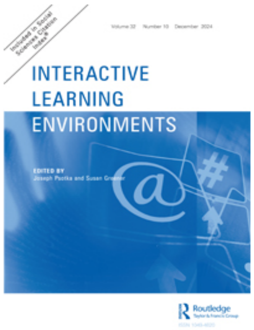

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Understanding students' backtracking behaviors in digital textbooks: a data-driven perspective

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ABSTRACT

The purpose of this study is to explore students' backtracking patterns in using a digital textbook, reveal the relationship between backtracking behaviors and academic performance as well as learning styles. This study was carried out for 2 semesters on 102 university students and they are required to use a digital textbook system called DITeL to review courseware. Students' backtracking behaviors are characterized by seven backtracking features extracted from interaction log data and their learning styles are measured by Felder–Silverman learning style model. The results of this study reveal that there is a subgroup of students called backtracker who backtrack more frequently and performed better than the average students. Furthermore, the causal inference analysis reveals that a higher initial ability can directly cause a higher frequency of backtracking, thus affecting the final test score. In addition, the significance analysis reveals no significant correlation between backtracking behavior and learning style. Building upon these experimental findings, we offer several suggestions for the future advancement of digital teaching materials development.

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KEYWORDS
Digital textbook; backtracking; learning style; page-turning; machine learning

Introduction

Since the usage of the digital textbook is a screen reading, students' reading behavior pattern is different from that in using the printed textbook, the usability elements play a key role in optimizing students' reading experience (Jeong, 2012; Wan Sulaiman & Mustafa, 2020). Among several usability elements of digital textbooks, navigation is one of the most crucial elements affecting user experience. Multiple investigations demonstrate the ease of navigation that makes readers find the correct page more easily and hence improve readers' satisfaction (Bouck et al., 2016; Magdaș et al., 2017; Matraf & Hussain, 2018). Understanding how students navigate in the digital textbook would not only benefit the interaction design but also provide a fundamental component to the student model, which plays a crucial role in shifting digital textbooks to intelligent textbooks (Boulanger & Kumar, 2019; Kay & Kummerfeld, 2021).

In this study, we focus on a light-weighted navigation behavior we refer to cross-page backtracking. Typical backtracking refers to students flipping from a start page back to a previous page, rereading context in that page, and then flipping forward to the start page. This definition of backtracking is different from backtracking in web-page reading, where the backtracking points to the reader scrolling back or upward within a webpage (Marshall & Bly, 2005; Smadja et al., 2019). The

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backtracking defined in this work consists of a series of behaviors like backward page-turning, re-reading, and forward page-turning. Besides re-reading, students may also highlight, memo, or underline during backtracking. The backtracking is frequently occurred in reading academic materials. Flipping a page back to re-read context is a natural way for students to connect different contexts, they may look back to review related content when they comprehended a new concept or they missed a detail. Backtracking behavior is driven primarily by the textual content of the reading materials (Marshall & Bly, 2005; Smadja et al., 2019). A statistical result indicates that students flipped backward nearly half of the reading time in the digital textbooks (McKay, 2011). We might imagine cross-page backtracking in the digital textbook is relatively efficient as they are flipping by tapping a specific button, but it's a fundamentally discontinuous event where the students briefly lose contact with the text (Marshall & Bly, 2005). The processing time of students in page-turning in the digital book is significantly slower than page-turning in the printed books. Moreover, for the task of backward page-turning, the statistical result indicates that reading from the paper was nearly 50% faster than reading from a digital device (Shibata & Omura, 2020a). The difficulty of flipping back and forth between digital pages makes it users hard to scan the entire document clearly (Shibata et al., 2016).

One possible explanation for the discomfort experienced during cross-page backtracking is the high cognitive workload resulting from page-turning in digital textbooks. First, students with lower working memory capacity are more likely to revisit pages (Çebi & Güyer, 2022). Second, the presence of distractions such as icons, gadgets, menus, and toolbars can divert the attention of students, especially those with limited working memory (Shibata & Omura, 2020b; Xu et al., 2021). This creates a negative cycle where students with lower working memory generally have an unsatisfactory reading experience. Recent research indicates a close connection between students' working memory and their learning styles (Abdul-Rahman & Du Boulay, 2014; Çakiroğlu et al., 2020; Graf et al., 2008). Learning styles reflect individuals' consistent patterns of perceiving, interacting with, and responding to the learning environment. Previous studies have demonstrated that students with different learning styles exhibit distinct navigation patterns in interactive learning environments (Bousbia et al., 2006; Graf et al., 2010; Hamdaoui et al., 2018; Popescu, 2009). This could be attributed to the limited working memory capacity of students, who tend to prefer selecting, organizing, and integrating information in digital reading based on their preferred learning styles (Graf et al., 2010; Popescu, 2009).

