSI and ILS, respectively.

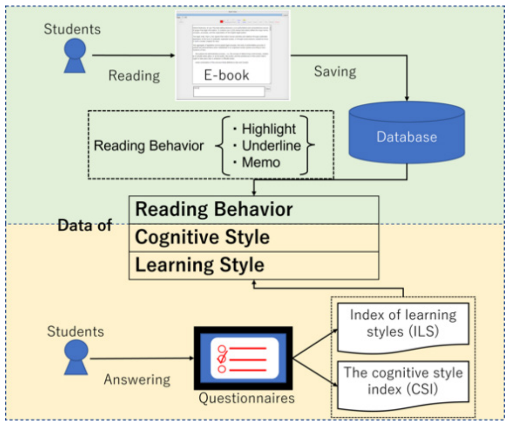

Figure 2. Data collection

3.3.1 Log Data

In this study, 925,965 records were collected from the DITel e-book system; however, because of missing data, only 856,341 records were used. The sample of the log data we used in this study is presented in Table 2. Students' reading behaviors, including page turning, highlighting, and writing memos, are presented in the column "Action". Here, "Prev" indicates students turning to the previous page, "Next" implies turning to the next page, "Page No" indicates the page the student has turned to, "Memo" refers to the notes taken by students, and "Text" indicates the contents typed by the students.

Table 2. Sample of log data

ID	User No	Action	Operation data	Device code	Page No.	Pages	Text
2578	s001	Prev	2017/03/02 18:08:36	PC	1	272	
2579	s001	Memo	2017/03/02 18:08:37	PC	2	272	Pointed out
2580	s014	Prev	2017/03/02 18:08:37	PC	2	272	
2581	s002	Next	2017/03/02 18:08:38	PC	4	272	
2582	s020	Next	2017/03/02 18:08:38	Mobile	45	272	
2583	s002	HL	2017/03/02 18:08:38	PC	5	272	Definition
2584	s003	UL	2017/03/02 18:08:38	PC	4	272	Solicitors and barristers

Additionally, the "Highlight" feature enables the students to highlight specific words or phrases, which are also referenced in the corresponding "Text" column.

3.3.2 Questionnaire of CSI

The CSI [39] is a psychometric measure designed to be used primarily by managerial and professional groups [25]. The CSI is a 38-item self-report questionnaire, where each item includes the response options "true," "uncertain," and "false" with scores of 2, 1 and 0, respectively. The nearer the total score is to the maximum of 76, the more "analytical" the respondent is, whereas the nearer it is to the minimum of zero, the more "intuitive" the respondent is. Thus, a total of five cognitive styles exist: intuitive, quasi-intuitive, adaptive, quasi-analytic and analytic.

Intuitive and analytics are the extreme ends of the spectrum of learners. However, the cognitive style of most people involves elements of both intuition and analysis. In the middle range, the 'Adaptive' style implies a balanced blend of the two cognitive modes [39].

3.3.3 Questionnaire of ILS

ILS [40] classifies learning styles into four dismissions with two sides each: active–reflective, sensing–intuitive, visual–verbal, and sequential–global. The ILS scores ranges between –11 and 11, with the negative numbers representing active, sensing, visual, and sequential, whereas the positive numbers indicating reflective, intuitive, verbal, and global characteristics [41]. Table 3 summarizes the feature of ILS.

Table 3. The feature of ILS

How you prefer to process information.	
Active Learn by doing something	**Reflective** Learn by thinking
How you prefer to take in information.	
Sensing Concrete and practical	**Intuitive** Abstract, original, and oriented towards theory
How you prefer information to be presented.	
Visual Visual presentations of material	**Verbal** Explanations with words
How you prefer to organize information.	
Sequent In a linear, orderly fashion	**Global** More holistically and in a seemingly random manner

4 Results

The five cognitive styles were grouped into intuitive, quasi-intuitive, adaptive, quasi-analytic, and analytic based on the CSI scores. Table 4 presents the number of students that implemented each of these styles. Only two students employed the intuitive cognitive style, thus presenting an insufficient sample size; hence, this style was excluded from the study.

