Geng et al. *Research and Practice in Technology Enhanced Learning* (2024) 19:11
https://doi.org/10.58459/rptel.2024.19011

Research and Practice in
Technology Enhanced Learning

RESEARCH Free and Open Access

Learning behavioral patterns of students with varying performance in a high school mathematics course using an e-book system

Xuewang Geng [1] *, Li Chen [2] , Yufan Xu [1] , Hiroaki Ogata [3] , Atsushi Shimada [2] and Masanori Yamada [1,4]

*Correspondence:
geng@mark-lab.net
Graduate School of Human-Environment Studies,
Kyushu University,
744 Motooka, Nishi-ku, Fukuoka,
819-0395 Fukuoka, Japan
Full list of author information is available at the end of the article

Abstract

Traditional textbooks are progressively being replaced by e-book systems, which are also being utilized more commonly in K–12 education. The study investigated learning behavioral patterns in a seven-week high school mathematics course using an e-book system. In this study, learning data from the BookRoll system was analyzed with lag sequential analysis to examine learning behavioral patterns, learning strategies, and the differences between students with different performances. The results of the learning behavior patterns of all students confirmed the usage of rehearsal and elaboration strategies. However, it demonstrated the lack of using metacognitive strategies in the e-book learning process. Additionally, the results also revealed different learning patterns among students with different learning performances. Students with decreased performance tended to use shallow cognitive processing strategies, while students with increased performance used deeper learning strategies, such as integrating information from the previous and next pages to highlight learning contents. Regarding the strategy usage of students with unchanged performance, students in the unchanged low and middle performance groups tended to utilize the re-reading strategy, while students in the unchanged high performance group utilized the elaboration strategy. Notably, students with increased performance employed fewer learning behavioral patterns than decreased performance students. The behavioral patterns of students with increased performance were more efficient and effective.

Keywords: Behavioral pattern, Lag-sequential analysis, E-book system, High school education, Learning analytics, Self-regulated learning, Learning sequence

Introduction

Advances in information and communication technologies are creating new opportunities in high school education, and they have the potential to employ new devices, such as iPads, to provide students with new learning experiences (Henderson & Yeow, 2012). E-book systems are gradually replacing traditional textbooks, as they offer numerous functionalities that are unavailable in traditional textbooks and allow students to interact with learning content at any time and place (Turel & Sanal, 2018; Zarzour et al., 2020). In addition, e-books systems provide an alternative to textbooks to support the classroom learning process (Embong et al., 2012). Unlike textbooks, e-book systems are equipped with additional features that support learning activities and improve the student learning process. E-book systems allow self-regulated learning (SRL) well-integrated with technology in the form of e-books and are an opportunity for students to become independent learners (Susantini et al., 2021). SRL is an active learning process involving cognitive, metacognitive, and behavioral engagement, including planning learning goals, choosing appropriate learning strategies, and regulating and monitoring learning strategies (Schunk, 2008; Susantini et al., 2021; Zimmerman, 1989). Previous research has demonstrated several advantages of adopting e-book systems with SRL. Chen and Su (2019) reported that students using an e-book system showed significant self-regulated learning and self-efficacy improvements. Hwang and Lai (2017) found that the use of an e-book system increased students' self-efficacy and learning achievement and was more effective for students with lower self-efficacy in elementary school.

E-book systems provide learning logs that are collected during the learning process. Learning analytics (LA) can be employed to understand learning behaviors and processes in e-book systems. SRL is one of the theoretical foundations of LA used to explain learning activities and generate feedback (Viberg et al., 2020). A growing number of studies have illustrated the potential benefits of LA as a method of examining student SRL behavior in online learning environments, such as e-book systems (Viberg et al., 2020). For instance, Chen and Su (2019) collected the reading behaviors and analyzed the improvement in self-regulated learning and self-efficacy of college students who used e-books. Chen et al. (2021) employed classifiers to predict academic achievement based on college students' reading behavior in an e-book system. So far, however, few studies have been available on taking into account the sequential nature of the behaviors, analyzing only the frequency of learning behaviors (e.g., Chen & Su, 2019; Chen et al., 2019; Chen et al., 2021; Ogata et al., 2017). It has been stated by Roll and Winne (2015) that SRL is not a learning activity, but rather a process of continuous learning. The temporal nature of learning should not be disregarded in the analysis of behavioral patterns and learning processes utilizing LA (Fan et al., 2021). As an LA method to determine the sequence between two actions, lag sequential analysis (Bakeman & Gottman, 1988) reveals whether the probability that one action will occur after another is statistically significant, based on the temporal nature of learning. Lag sequential analysis inspects the performance of SRL processes over time, focusing on the sequence of learned behaviors and considering the relationship of behavioral transitions to identify temporal differences in learning behaviors. Lag sequential analyses allow for identification and comparison of students' use of e-book systems, that is, their learning behavioral patterns, and effective SRL. This study aimed to investigate and analyze the behavioral patterns and SRL strategies of high school students using e-book systems by employing lag sequential analyses.

Literature review

E-book systems in high school education

The presentation of content using computing technologies in a format similar to printed books is referred to as an e-book (Smeets & Bus, 2012; Zhang et al., 2020). Readers can access digital content through e-books anytime and anywhere using mobile devices (Turel & Sanal, 2018; Zarzour et al., 2020). Furthermore, with the increasing use of multimedia and communication technologies in education, e-book systems with enhanced functions beyond traditional books have emerged. For instance, BookRoll is an e-book system that allows students to read and highlight digital textbooks used in lectures, along with augmented functions, such as bookmarking, taking notes, and searching (Ogata et al., 2015). As such, e-book systems offer students the possibility of SRL, allowing them to be active learners. Some previous studies have demonstrated that the augmented functions of e-book systems improve students' learning outcomes, motivation, and self-efficacy and reduce learning anxiety (Chen & Su, 2019; Chen et al., 2019; Hwang & Lai, 2017; Turel & Sanal, 2018).

Due to the advantages of e-books, such as flexibility of content design and Internet accessibility (Yamada et al., 2017), their application in university settings has been rapidly growing (Chen et al., 2019; Chen et al., 2020; Shimada et al., 2019; Zarzour et al., 2020). Previous research on e-books has focused on undergraduate students, while few empirical studies have investigated the use of e-books in K–12 education (Huang et al., 2012). Tang (2021) reviewed 79 published articles related to e-books from 2010 to 2019, and the results reported a gradual increase in investigations at the elementary and secondary levels from 2015, however, mainly focused on motivation and satisfaction. For example, Hwang et al. (2017) developed a concept mapping-based e-book system, and explored the impact of e-book on middle school students' motivation. Tang (2021) also noted that more advanced learning functions of e-book systems can potentially bring new learning experiences and performance for learners. Thus, the usage patterns of e-book systems with a variety of learning functions and their impact on learning performance remain unclear, especially in K–12 education. Furthermore, some studies on e-book systems were limited by the short duration of the experiments, such as Yin et al. (2017), who investigated the behavioral patterns of graduate students using an e-book system to read academic papers with an experimental period of 1.5 hours. As SRL is continuous rather than short-term (Winne & Nesbit, 2009), the present study conducted a seven-week experiment in high school.

Learning analytics for e-book learning behaviors

Furthermore, e-books differ from traditional paper-based textbooks in that e-books allow for the collection of student learning logs. For instance, BookRoll records students' activities, such as turning to the previous and next pages, highlighting, and taking notes, in the server databases (Ogata et al., 2015; Yamada et al., 2017). Therefore, researchers and teachers can utilize LA to understand learning behaviors using e-books. LA can measure, collect, analyze, and report data regarding learners and their contexts to understand learning processes (Learning Analytics & Knowledge, 2011). LA can be utilized for research on student behavior modelling, performance prediction, dropout prediction, improvement assessment, and recommendation of resources (Papamitsiou & Economides, 2014). Furthermore, LA utilizing student e-book learning logs can identify students' learning levels, help improve learning materials, determine at-risk students, and predict final grades (Yamada et al., 2017). Several studies have reported the benefits of applying LA to research on e-book learning behaviors. Geng et al. (2020) revealed that e-book learning behaviors related to rehearsal strategies, such as bookmarking and highlighting, affected learning outcomes. Zarzour et al. (2020) investigated Facebook-based e-book learning behaviors and found significant differences in liking, commenting, and sharing behaviors among students with different levels of engagement.