The purpose of the study is to identify students' cross-page backtracking patterns in using digital textbooks, examine the influence of backtracking on academic performance, and investigate whether there is a relationship between backtracking behavior and Learning styles. In the existing research, Cho and Afflerbach (2017) found that rereading and linking previous text can help determine the overall meaning and structure of the text. Bråten and Ferguson, (2013) reported that when several related cognitive and motivational variables were controlled, students' comprehensive comprehension ability could be predicted by their behavior of reading and rereading text fragments on the computer. Also, some studies have found that the strategic backtracking in the reading process may transform into a higher level of behavioral participation (i.e. productivity) in the evaluation process (Bråten & Latini, 2022; Haverkamp & Bråten, 2022; Latini et al., 2019). Although there have been studies investigating navigation in digital textbooks (Bråten & Ferguson, 2013; Garner et al., 1984), few have explored the relationship between backtracking behavior and learning styles. The research questions of this work are as follows:

- RQ 1: What is the characteristic of students' overall cross-page backtracking behaviors?
- RQ 2: Does students' cross-page backtracking affect their academic performance?
- RQ 3: Is cross-page backtracking related to students' learning style?

Related work

Digital book has been increasingly used in many reading sceneries, but the paper book is still overwhelming preferred as the medium of reading (Baron et al., 2017; Kazanci, 2015; Nicholas et al., 2010; Shibata & Omura, 2010). Shibata and Omura (2010) surveyed 826 office workers to investigate their attitude to a digital book. The result shows that most of them prefer to read in a paper book. Another 6-year longitudinal study conducted on 792 university students also reveals that the majority of the students still prefer traditional printed paper instead of the digital screen for their reading activities and this preference them have not changed in 6 years (Kazanci, 2015). A more recent survey data from 429 university students in 5 counties indicates that more than four-fifths reported that they prefer paper books for both schoolwork and pleasure reading (Baron et al., 2017).

Although it can't be fully explained currently, several studies demonstrate that the human–computer interaction factor especially the usability factor plays a very important role in interpreting this phenomenon. The usability factor is the most influential factor when developing interactive software systems like the digital textbook interface. The ISO 9241-11 (2018) identified efficiency, effectiveness, and satisfaction as major attributes of usability. An investigation from more than 5000 students and staff in 127 universities shows that the main reason for using digital textbooks is the ease of access and convenience, but one of the main problems readers encountered in using a digital textbook is poor navigation (Nicholas et al., 2010). In the study of Shibata and Omura (2010), the participants were requested to evaluate the 18 different usability factors of paper reading and digital reading. The statistical results suggest that the paper reading outperformed digital reading on almost all usability dimensions, such as ease of concentration, ease of understanding, ease of overviewing the whole, ease of switching pages, and so on. Baron et al. (2017) also find that nearly 92% of participants reported they concentrated best when reading in a paper book and the primary disadvantages of the digital book were eyestrain and distraction. More recently, Shibata and Omura (2020b) found this distraction may be caused by disturbances of concentration such as the blinking of a cursor, the background screen, icons, gadgets, menus, toolbars, and so on. Another large-scale investigation on 1053 office workers suggests three factors that contribute to the difficulty of digital reading (Shibata & Omura, 2020b). The three factors are display characteristics that are not eye-friendly, operational and physical constraints, and disturbances of concentration.

Among the numerous human–computer interaction factors, backtracking, as a frequent human reading activity, attracts our attention. A recent survey reported that learners spent more than half of their time on backtracking when reading digital textbooks (McKay, 2011). Smadja et al. improve the interactivity of text navigation to improve the learning effect by analyzing three types of backtracking modes (i.e. simple backtracking mode, continuous backtracking mode, and complete backtracking mode) when learners read in the web page (Smadja et al., 2019). Zhang et al. analyzed the backtracking mode of learners during watching videos, then designed and implemented an intelligent link jump mechanism to improve learning outcomes (Zhang et al., 2017). Ogata et al. (2015), Mouri et al.(2017), and Yin et al.(2019a) also analyzed the improvement effect of backtracking behavior on learning outcomes.

On the other hand, there are still many deficiencies in the backtracking behavior of digital textbooks. For instance, the unsmooth page-turning in the digital textbook is a specific operational constraint. An earlier study by Marshall and Bly (2005) compared participants' reading page-turning behaviors in using the paper book and digital book by videotape analysis. They found that turning pages in the digital book is relatively efficient, but the readers lose contact with the text. More importantly, turning a digital page cannot provide readers an incidental exposure to the broader context by glancing briefly at a two-page spread. The readers also have no opportunity to do all of the subtle looks ahead. However, Takano et al. (2012) compared the cognitive load of reading in the different mediums using the dual-task method and the experiment result suggests that page-turning with a tablet-based digital book had a larger cognitive load than page-turning in a paper book. Shibata et al. (2016) also found the difficulty of moving back and forth between digital pages makes users hard to scan the entire document. A more recent experiment conducted by Shibata and Omura (2020a) shows that students processing time in page-turning in a digital book is significantly slower than page-turning in the printed book, and readers' reading speed on a digital book is slower than reading on a paper book. Moreover, for the task of backward page-turning, the statistical result indicates that reading from the paper was nearly 50% faster than reading from a digital device.