Table 4. Number of users grouped by cognitive style

	Students	E-book Records
Intuitive	2	11223
Quasi-intuitive	22	100231
Adaptive	38	371730
Quasi-analytic	31	275176
Analytic	9	97981
Total	102	856341

4.1 Correlation Coefficient Between Cognitive and Learning Style Scores

The participants in this experiment answered a questionnaire to determine their learning styles.

Table 5 summarizes the results of the correlation test between the CSI and ILS scores; evidently, visual–verbal negatively correlated with the CSI score, whereas sensing–intuitive and sequential–global positively correlated with the CSI score. These results suggest that the more analytical the person, the more likely the person is to be intuitive, visual, and global. However, no variables exhibited a high correlation coefficient.

Table 5. Analysis of the correlation test (Pearson) score between CSI and ILS scores

Learning style	Active-reflective	Sensing-intuitive	Visual-verbal	Sequential-global
R	0.19	0.25	–0.17	0.17
P	0.0607	0.0102**	0.0202**	0.0227**

** *p<0.05*

Table 6 summarizes the number of students belonging to the four learning styles in the four cognitive groups. The number of students in the quasi-intuitive group was 22. In terms of the four abovementioned dimensions, 11 students belonged to active, whereas 11 belonged to reflective; 7 students belonged sensing, whereas 15 belonged to intuitive; 5 students belonged to visual, whereas 17 belonged to verbal; and 14 students belonged to sequential, whereas 8 belonged global. The students in the analytic group showed a higher correlation with global than with the others (Global: 8 students, 89%; Sequential: 1 student, 11%). Thus, a statistically significant difference was found (2(3) = 8.14, p <0.05).

4.2 Note Taking

Note taking is an important reading activity, and the DITel system allows students to record their notes in the system. Table 7 summarizes the note inputs by the students in the four cognitive groups. A significant difference was observed between the analytic (Mean: 34.44, SD: 12.61) and adaptive groups (Mean: 19.34, SD: 15.18) ($p < 0.05$) ("ana-ada" in Figure 3).

Table 6. Relationship between learning and cognitive styles

Cognitive styles / Learning styles	Quasi-intuitive (22)	Adaptive (38)	Quasi-analytic (31)	Analytic (9)
Active	11 (50%)	29 (76%)	21 (68%)	7 (78%)
Reflective	11(50%)	9 (24%)	10 (32%)	2 (22%)
Sensing	7 (32%)	11 (29%)	7 (23%)	1 (11%)
Intuitive	15 (68%)	27 (71%)	24 (77%)	8 (89%)
Visual	5 (23%)	6 (16%)	9 (29%)	3 (33%)
Verbal	17 (77%)	32 (84%)	22 (71%)	6 (67%)
Sequential**	14 (64%)	23 (61%)	17 (55%)	1 (11%)
Global	8 (36%)	15 (39%)	14 (45%)	8 (89%)

Table 7. Notes input by the four groups

	Mean	SD
Quasi-intuitive	18.82	15.61
Adaptive	19.34	15.18
Quasi-analytic	26.32	16.08
Analytic	34.44	12.61

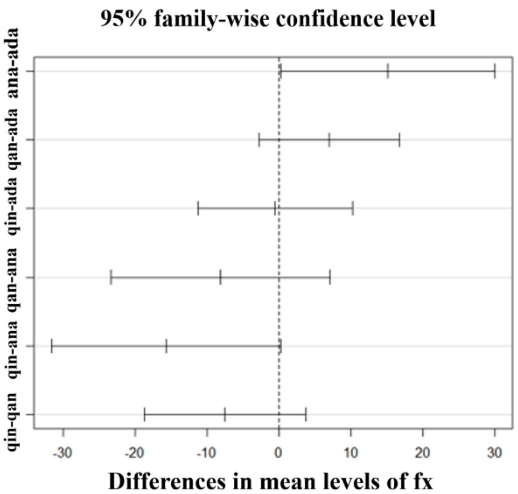

Figure 3. Result of Tukey's HSD test of the test score in the four groups

4.3 Achievement – Test Score

The teacher conducted a test during the experiment. The test scores were analyzed to determine the differences in the students' achievements. However, we used a missing value processing method to substitute some missing values in the test results with the average value.