SRL is closely related to cognition, metacognition, motivation, and behavior (Zimmerman, 1989). Cognition and metacognition involve the ability of the learner to plan, monitor, regulate, and evaluate learning. Students can use e-books to conduct SRL activities, such as planning (setting learning goals and planning learning strategies prior to reading e-books), monitoring (highlighting content to mark mastered and less understood text and using the memo function to summarize learning content), regulation (adjusting learning strategies based on the results of monitoring), and evaluation of the achievement of learning goals and effectiveness of learning strategies using the quiz function. LA can identify learning behavioral patterns based on e-book logs in order to understand students' SRL strategy utilization. As such, LA avoids the necessity of surveys, the labor-consuming complexity of observation, and the inaccuracy of learner self-reports (Chen & Li, 2021; Winne & Nesbit, 2009). Chen and Li (2021) utilized LA to examine the behavioral patterns of online learning and found that students engaged in SRL using strategies such as rehearsing, repeating, evaluating, and searching. LA focuses on learning behavioral patterns, providing an opportunity to analyze SRL to build learning models and instructional design (Carthy et al., 2014).

Learning strategies used by students are often related to learning performance during independent study and lectures (Chen et al., 2020). Broadbent and Poon (2015) revealed that SRL strategies were significantly correlated with online learning performance. Furthermore, Wang et al. (2013) demonstrated that the utilization of SRL strategies predicted high learning performance. Therefore, it is critical to understand the learning behavior patterns and learning strategies, such as e-book use, of students with different learning performances. Previous research indicates that learning behavioral patterns and strategies of students with higher and lower learning performance may differ (Yamada et al., 2018). However, few studies utilized LA to explore the learning behavioral patterns of high school students with different learning performances using e-books. Lag sequential analysis addresses the limitation of focusing on the frequency of behaviors and psychological data and investigates the behavioral patterns and strategies of students during SRL. Therefore, this study aimed to investigate the learning behavioral patterns of high school students utilizing e-books through a lag sequential analysis and to explore the differences in behavioral patterns and learning strategies of students with different performances. This study posed the following research questions (RQs):

RQ1: What were the learning behavioral patterns of students using the e-book system?

RQ2: What were the differences in learning behavioral patterns using the e-book system among students with different performances?

Methodology

Course and participants

Eighty 10th-grade students from a Japanese high school participated in this study. The study was conducted during a seven-week mathematics course, which focused on quadratic functions, the law of sines and cosines, and other geometric knowledge. There were five lectures per week, each session lasting 50 minutes. Each participant was provided with an iPad and an Apple pencil for learning in class. Participants accessed the e-book system using their own smartphones and computers for learning outside of class. All participants learned and mastered the use of iPads before the experiment.

Experimental procedure

At the beginning of the study, participants were given a pre-test to check their existing mathematical knowledge. This study utilized the BookRoll e-book system. Teachers instructed the participants on BookRoll use to ensure that each participant could master the operation of the iPad and the functions of BookRoll. During the course, teachers uploaded digital learning materials and textbooks to BookRoll, of which participants could access before lectures. The digital learning material mainly included supplementary reading

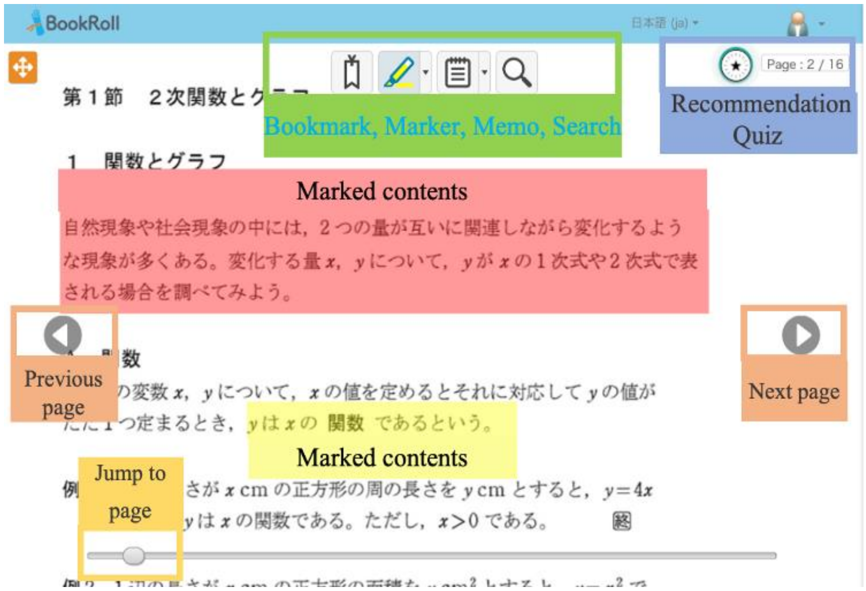

Fig. 1 The main interface of BookRoll

material provided by the teachers, such as explanations and examples of knowledge points. The quizzes were administered via BookRoll's quizzes function and paper test sheets. Each participant logged into BookRoll using their own account for learning activities. In class, participants were allowed to use BookRoll to read textbooks and materials and make annotation, turn pages, add bookmarked text and handwritten memos, view teacher-recommended learning content, answer teacher-prepared quizzes, and search for materials and memos (Figure 1). After the class, participants were allowed to preview and review materials posted on BookRoll.

Participants studied the learning materials using BookRoll. As shown in Figure 1, participants could turn pages, return to previous pages, jump to pages, bookmark pages, mark important or difficult content, and attach memos. In addition, participants could use BookRoll to answer quizzes and add handwritten or text notes based on lectures. Outside the classroom, BookRoll provided participants with extended knowledge on relevant topics, while bookmarking and search functions aided participants in locating content and notes for quicker preview and review. The course lasted seven weeks. At the end of the course, participants took a post-test on the course content.

Data collection and analysis

Pre- and post-test scores and behaviors of the participants while using the BookRoll system were recorded. Concerning the tests, based on the 10th-grade mathematics curriculum, the questions of the pre-test covered rational numbers, irrational numbers, monomials, and quadratic equations; the post-test consists of 30 questions related to factorization, quadratic function, quadratic inequality, etc. The tests were designed by the teachers, and the perfect score was 100. As the two tests differed in content and difficulty, pre- and post-test scores were divided into high, low, and intermediate groups based on the maximum value minus standard deviation, minimum value plus standard deviation, and the scores between these values. Changes between pre- and post-test scores in the high, intermediate, and low groups are shown in Figure 2. Based on these changes, students were divided into three groups: increased performance (IP), unchanged performance (UP), and decreased performance (DP). Students in the IP group belonged to the low and medium performance groups in the pre-test, and their performances improved to the intermediate or high score groups in the post-test (represented by the black line in Figure 2). Students in the UP group had no change in pre- and post-test performance (represented by the grey line in Figure 2). Students in the DP group were in the high or intermediate performance group in the pre-test and dropped to the intermediate or low performance group in the post-test (represented by the dotted line in Figure 2). The IP, UP, and DP groups included 5, 51, and 24 students, respectively.

Participants' behaviors while using BookRoll were automatically stored in the database, which comprised 22 learning behaviors. A total of 149,369 records were collected. To answer RQ1, behavior patterns of participants were examined using lag sequential analyses (Bakeman & Gottman, 1988). A total of 304 behavioral sequences were obtained. In addition, adjusted residuals were calculated, indicating that a value of 1.96 or higher was considered a significant sequence at the 5% significance level. RQ2 was examined by comparing the learning behaviors and behavioral patterns of the IP, UP, and DP groups.

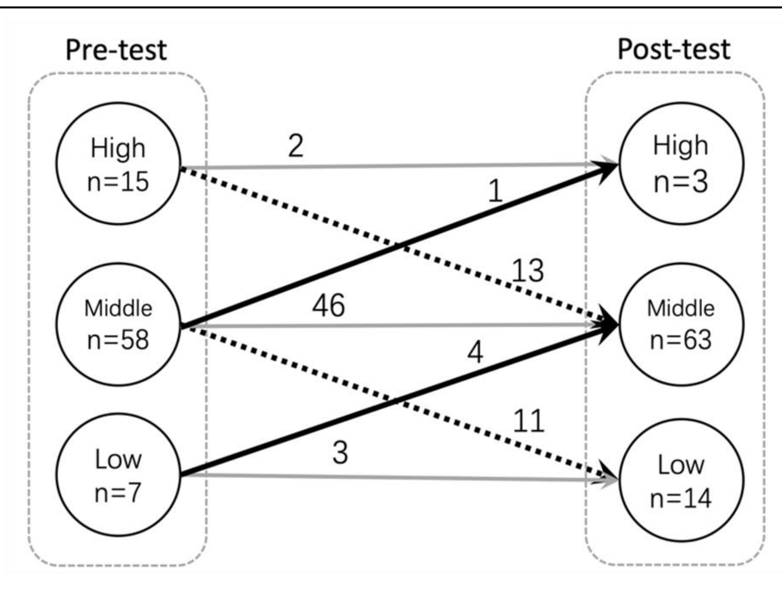

Fig. 2 Changes in pre- and post-test scores in the high, intermediate, and low performance groups

Table 1 Learning behavior codes in BookRoll

Code	Learning behavior	Code	Learning behavior
AHMM	Adding a handwritten memo	CLOSE	Closing read material
NEXT	Turning to the next page	QA	Answering a quiz
AMK	Adding a marker	BMKJ	Using a bookmark to jump to a page of the material
UHMM	Undoing a handwritten memo	ABMK	Adding a bookmark to the material
PREV	Turning to the previous page	DBMK	Deleting an added bookmark
OPEN	Opening and accessing material	CRC	Clicking the recommendation button to see learning content recommended by the teacher
DMK	Deleting a marker	DMM	Deleting a memo
PJ	Selecting a page and jumping to it	SEARCH	Searching for memos and learning content
CHMM	Deleting a handwritten memo	MMJ	Jumping to a memo from search results
QAC	Correctly answered a quiz	SJ	Jumping to content from search results
AMM	Adding a memo	CMM	Changing the previous memo

Results

Learning behavioral pattern

Table 2 shows the frequency and percentage of learning behaviors of all participants. The most frequent behavior was adding a handwritten memo (AHMM), which accounted for 48.32% of all learning behaviors. The rates of turning to the next page (NEXT), adding a marker (AMK), undoing a handwriting memo (UHMM), turning to the previous page (PREV), opening material (OPEN), and deleting a marker (DMK) were 9.02%, 8.80%, 5.76%, 5.27%, 3.84%, and 3.68%, respectively, among all learning behaviors. Deleting a memo (DMM), searching for memos and learning content (SEARCH), jumping to memos from search results (MMJ), and jumping to material content from search results (SJ) accounted for less than 0.01% of all learning behaviors. Lag sequential analyses (LSA, Bakeman & Gottman, 1988) were conducted to explore the behavioral patterns of students using BookRoll for learning. A part of the adjusted residual table indicating results of the seven high-frequency behaviors obtained through the lag sequential analyses is shown in Table 3. Adjusted residual values above 1.96 indicated that the occurrence of behavior transformation sequences was significant. Among the 484 generated behavior transformation sequences, 103 sequences were significant at the 0.05 level. Behavior transformation sequences with over 100 occurrences were visualized, and the behavior transformation diagram is shown in Figure 3.

Table 2 Frequency and percentage of participants' learning behaviors

Code	Frequency	Percentage %
AHMM	72181	48.324%
NEXT	28411	19.021%
AMK	13148	8.802%
UHMM	8597	5.756%
PREV	7878	5.274%
OPEN	5729	3.835%
DMK	5498	3.681%
PJ	2741	1.835%
CHMM	1323	0.886%
QAC	1129	0.756%
AMM	768	0.514%
CMM	424	0.284%
CLOSE	354	0.237%
QA	288	0.193%
BMKJ	212	0.142%
ABMK	189	0.127%
DBMK	154	0.103%
CRC	144	0.096%
DMM	133	0.089%
SEARCH	39	0.026%
MMJ	26	0.017%
SJ	3	0.002%

Table 3 Adjusted residual table of participants' learning behavior sequences (part of the full table)

	AMK	AHMM	DMK	NEXT	OPEN	PREV	UHMM
AMK	244.773*	-114.995	66.526*	-24.821	-0.504	-17.35	-29.522
AHMM	-115.935	345.323*	-72.961	-180.495	-70.206	-87.771	-43.698
DMK	52.522*	-72.315	224.664*	-25.978	-3.818	-12.727	-18.378
NEXT	-12.049	-176.797	-29.742	249.961*	21.907*	48.212*	-45.795
OPEN	-20.482	-70.076	-14.429	61.453*	82.046*	-17.893	-18.65
PREV	-8.606	-85.874	-12.032	25.491*	23.22*	180.248*	-22.073
UHMM	-29.211	-48.168	-18.558	-45.795	-15.566	-22.295	275.358*

*$p<0.05$

There were 16 nodes and 34 arrows, which represented 24 learning behaviors in 34 behavioral transformation sequences (Figure 3). The direction of the arrow in the behavioral transition diagram denotes the direction of the transformation, and numbers written on the lines are the adjusted residuals. The behavioral transition diagram was divided into five areas based on BookRoll functions: reading material, annotation, highlighting, bookmarks, and answering quizzes. The reading material area revealed that NEXT, PREV, OPEN, and PJ were sequentially correlated, and there was a two-way transition relationship between these four behaviors (PREV⇄NEXT⇄OPEN⇄PJ, reading multiple materials thoroughly, the following is labeled as "QuitAndRead-multiple" , the

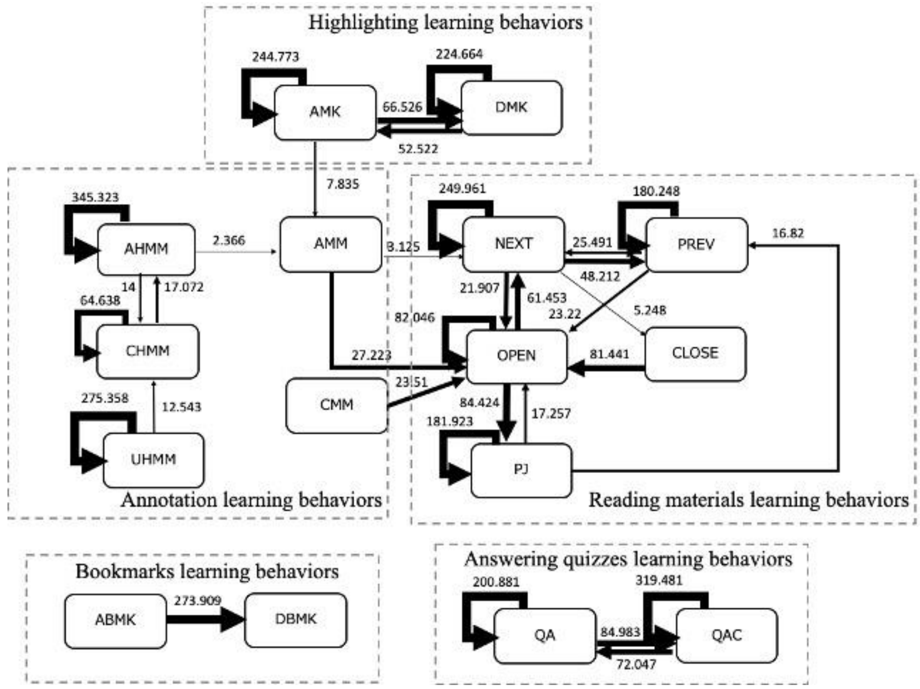

Fig. 3 Behavioral transition diagram

following is labeled as "ReadNew"). The behavioral pattern of OPEN→PJ→PREV and the cycle of three behavioral transitions (purposeful opening of new materials), OPEN→NEXT→CLOSE→OPEN (confirmation of the content of multiple new materials, the following is labeled as "QuitAndRead-new"), were observed. For annotation, the learning behavioral patterns of UHMM→CHMM⇄AHMM (revision of note-taking, the following is labeled as "ReviseNote") and AHMM→AMM (writing annotations after note-taking, the following is labeled as "NoteToAnnotation") were found. However, there was no transition between AMM and CMM (revision of annotations). Furthermore, the other three areas showed significant transformation of behaviors, such as AMK⇄DMK, QA⇄QAC, and ABMK→DBMK. Interestingly, AMK→AMM→NEXT (turning to the next page after highlighting and annotation) and AMK→AMM→OPEN (opening new material after highlighting and annotation) behavioral transition patterns were observed, indicating that students highlighted and annotated parts of the content before engaging with reading materials.

Comparisons of learning behavioral patterns among students with different performances

The frequency and percentage of learning behaviors of students in the DP and IP groups are shown in Appendix A. The result indicated that the percentage of AHMM and QAC learning behaviors was higher for students in the IP group compared with those in the DP group and all students. To analyze the correlation between performance improvement and reduction and differences in learning behavior, the Mann-Whitney U-test was conducted on the IP and DP groups (shown in Appendix B). The results revealed that the IP group significantly used some learning behaviors more frequently than the DP group: changing memo (CMM: $U=23.5$, $p<0.05$), answering the quiz correctly (QAC: $U=25$, $p<0.05$), and adding memo (AMM: $U=27.5$, $p<0.1$).