The test outcomes revealed statistical differences in the scores between the groups (F (3, 96) = 5.37, $p < 0.05$). The ANOVA results are presented in Table 8. The scores of students in the analytic group were the best, and the standard deviation for this group was the smallest (mean: 95.56, SD: 3.91). The result of the Tukey's HSD test is shown in Figure 4. The analytic ("ana" in the figure) group exhibited a significant difference compared with the quasi-intuitive ("qin" in the figure) and quasi-analytic ("qan" in the figure) groups. These two lines were exclusively on one side of the bar (** $p<0.05$).

Table 8. Analysis of ANOVA results of the test score of the four groups

Group	Mean	SD	F (3,96)
Quasi-intuitive (N = 22)	85.49	7.72	5.37**
Adaptive (N = 38)	90.20	7.92	
Quasi-analytic (N = 31)	85.41	9.16	
Analytic (N = 9)	95.56	3.91	

** $p<0.05$

4.4 Reading Style

The "Prev" and "Next" buttons were designed to track the reading activity of the readers. The bookmark function could be used to save the current page, and students were allowed to skip pages. For data visualization, network diagrams were created using R, a programming language and free software environment for statistical computing and graphics. Each time the user clicked on the next or previous buttons, took notes, or highlighted text, the number of pages was recorded. If users stayed on a page for more than 30 min, we assumed that the reading was interrupted; such pages were not recorded as read. Owing to the different number of students in each group, we performed data extraction to avoid the effect of the number of students on the reading trajectory. In addition to the data of the first group with nine students, we randomly selected the data of nine students from other groups.

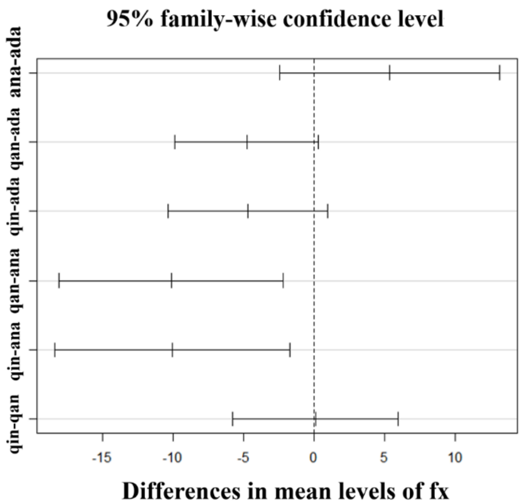

Figure 4. Result of the test on the four styles

4.5 Network Diagram

The network graphs of the four groups visualized the students' reading activities. The shape of the graphs were automatically generated by R, which adjusts to the optimal position within a limited range of sizes. Essentially, the difference in the overall shape depicted in Figure 5 to Figure 8 requires only limited attention. The dots and arrows, representing the pages and direction of the page turn, respectively, should be discussed.

The nodes include the start and end pages; each yellow dot indicates a page, the gray arrows represent the direction of movement, and the two-way arrows on the two pages represent the student going back and forth between two pages. The closer the dots, the more the students moved between the pages. The intersections between lines indicate the repeated reading of two or more pages that are farther apart.

4.6 Explanation of Reading Style for the Cognitive Group

The reading trajectories revealed the following. Students in the quasi-intuitive group repeatedly read multiple pages in the first half of the e-book (until page 136) and pages 157–162 in the last half (Figure 5). Students in the adaptive group repeatedly reread multiple pages in the first half of the e-book until page 160, in addition to pages 227–251; subsequently, they tended to move back and forth between the two pages in the entire book (Figure 6). The quasi-analytic group exhibited a pattern similar to that of the adaptive group: the students reread multiple pages until 148, and then moved back and forth between the two pages, as indicated by the two-way arrows (Figure 7). The analytic group exhibited a more concise reading pattern compared with the other groups: before page 119, the reading track was relatively complex, and the dots on pages 1–119 were very close, thus indicating that they were read repeatedly. Further, the students of this group exhibited a two-way reading pattern between pages 119 and 154; however, after page 154, their reading progressed in a single direction, with no sign of rereading (Figure 8).