The adjusted residual tables of the learning behavior sequences for the IP and DP groups are presented in Tables 4 and 5, respectively. The behavioral transition diagrams with occurrences over 100 for the two groups are shown in Figure 4 and Figure 5, respectively. The DP group had 12 learning behaviors and 21 behavioral transition sequences, while the IP group had seven learning behaviors and 12 behavioral transition sequences. In other words, the IP group had fewer significant behavioral transformation sequences than the DP group. Participants in the DP group demonstrated patterns related to highlighting (AMK⇄DMK), annotation (CHMM⇄AHMM→AMM), and material reading (PREV⇄NEXT⇄OPEN,OPEN→PJ). Only patterns of material reading (PREV⇄NEXT⇄OPEN) were found in the IP group. Interestingly, although there were fewer behavioral transitions in the IP group than in the DP group, the NEXT→AMK sequence observed in the IP group was not revealed in the DP group.

Table 4 Adjusted residual table for learning behavioral sequences in the DP group (part of the full table)

	AMK	AHMM	DMK	NEXT	OPEN	PREV	UHMM
AMK	122.74*	-55.745	29.759*	-18.807	-2.571	-11.849	-13.785
AHMM	-56.247	180.965*	-35.887	-91.926	-32.616	-43.879	-15.172
DMK	23.785*	-35.384	116.712*	-18.804	-3.087	-8.53	-8.863
NEXT	-12.331	-90.094	-20.052	127.26*	7.446*	17.801*	-22.572
OPEN	-12.406	-32.85	-8.602	28.984*	35.914*	-10.652	-8.481
PREV	-8.414	-42.732	-8.033	6.208*	8.861*	96.344*	-10.474
UHMM	-13.366	-17.46	-8.743	-22.469	-6.899	-10.791	146.466*

*p<0.05

Table 5 Adjusted residual table for learning behavioral sequences in the IP group (part of the full table)

	AMK	AHMM	DMK	NEXT	OPEN	PREV	UHMM
AMK	75.187*	-31.715	27.658*	-0.854	2.758*	-1.377	-6.29
AHMM	-32.398	113.582*	-16.923	-64.146	-28.53	-33.308	-26.281
DMK	21.28*	-16.764	49.731*	-1.429	2.729*	-0.853	-2.964
NEXT	2.877*	-62.519	-1.877	78.554*	14.024*	19.277*	-12.181
OPEN	-2.597	-28.503	-2.015	27.701*	25.763*	-4.671	-5.449
PREV	2.754*	-33.171	0.301	11.021*	10.683*	57.392*	-6.411
UHMM	-6.29	-26.91	-3.29	-12.279	-5.039	-6.589	93.961*

*p<0.05

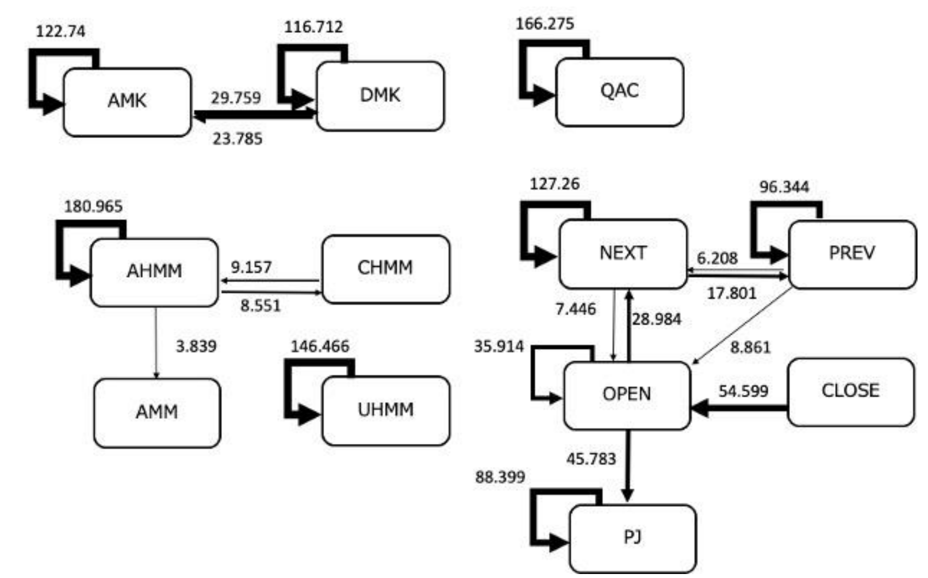

Fig. 4 Behavioral transition diagram for the DP group

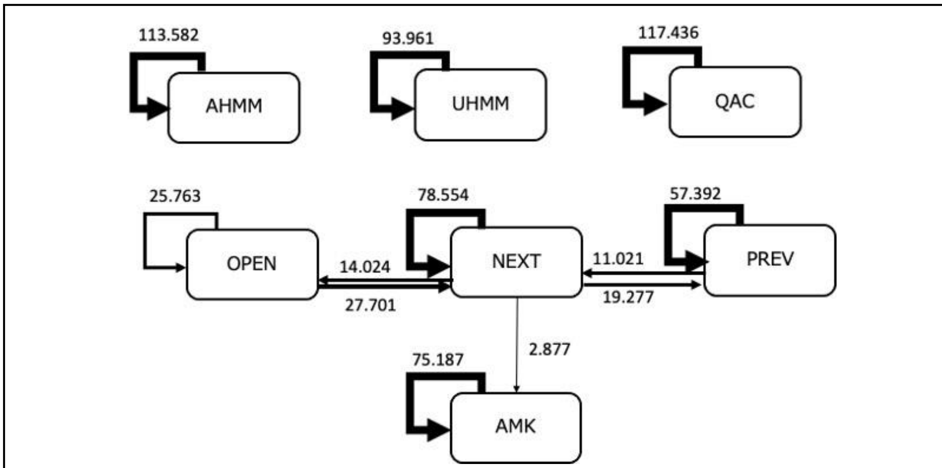

Fig. 5 Behavioral transition diagram for the IP group

To provide more comprehensive insight into the behavioral patterns of learners for each learning outcome and to evaluate behavioral patterns, the behavioral transition diagrams of learners in UP were also plotted based on the adjusted residuals determined by LSA. LSA was performed on students in the UP group, which refers to those who maintained their academic performance. The students were categorized as low to low (3 students), medium to medium (46 students), and high to high (2 students) groups according to their pre-test and post-test, and their behavioral transition diagrams are shown in Figure 6, Figure 7 and Figure 8. The middle-to-middle group demonstrated a higher count of behavioral transition sequences as compared to both the high-to-high and low-to-low groups. The transition

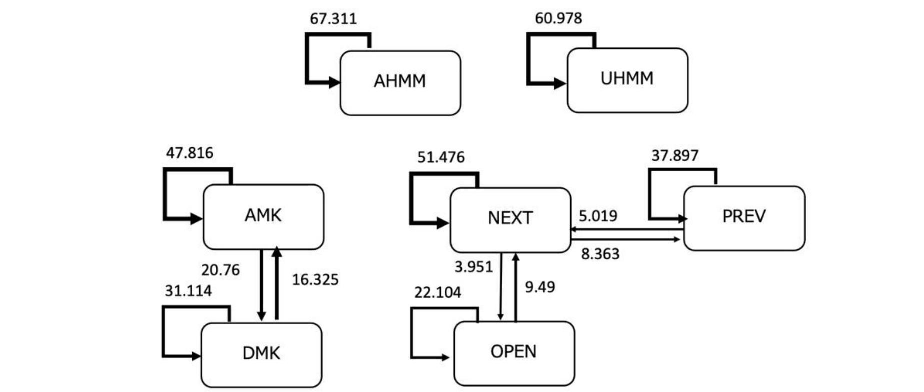

Fig. 6 Behavioral transition diagram for the low-to-low group of the UP group

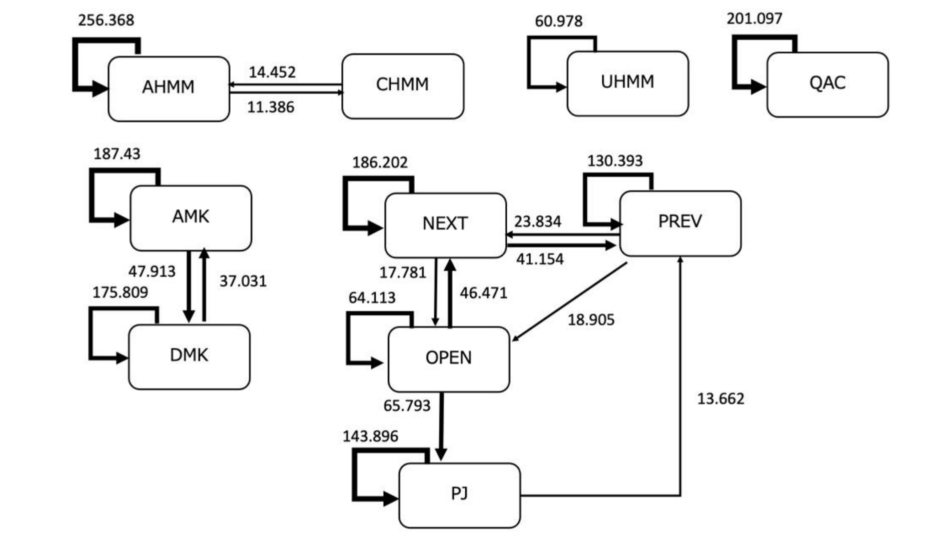

Fig. 7 Behavioral transition diagram for the middle-to-middle group of the UP group

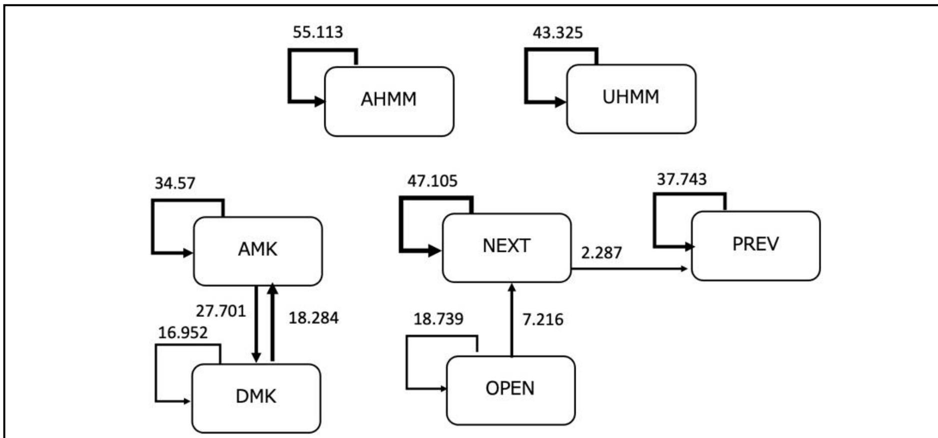

Fig. 8 Behavioral transition diagram for the high-to-high group of the UP group

sequences of both the low-to-low group and the high-to-high group are related to the seven behaviors, namely AMK, DMK, NEXT, OPEN, PREV, AHMM, and UHMM. The high-to-high group showed a unidirectional behavioral pattern for reading materials (OPEN→NEXT→PREV), whereas the low-to-low group demonstrated a bidirectional behavioral sequence (OPEN⇄NEXT⇄PREV). Concerning the middle-to-middle group's learning behaviors in the reading materials, in addition to the OPEN⇄NEXT⇄PREV sequence, the behavioral pattern of OPEN→PJ→PERV, which uses the page jump to quickly locate the content to be read, was also shown. As one of the differences between the low-to-low and high-to-high groups, the behavioral patterns of adding and deleting handwritten notes (AHMM⇄CHMM) was only demonstrated in the middle-to-middle group. Furthermore, the most striking result from the behavioral transition diagrams is that none of the three UP groups showed the pattern of adding highlight behaviors to the process of reading the material in the IP group (NEXT→AMK).

Discussion

The first research question aimed to determine the learning behavior model approach for all participants when learning with BookRoll. Learning behavioral patterns of students while using BookRoll were indicated by the results of the lag sequential analysis and the behavioral transition diagram.

Searching and jumping to search results (SEARCH, MMJ, and SJ), which had a lower frequency, showed no significant behavioral transition, indicating that students did not use search strategies to locate learning content. Coordinating information sources and finding locations in the e-book system is an effective strategy for regulating SRL (Azevedo & Cromley, 2004). "ReviseNote" and "NoteToAnnotation" behaviors illustrated that students took notes to expand their knowledge. This finding indicates that, when performing cognitive activities, students stopped at the stage of expanding knowledge and did not take the next step of locating information. It demonstrates the insufficiency of SRL activities among high school students using BookRoll and indicates the necessity of improving BookRoll and providing instructor guidance to support SRL. Numerous studies have shown the potential for further development of BookRoll to support SRL. Concerning the enhancement of metacognition, for instance, Flanagan et al. (2018) created an automatically produced content model based on the textbooks in BookRoll to assist students in understanding the connections between knowledge fast. Additionally, the advancement of LA also opens up previously unexplored prospects for SRL based on digital e-book systems. The design and implementation of BookRoll-based dashboards demonstrate that the dashboard facilitates monitoring the learners' current learning situation, indicates the following learning contents, and also provides instructional clues for teachers (e.g., Chen & Su, 2019; Chen et al., 2019; Majumdar et al., 2021). Employing tracking learning data allows students to obtain personalized scaffolding to optimize the learning process when necessary in SRL (e.g., Lim et al., 2023). Moreover, the results revealed that students not only repeatedly read one material for confirmation but also purposefully opened additional materials for reading and confirmation (e.g., “ReadNew”, “QuitAndRead-new”, “QuitAndRead-multiple”). This result suggests that students used rehearsal learning strategies, that is, repeatedly studying the same content, and elaboration strategies, which fused new information with existing information in order to learn new material (Broadbent & Poon, 2015). As such, the participants employed both surface and high-level cognitive strategies. This behavioral pattern was not observed in studies on other e-book systems, where there was no bidirectional transition between the behaviors of turning to the next and previous pages (Yin et al., 2017; Zarzour et al., 2020). This could be due to the short duration of experiments conducted in previous studies, which were 1.5 hours (Zarzour et al., 2020) and 4 days (Yin et al., 2017). As SRL is a continuous learning process, it is difficult to explore it completely through short-term learning activities (Winne & Nesbit, 2009).

Bookmarking and quiz answering behaviors did not have any significant behavioral sequences with the reading material. On the other hand, sequential behavioral patterns (AMK→AMM→NEXT and AMK→AMM→OPEN, continuing reading backward after highlighting and annotating) were found between the behaviors of highlighting, annotation, and reading material activities. The results indicated that students first marked the learning content and then summarized or commented on it, followed by turning to the next page of the material or opening new material. However, this learning behavioral pattern did not use metacognitive strategies. Learners who use metacognitive strategies tend to be confused about the material and consciously go to the previous page to aid their understanding (e.g., AMK→AMM→PERV was not significant). Therefore, this study analyzed learning behavioral patterns of the e-book system employing LA and presented students’ utilization of SRL strategies.

To answer Research Question 2, students were divided into 3 groups. Based on pre- and post-test results, five students with increased performance and 24 students with decreased performance were identified. This study focused on investigating the learning behaviors of students in the increased and decreased performance groups in order to determine the differences in behavioral frequency. The results revealed that students with increased performance more frequently added and changed annotations and answered quizzes correctly than students with decreased performance. The positive impact of the addition and modification of annotations on learning materials on student engagement and learning performance has been reported in several literatures (Chen et al., 2021; Majumdar et al., 2021; Wakefield et al., 2018). For instance, Chen et al. (2021) investigated the e-book reading behaviors of 100 first-year undergraduates, and indicated that annotation function was a significantly positive correlation with academic performance. Adding and changing annotations tends to be closely related to organizational strategies, unlike highlighting, which requires more powerful cognitive and metacognitive processing to help understand summary content (Broadbent & Poon, 2015). Therefore, students need to have a sufficient comprehension of the materials to add and modify annotations on the e-book system. Nesbit et al. (2006) argues that highlighting selected text is a surface learning due to the process of text selection only, requiring less cognitive processing; the use of annotations is a deeper learning method that integrates relevant information and links the text to previous knowledge in a way that often requires more cognitive processing. The frequency of correctly answering quizzes verified that the learning performance of the increased performance group was better than that of the decreased group.

Lag sequential analyses and behavioral transition diagrams revealed that students with increased performance employed fewer learning behavioral patterns than those with decreased performance. In other words, the behavioral patterns of students with increased performance were more efficient and effective in terms of learning performance. Furthermore, difference in the sequence of behavioral transitions between the two groups demonstrated that the behaviors of increased performance students repeatedly performed the same behavior mostly, such as AHMM→AHMM (adding handwritten notes multiple times). In contrast, students with decreased performance showed many transitions between different behaviors, such as AMK⇄DMK (repeatedly adding and removing highlighting) and CHMM⇄AHMM (repeatedly adding and deleting handwritten notes). For instance, the learning behavioral pattern of highlighting in the DP group illustrated that learners simply repeated the behaviors of highlighting and deleting highlights. This finding could be due to students marking content that they did not understand without cognitive learning. It was confirmed in interviews with the teacher. Students tended to find answers to content they did not understand and seldom engaged in SRL activities, such as judging and evaluating based on learning goals. Likewise, deleting highlights, students felt that they achieved understanding and did not engage in SRL evaluation activities. Therefore, the bidirectional sequence between different behaviors of students in the DP group was likely a surface processing strategy (Bernacki et al., 2012), indicating that students with increased performance had more efficient and effective learning behavioral patterns.