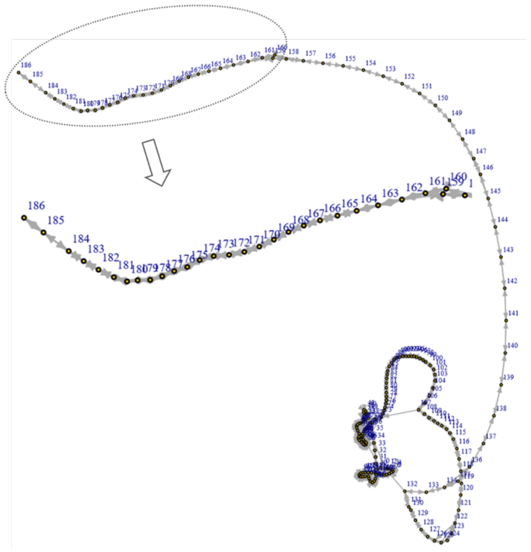

Figure 5. Reading trajectories of the quasi-intuitive style

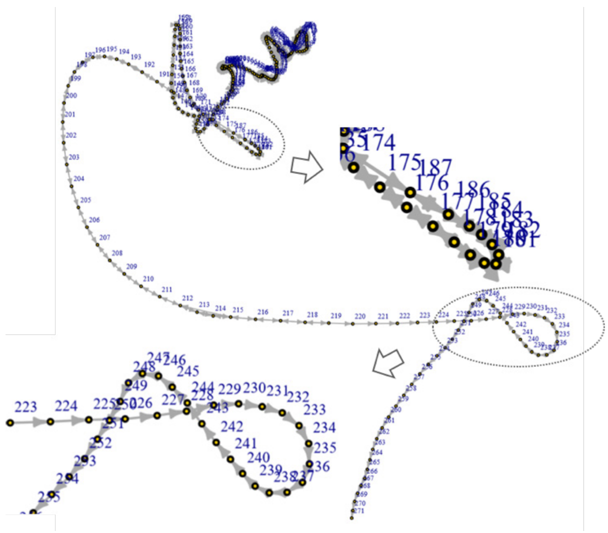

Figure 6. Reading trajectories of the adaptive style

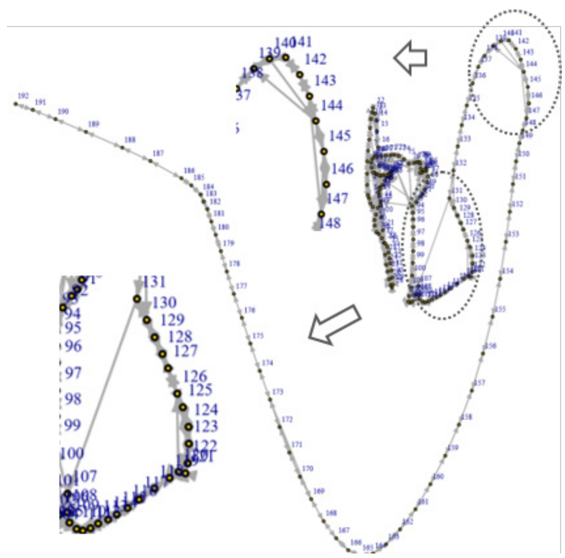

Figure 7. Reading trajectories of the quasi-analytic style

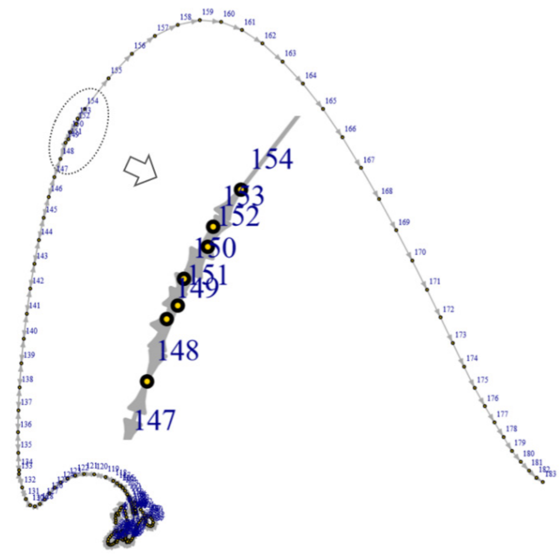

Figure 8. Reading trajectories of the analytic style

5 Discussion

5.1 Cognitive Style, Leaning Style, and Reading Behavior

The results of this study show that most analytic learners belong to the global learning style. Sequential–global, which is the fourth dimension of the learning style, indicates how people prefer to organize and process information. Graf et al. [42] reported that sequential learners learn in small incremental steps, and therefore, they have a linear learning progress. By contrast, global learners use a holistic-thinking approach and learn in large leaps. They tend to absorb learning material almost randomly without making connections until they have learned sufficient material to understand the complete picture. Because the complete picture is important for global learners, they tend to be more interested in overviews and broad knowledge, whereas sequential learners are more interested in the details.

The analytic group exhibited different reading patterns compared with the other groups. In the first half of the book, the students in the analytic group read repeatedly. From the middle to the end, they still exhibited occasional repeated reading of multiple pages. However, after that, their reading pattern showed a one-way movement to the next page. Combined with the results related to reading style, this suggests that analytic thinkers read frequently at the beginning to understand the complete picture, and once this is achieved, they read the remaining pages relatively smoothly.

5.2 Note Taking and Achievement

Learners take notes to collect and organize their thoughts or feelings regarding the topic at hand.. When a student moves to the next step and gets stuck, they can review their notes and reread the materials. Thus, taking notes helps students understand the material and organize their thinking.

Herein, taking notes was a voluntary activity, and analytic students took more notes compared with students of the other groups. Consequently, students of the analytic group exhibited the best performance between the four groups, and statistically significant differences between the analytic and quasi-analytic groups, and between the analytic and quasi-intuitive groups were obtained. The mean score of the analytic group was ten points higher than those of the quasi-analytic and quasi-intuitive groups.

Armstrong [43] reported that analytic thinkers achieve higher grades for long-term, solitary tasks involving careful planning and analysis of information. In our study, the teachers provided students with the same lectures and reading tasks. The reading tasks were executed after class, and no one verified if the tasks were completed. The experiment was conducted over 4 months. Our experiment satisfied these requirements. Thus, we verified the results of the previous study and found that the analytic group was more willing to take notes when using an E-book outside of class.