Moreover, there was no transition between learning behavior areas, such as reading materials and annotation, in the DP group; however, there were PREV⇄NEXT→AMK (adding highlights during the reading of new material) and OPEN⇄NEXT→AMK (add highlighting during repeated reading of material) sequences in the IP group. This demonstrated that students in the IP group read the material before highlighting the annotated text. This behavioral pattern differed from repetitive highlighting and deletions, which is the first step toward achieving a deeper learning strategy (Leutner et al., 2007).

Leutner et al. (2007) stated that the highlighting behavioral pattern requires identifying and focusing on important information, integrating existing information, and processing that information in working memory in order to successfully achieve the goal of SRL strategies.

Concerning the learning behavioral patterns of the UP group, this study found that students who remained in the high-performance group had different reading patterns compared to those who remained in the low- and middle-performance group. Specifically, the high-to-high students made linking new information to previous pages as they sequentially read the materials (OPEN→NEXT→PREV). In contrast, the students who remained unchanged in the low and middle groups were more likely to repeat the reading materials (NEXT⇄PREV). It indicates that the high-to-high group employed more elaboration strategies, whereas the low-to-low group and the middle-to-middle group employed re-reading strategies. The finding is probably due to differences in the prior knowledge levels of the students, as the high-to-high groups of students had higher prior knowledge levels and were, therefore, better able to establish links between prior knowledge (Glogger et al., 2012). On the other hand, due to the relative insufficiency of previous knowledge, the middle-to-middle group and low-to-low group might read repeatedly to help them remember and understand. In fact, students may not be able to locate the difficulties and key points of their own knowledge in re-reading. Re-reading strategies give students an incorrect sense that they are reading effectively to facilitate learning (Miyatsu et al., 2018). However, the re-reading strategy can be made more effective by using highlight behaviors of the meta-recognition strategy to mark out key content in the materials and stimulate students' thinking about knowledge (Miyatsu et al., 2018; Rawson et al., 2000). This was supported by the IP group's PREV⇄NEXT→AMK behavioral pattern which is underlining the text after reading the materials. The students in the IP group did not just reread the materials mechanically. Instead, they engaged in metacognitive processing after reading, further identified important information in the materials in greater depth, and their performance on the post-test improved. Furthermore, it is noteworthy that the middle-to-middle students reveal similar sequences of learning behavioral transitions to those in the DP group, particularly in relation to handwritten note-taking behaviors.

Furthermore, it is noteworthy that the middle-to-middle students reveal similar sequences of learning behavioral transitions to those in the DP group, particularly in relation to handwritten note-taking behaviors (AHMM⇄CHMM). The frequent addition and deletion of handwritten notes were observed to be caused by students always recording the teacher's narration and blackboard writing verbatim. Due to the focus on recording, it was difficult to determine the suitable locations of pages in the materials to take notes, resulting in repeated additions and deletions. Similar to the process of annotation, the activity of note-taking also requires information positioning to ensure the relevance of the teacher's narration, blackboard writing, and learning materials. Note-taking is commonly considered a deeper method of information processing and a productive approach to learning (Nesbit et al., 2006). Miyatsu et al. (2018) have argued that the act of copying material verbatim during note-taking by students is a shallow method of processing information, which does not improve learning outcomes more than simply not taking notes. Therefore, it is essential to provide support for students in information positioning to improve their materials reading more effectively. For example, providing students with structured note formats to assist students in effectively locating information. Kauffman et al. (2011) examined the impact of three note formats, including conventional, outline, and matrix on 119 students, and the results demonstrated that outline and matrix notes can assist students in retrieving information and enhancing their performance.

The present findings are significant in two major aspects. First, this study applied the LA approach to visualize the learning behavioral patterns of students using an e-book system, addressing the labor-consuming complexity of observation and inaccuracy of learner self-reports regarding SRL. Second, this study addressed the limitations of some existing studies, such as the inability to identify specific learning behavioral patterns. For instance, Geng et al. (2020) only analyzed the relationship between the learning behaviors using e-book systems and learning performance without considering the significant temporal sequential behavior transitions.

Conclusion and future works

This study investigated learning behavioral patterns in a seven-week high school mathematics course using an e-book system. This study used the BookRoll e-book system to support students' learning and collect learning logs. The learning behavioral patterns of students while using BookRoll were identified through lag sequential analyses. The results of the analysis revealed that the use of search strategies was not significant using the e-book system and that the functions of bookmarks and quiz responses did not effectively correlate with the reading material for all students. The usages of rehearsal and elaboration strategies were confirmed in the e-book learning behaviors of all students. In addition, this study also employed LA to investigate behavioral differences and learning strategies among students with different learning performances. The results indicated that the students with increased learning performance utilized more efficient and effective behavioral patterns. Especially, students with decreased performance employed surface processing strategies of repeatedly adding and deleting highlights, while students with increased performance read the material before highlighting the contents. Students with unchanged performance relied on different levels of prior knowledge and had different learning behavioral patterns. Students in the unchanged low and middle performance groups were found to adopt the same re-reading strategies as the students with decreased performance, while students in the unchanged high group were found to employ more elaboration strategies. Moreover, the present study also highlighted that e-book systems should further support cognitive and metacognitive activities, such as providing structured note formats and adding dashboard functions to assist students in monitoring and reflecting on their learning process.

There were a few limitations with this study. Future studies should interview students and collect student psychological data, such as the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich & Groot, 1990), to validate the findings of the present study. Considering that the present study only examined students with different learning performances, further research should be undertaken to investigate students classified under different dimensions, such as different SRL motivations. In addition, further research is required to investigate how SRL strategies can be supported in high schools. This study used the definition of increased performance and decreased performance based on changes in performance groups. As such, direct changes in academic performance could not be analyzed. Future studies should consider that the pre-test is at the same level of difficulty as the post-test. Moreover, this study included only the 10th-grade mathematics curriculum. Therefore, further research is needed to analyze additional subjects.

Appendix A

Table 6 The frequency and percentage of learning behaviors in the DP and IP groups

Code	DP group (n=24)		IP group (n=5)	
	Frequency	Percentage %	Frequency	Percentage %
AHMM	16133	41.31%	9952	62.64%
NEXT	9254	23.69%	2160	13.60%
AMK	4054	10.38%	611	3.85%
UHMM	1592	4.08%	931	5.86%
PREV	2559	6.55%	668	4.20%
OPEN	1672	4.28%	527	3.32%
DMK	1765	4.52%	172	1.08%
PJ	818	2.09%	83	0.52%
CHMM	282	0.72%	62	0.39%
QAC	235	0.60%	299	1.88%
AMM	191	0.49%	89	0.56%
CMM	98	0.25%	57	0.36%
CLOSE	153	0.39%	4	0.03%
QA	44	0.11%	21	0.13%
BMKJ	14	0.04%	136	0.86%
ABMK	43	0.11%	46	0.29%
DBMK	36	0.09%	28	0.18%
CRC	34	0.09%	24	0.15%
DMM	59	0.15%	9	0.06%
SEARCH	12	0.03%	5	0.03%
MMJ	9	0.02%	2	0.01%
SJ	1	0.00%	2	0.01%

Appendix B

Table 7 Results of the Mann Whitney U-test for learning behaviors of the IP and DP groups

Code	DP group (n=24)		IP group (n=5)		U	p
	Mean	SD	Mean	SD		
ABMK	1.79	2.41	9.20	12.19	44	0.382
AMK	168.92	94.64	122.20	136.55	37.5	0.201
AMM	7.96	10.64	17.80	15.96	27.5†	0.059
AHMM	672.21	538.92	1990.40	2365.65	41	0.295
BMKJ	0.58	1.72	27.20	51.84	42	0.323
CMM	4.08	6.54	11.40	12.44	23.5*	0.032
CHMM	11.75	11.49	12.40	9.40	52	0.674
CRC	1.42	3.48	4.80	4.15	25*	0.044
CLOSE	6.38	14.49	0.80	1.79	52.5	0.674
DBMK	1.50	2.47	5.60	6.66	40	0.270
DMK	73.54	63.67	34.40	30.99	34	0.145
DMM	2.46	5.47	1.80	2.17	55	0.801
MMJ	0.38	1.24	0.40	0.89	57	0.889
NEXT	385.58	269.72	432.00	324.77	60	1.000
OPEN	69.67	51.81	105.40	65.49	41	0.295
PJ	34.08	23.58	16.60	14.15	32.5	0.114
PREV	106.63	101.71	133.60	97.17	46	0.448
QA	1.83	4.11	4.20	6.69	35.5	0.162
QAC	9.79	21.39	59.80	72.30	23*	0.032
SEARCH	0.50	0.98	1.00	2.24	58	0.933
SJ	0.04	0.20	0.40	0.89	50	0.594
UHMM	66.33	71.78	186.20	189.68	34.5	0.145

†$p<0.1$, * $p<0.05$

Abbreviations

SRL: Self-regulated learning; LA: Learning analytics; IP: Increased performance group; UP: Unchanged performance group; DP: Decreased performance group; LSA: Lag sequential analysis.