5.3 Limitations

Data were collected from 102 students divided into five groups. However, only two students were in the intuitive group and nine in the analytic group; almost all students were in quasi-intuitive, adaptive, or quasi-analytic groups. Although the intuitive group was eliminated from data analysis, all positive distributions had low data on both extremes and more data in the middle.

5.4 Contribution

Our study contributes both to theoretical understanding and practical implications.

We examined the relationship between students' cognitive styles, learning styles, and reading behavior during online learning. These findings contribute to the theoretical foundations of personalized learning, which is an educational pedagogy that designs an effective knowledge [44-45] acquisition track for each student to match the learner's strengths.

This also provides tangible evidence that supports teachers in considering students' individual characteristics when designing classroom activities; additionally, it assists students in designing their own learning plans to align with their unique traits. We found that students with different cognitive styles applied different learning styles and exhibited different reading behaviors when learning online. For example, as the analytical type students prefer knowing the whole picture at the beginning of reading, teachers can provide overall learning materials earlier, rather than partially per lesson, and adjust their teaching plan for an individual learner.

6 Conclusion

In this study, we analyzed the reading behavior of students in each cognitive style. We introduced an e-book system in the commercial law classes of 102 undergraduate students at a university in China and administered two questionnaires in the classes to define the relationship between students' cognitive and learning styles. After analyzing the data, we drew the following conclusions.

- Analytic thinkers tend to belong to the global learning style. They exhibit higher performance compared with other groups, and they are more willing to write memos to improve their reading.
- Analytic thinkers tend to focus on the complete picture, following which, they think very efficiently; this trait affects reading behavior.

Our findings can be used to improve teaching skills. For example, teachers can let analytic thinkers write more notes to help their reading and provide them with pictures to help their understanding. In future, we intend to apply the results of our analysis to classroom teaching activities, such as providing different forms of teaching materials for students with different cognitive and learning styles to test whether they are helpful to learning.

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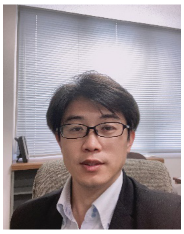

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