Acknowledgements

We would like to thank F High School and Fukuoka City Board of Education for their cooperation in this research.

Authors' contributions

Xuewang Geng and Masanori Yamada designed this research overall. Xuewang Geng and Masanori Yamada were engaged in analysis method of this study. Hiroaki Ogata and Atsushi Shimada developed and deployed the learning analytics platform. Xuewang Geng, Li Chen, Yufan Xu and Masanori Yamada advised the improvement of the instructional design. Masanori Yamada supervised this research. All authors read and approved the final manuscript.

Authors' information

Xuewang Geng is a doctoral student at the Graduate School of Human-Environment Studies, Kyushu University, Japan. He received his master's degree in education from Kyushu University in 2020. His research interests include augmented reality, mobile learning, cognitive load, and learning analytics.

Li Chen is an assistant professor at the Faculty of Information Science and Electrical Engineering, Kyushu University, Japan. She received her Ph.D. in education from Kyushu University in 2021. Her research interests include learning analytics, self-regulated learning, and collaborative problem-solving in STEM education.

Yufan Xu received his master's degree in education from Kyushu University, Japan in 2021. His research interests include social presence, data visualization, and learning analytics.

Hiroaki Ogata is a professor at the Academic Center for Computing and Media Studies, and the Graduate School of Informatics, Kyoto University, Japan. His research includes learning analytics, educational data science, evidence-informed education, CSCL, CSCW, and CALL.

Atsushi Shimada received his DE degree from Kyushu University, Japan in 2007. He is a professor at the Faculty of Information Science and Electrical Engineering, Kyushu University, Japan. His current research interests include learning analytics, pattern recognition, media processing, and image processing.

Masanori Yamada is a professor in the Data-Driven Innovation Initiative and the Graduate School of Human-Environment Studies at Kyushu University, Japan. He is engaged in learning analytics research, in particular, the relationship between learning behaviors and psychological factors such as self-regulated learning.

Funding
This research was supported in part by JST AIP Grant No. JPMJCR19U1, JSPS KAKENHI JP21K18134, JP21KK0184, JP22H00552, and the Cross-Ministerial Strategic Innovation Promotion Program of the Cabinet Office.

Availability of data and materials
All data generated or analyzed during this study are included in this published article.

Declarations

Competing interests
No conflict of interest.

Author details
[1] Graduate School of Human-Environment Studies, Kyushu University, Fukuoka, Japan

[2] Faculty of Information Science & Electrical Engineering, Kyushu University, Fukuoka, Japan

[3] Academic Center for Computing and Media Studies, Kyoto University, Kyoto, Japan

[4] Data-Driven Innovation Initiative, Kyushu University, Fukuoka, Japan

Note: Mr. Yufan Xu's affiliation refers to his affiliation at the time of submission.

Received: 8 June 2022 Accepted: 2 July 2023
Published online: 1 January 2024 (Online First: 18 July 2023)

References

Azevedo, R., & Cromley, J. G. (2004). Does training on self-regulated learning facilitate students' learning with hypermedia? *Journal of Educational Psychology*, *96*(3), 523–535. https://doi.org/10.1037/0022-0663.96.3.523

Bakeman, R., & Gottman, J. M. (1988). Observing interaction: An introduction to sequential analysis. *Journal of Educational Statistics*, *13*(3), 295–297. https://doi.org/10.2307/1164658

Bernacki, M. L., Byrnes, J. P., & Cromley, J. G. (2012). The effects of achievement goals and self-regulated learning behaviours on reading comprehension in technology-enhanced learning environments. *Contemporary Educational Psychology*, *37*(2), 148–161. https://doi.org/10.1016/j.cedpsych.2011.12.001

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, *27*, 1–13. https://doi.org/10.1016/j.iheduc.2015.04.007

Carthy, A., Gray, G., McGuinness, C., & Owende, P. (2014). A review of psychometric data analysis and applications in modelling of academic achievement in tertiary education. *Journal of Learning Analytics*, *1*(1), 75–106. https://doi.org/10.18608/jla.2014.11.5

Chen, C.-H., & Su, C.-Y. (2019). Using the BookRoll E-book system to promote self-regulated learning, self-efficacy and academic achievement for university students. *Educational Technology & Society*, *22*(4), 33–46. https://www.jstor.org/stable/26910183

Chen, C. H., Yang, S. J., Weng, J. X., Ogata, H., & Su, C. Y. (2021). Predicting at-risk university students based on their e-book reading behaviours by using machine learning classifiers. *Australasian Journal of Educational Technology*, *37*(4), 130–144. https://doi.org/10.14742/ajet.6116

Chen, K.-Z., & Li, S.-C. (2021). Sequential, typological, and academic dynamics of self-regulated learners: Learning analytics of an undergraduate chemistry online course. *Computers & Education: Artificial Intelligence*, *2*, 100024. https://doi.org/10.1016/j.caeai.2021.100024

Chen, L., Goda, Y., Shimada, A., & Yamada, M. (2019). Factors investigation of learning behaviors affecting learning performance and self-regulated learning. In *2019 IEEE International Conference on Engineering, Technology and Education* (pp. 1–6). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/tale48000.2019.9225926

Chen, L., Lu, M., Goda, Y., Shimada, A., & Yamada, M. (2020). Factors of the use of learning analytics dashboard that affect metacognition. In *Proceedings of 17th International Conference Cognition and Exploratory Learning in Digital Age 2020* (pp. 295–302). https://doi.org/10.33965/celda2020_202014l038

Embong, A. M., Azelin, M. N., Mohd Hashim, H., & Shaari, Z. H. (2012). E-Books as textbooks in the classroom. *Procedia-Social and Behavioral Sciences*, *47,* 1802–1809. https://doi.org/10.1016/j.sbspro.2012.06.903

Fan, Y., Saint, J., Singh, S., Jovanovic, J., & Gašević, D. (2021). A learning analytic approach to unveiling self-regulatory processes in learning tactics. In *LAK21 Conference Proceedings - The Impact we Make: The contributions of learning analytics to learning* (pp. 184–195). Association for Computing Machinery (ACM). https://doi.org/10.1145/3448139.3448211

Flanagan, B., Akcapinar, Gökhan, Majumdar, R., & Ogata, H. (2018). Automatic generation of contents models for digital learning materials. In *Main Conference Proceedings of the 26th International Conference on Computers in Education* (pp. 804–806). Asia-Pacific Society for Computers in Education. https://apsce.net/icce/icce2018/wp-content/uploads/2018/12/C7-19.pdf

Geng, X., Xu, Y., Chen, L., Ogata, H., Shimada, A., & Yamada, M. (2020, July). Learning analytics of the relationships among learning behaviors, learning performance, and motivation. In *2020 IEEE 20th International Conference on Advanced Learning Technologies (ICALT)* (pp. 161–163). Institute of Electrical and Electronics Engineers (IEEE).

Glogger, I., Schwonke, R., Holzäpfel, L., Nückles, M., & Renkl, A. (2012). Learning strategies assessed by journal writing: Prediction of learning outcomes by quantity, quality, and combinations of learning strategies. *Journal of Educational Psychology*, *104*(2), 452–468. https://doi.org/10.1037/a0026683

Henderson, S., & Yeow, J. (2012). iPad in education: A case study of iPad adoption and use in a primary school. In *2012 45th Hawaii International Conference on System Sciences* (pp. 78–87). https://doi.org/10.1109/hicss.2012.390

Huang, Y. M., Liang, T. H., Su, Y. N., & Chen, N. S. (2012). Empowering personalized learning with an interactive e-book learning system for elementary school students. *Educational Technology Research and Development*, *60*(4), 703–722. https://doi.org/10.1007/s11423-012-9237-6

Hwang, G. J., & Lai, C. L. (2017). Facilitating and bridging out-of-class and in-class learning: An interactive e-book-based flipped learning approach for math courses. *Journal of Educational Technology & Society*, *20*(1), 184–197. https://dblp.uni-trier.de/db/journals/ets/ets20.html#HwangL1

Hwang, G. J., Sung, H. Y., & Chang, H. (2017). Effects of concept-mapping-based interactive e-books on active and reflective-style students' learning performances in junior high school law courses. *Interactive Learning Environments*, *25*(7), 877–888. https://doi.org/10.1080/10494820.2016.1224253

Kauffman, D. F., Zhao, R., & Yang, Y. S. (2011). Effects of online note taking formats and self-monitoring prompts on learning from online text: Using technology to enhance self-regulated learning. *Contemporary Educational Psychology*, *36*(4), 313–322. https://doi.org/10.1016/j.cedpsych.2011.04.001

Lim, L., Bannert, M., Van Der Graaf, J., Singh, S., Fan, Y., Surendrannair, S., Rakovic, M., Molenaar, I., Moore, J., & Gašević, D. (2023). Effects of real-time analytics-based personalized scaffolds on students' self-regulated learning. *Computers in Human Behavior*, *139*, 107547. https://doi.org/10.1016/j.chb.2022.107547

Learning Analytics & Knowledge. (2011). *Proceedings of the 1st International Conference on Learning Analytics and Knowledge*. Association for Computing Machinery (ACM). https://doi.org/10.1145/2090116

Leutner, D., Leopold, C. S., & Elzen-Rump, V. D. (2007). Self-regulated learning with a text-highlighting strategy. *Zeitschrift Für Psychologie Mit Zeitschrift Für Angewandte Psychologie*, *215*(3), 174–182. https://doi.org/10.1027/0044-3409.215.3.174

Majumdar, R., Bakilapadavu, G., Majumder, R., Chen, M. R. A., Flanagan, B., & Ogata, H. (2021). Learning analytics of humanities course: Reader profiles in critical reading activity. *Research and Practice in Technology Enhanced Learning*, *16*, 25. https://doi.org/10.1186/s41039-021-00164-w

Miyatsu, T., Nguyen, K., & McDaniel, M. A. (2018). Five popular study strategies: Their pitfalls and optimal implementations. *Perspectives on Psychological Science*, *13*(3), 390–407. https://doi.org/10.1177/1745691617710510

Nesbit, J. C., Winne, P. H., Jamieson-Noel, D., Code, J., Zhou, M., Allister, K. M., Bratt, S., Wang, W., & Hadwin, A. (2006). Using cognitive tools in gStudy to investigate how study activities covary with achievement goals. *Journal of Educational Computing Research*, *35*(4), 339–358. https://doi.org/10.2190/h3w1-8321-1260-1443

Ogata, H., Oi, M., Mohri, K., Okubo, F., Shimada, A., Yamada, M., Wang, J., & Hirokawa, S. (2017). Learning analytics for e-book-based educational big data in higher education. In H. Yasuura, C. M. Kyung, Y. Liu & Y. L. Lin (Eds.), *Smart sensors at the IoT frontier* (pp. 327–350). Springer International Publishing. https://doi.org/10.1007/978-3-319-55345-0_13

Ogata, H., Yin, C., Oi, M., Okubo, F., Shimada, A., Kojima, K., & Yamada, M. (2015). E-Book-based learning analytics in university education. In B. Chang, G. Biswas, W. Chen, X. Gu, H. Ogata, W. Chen, S. C. Kong & F. Qiu (Eds.), *Doctoral Student Consortium (DSC) Proceedings of the 23rd International Conference on Computers in Education ICCE 2015* (pp. 401–406). Asia-Pacific Society for Computers in Education.

Papamitsiou, Z. K., & Economides, A. A. (2014). Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. *Educational Technology & Society*, *17*(4), 49–64.

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, *82*(1), 33–40. https://doi.org/10.1037/0022-0663.82.1.33

Rawson, K. A., Dunlosky, J., & Thiede, K. W. (2000). The rereading effect: Metacomprehension accuracy improves across reading trials. *Memory & Cognition*, *28*, 1004–1010. https://doi.org/10.3758/BF03209348

Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *Journal of Learning Analytics*, *2*(1), 7–12. https://doi.org/10.18608/jla.2015.21.2

Schunk, D. H. (2008). Metacognition, self–regulation, and self-regulated learning: Research recommendations. *Educational Psychology Review*, *20*(4), 463–467. https://doi.org/10.1007/s10648-008-9086-3

Shimada, A., Minematsu, T., & Yamada, M. (2019). Advanced tools for digital learning management systems in university education. In N. Streitz & S. Konomi (Eds.), *Distributed, Ambient and Pervasive Interactions - 7th International Conference, DAPI 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Proceedings* (pp. 419–429). https://doi.org/10.1007/978-3-030-21935-2_32

Smeets, D. J., & Bus, A. G. (2012). Interactive electronic storybooks for kindergartners to promote vocabulary growth. *Journal of Experimental Child Psychology*, *112*(1), 36–55. https://doi.org/10.1016/j.jecp.2011.12.003

Susantini, E., Puspitawati, R. P., & Suaidah, H. L. (2021). E-book of metacognitive learning strategies: Design and implementation to activate student's self-regulation. *Research and Practice in Technology Enhanced Learning*, *16*, 13. https://doi.org/10.1186/s41039-021-00161-z

Tang, K. Y. (2021). Paradigm shifts in e-book-supported learning: Evidence from the Web of Science using a co-citation network analysis with an education focus (2010–2019). *Computers & Education*, *175*, 104323. https://doi.org/10.1016/j.compedu.2021.104323

Turel, Y. K., & Sanal, S. O. (2018). The effects of an ARCS based e-book on student's achievement, motivation and anxiety. *Computers & Education*, *127*, 130–140. https://doi.org/10.1016/j.compedu.2018.08.006

Viberg, O., Khalil, M., & Baars, M. (2020). Self-regulated learning and learning analytics in online learning environments: A review of empirical research. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge, LAK '20* (pp. 524–533). Association for Computing Machinery (ACM). https://doi.org/10.1145/3375462.3375483

Wakefield, J., Frawley, J. K., Tyler, J., & Dyson, L. E. (2018). The impact of an iPad-supported annotation and sharing technology on university students' learning. *Computers & Education*, *122*, 243–259. https://doi.org/10.1016/j.compedu.2018.03.013

Wang, C. H., Shannon, D. M., & Ross, M. E. (2013). Students' characteristics, self-regulated learning, technology self-efficacy, and course outcomes in online learning. *Distance Education*, *34*(3), 302–323. https://doi.org/10.1080/01587919.2013.835779

Winne, P. H., & Nesbit, J. C. (2009). Supporting self-regulated learning with cognitive tools. In D. J. Hacker, J. Dunlosky & A. C. Graesser (Eds.), *Handbook of metacognition in education* (pp. 259–277). Routledge/Taylor & Francis Group.

Yamada, M., Shimada, A., Okubo, F., Oi, M., Kojima, K., & Ogata, H. (2017). Learning analytics of the relationships among self-regulated learning, learning behaviors, and learning performance. *Research and Practice in Technology Enhanced Learning*, *12*, 13. https://doi.org/10.1186/s41039-017-0053-9

Yamada, M., Shimada, A., Terai, M., Taniguchi, Y., & Konomi, S. (2018). Br-MAP: Concept map system using e-book logs. In *15th International Conference on Cognition and Exploratory Learning in the Digital Age, CELDA 2018* (pp. 248–254). IADIS Press.

Yin, C., Uosaki, N., Chu, H. C., Hwang, G. J., Hwang, J. J., Hatono, I., & Tabata, Y. (2017). Learning behavioral pattern analysis based on students' logs in reading digital books. In W. Chen, J.-C. Yang, A. F. Mohd Ayub, S. L. Wong & A. Mitrovic (Eds.), *Main Conference Proceedings of the 25th International Conference on Computers in Education, ICCE 2017* (pp. 549–557). Asia-Pacific Society for Computers in Education.

Zarzour, H., Bendjaballah, S., & Harirche, H. (2020). Exploring the behavioral patterns of students learning with a Facebook-based e-book approach. *Computers & Education*, *156*, 103957. https://doi.org/10.1016/j.compedu.2020.103957

Zhang, R., Zou, D., Xie, H., Au, O. T. S., & Wang, F. L. (2020). A systematic review of research on e-book-based language learning. *Knowledge Management & E-Learning: An International Journal*, *12*(1), 106–128. https://doi.org/10.34105/j.kmel.2020.12.006

Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology*, *81*(3), 329–339. https://doi.org/10.1037/0022-0663.81.3.329

Publisher's Note

The Asia-Pacific Society for Computers in Education (APSCE) remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.