The shortcomings of digital textbook reading have shed light on the connection between reading, backtracking, and human working memory. Recent research by Çebi and Güyer (2022) has revealed a correlation between backtracking behavior, learning performance, and working memory. They found that when working memory is low, the positive relationship between navigation indicators (such as revisiting, time spent, and academic performance) becomes stronger. However, for individuals with high working memory capacity, no significant relationship was observed between navigation indicators and hypermedia issues. Moreover, several studies, including those conducted by Graf et al. (2008, 2010), Popescu (2009), Abdul-Rahman and Du Boulay (2014), and Çakiroğlu et al. (2020), have discovered a link between working memory and learning style. These findings offer valuable insights into exploring the potential correlation between backtracking behavior and learning style. These studies establish an indirect connection between backtracking behavior and learning style through working memory. Hence, we are eager to explore whether there exists a correlation between backtracking behavior and learning style.

Methodology

Instruments

There are two data sources used in this study. The first data source is students' reading behavior data generated when they used a digital textbook called DITeL (Digital Textbook for Teaching and Learning), which was developed by Yin et al. (2019b). The interface of DITeL is shown in Figure 1. In the DITeL, students can bookmark, memos, highlight, and underline by clicking the interactive buttons with different colors. Students' all fine-grained operations are stored in the interaction log files, from which students' several reading features are extracted. The second data source is students'

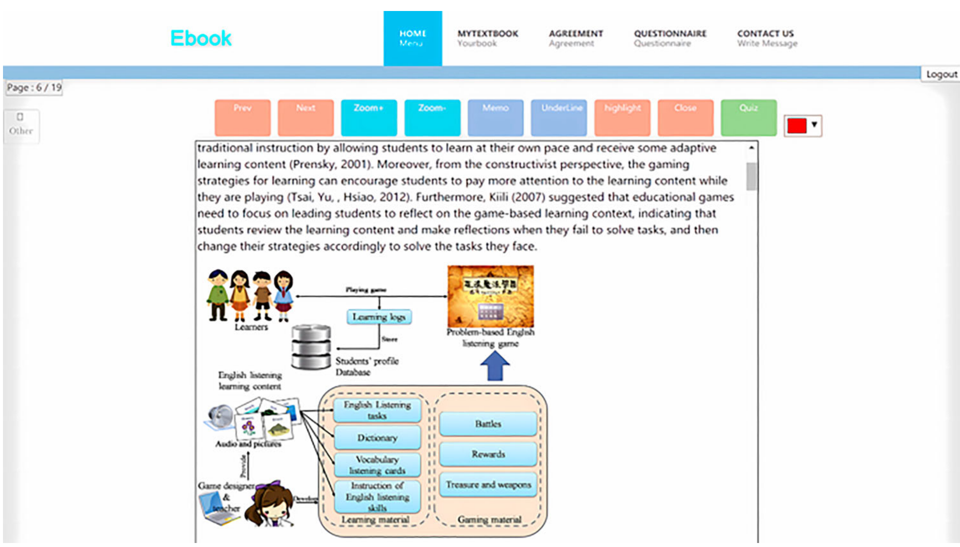

Figure 1. Screenshot of the interface of DITeL.

assessment data. Two assessments were used in this study. The first one is students' learning style assessment that is measured by the Felder–Silverman learning styles model (FSLSM), which uses four dimensions to describe how people process information. The four dimensions of FSLSM are *active/reflective*, *sensing/intuitive*, *visual/verbal*, and *sequential/global*. Each student is characterized by a specific preference for each of these dimensions. The second assessment is the pre-test and post-tests of students' knowledge state. For all students, data from the three sources are combined in this study.

Participants

The participants of this study were recruited from the "Business Law" course in 2 school years at Jinan University, China. The DITeL was used as a digital reading platform for 234 college students (aged 18–19) to read the courseware of the "Business Law" course. This is a digital textbook reading course. It only has online learning mode, and teachers can distribute, manage, and update the teaching content online. These students can preview and review the tutorial material via PC, mobile phone, and tablet. There are a total of 272 pages of slides covered 12 chapters of this course, each of which contains 1–10 sections. The 234 participants were also required to complete the Felder–Silverman learning style questionnaire to measure their learning styles. In each school year, our study lasted over an overall semester. Although all participants completed the Felder–Silverman learning style questionnaire, some participants dropped out during the first week among the 234 individuals. Only 102 people persevered in using DITeL for previewing and reviewing course materials for more than 3 weeks. These remaining 102 individuals were labeled as frequent users, as their data was more comprehensive and suitable for the experiment. Therefore, our research is based on the data generated from these 102 participants.

Data description

Cross-page backtracking data

The DITeL collects and stores students' fine-grained interaction data in log files. The 102 participants generated 860,801 log entries, which record students' interaction with the digital book. These log files were used for extracting several reading behaviors features, such as the device type (PC, tablet, or mobile phone), reading duration, highlight count, underline count, memo count, bookmark count, and so on. This study focuses on students' cross-page backtracking process, so the specific reading and learning behaviors during backtracking should be identified and extracted.

The cross-page backtracking in a digital book is defined as a backward page-turning behavior that turns the book from the current page to any page prior. In DITel, students turn pages forward by clicking the "*Next*" button and backward by clicking the "*Prev*" button. Considering a common page-turning pattern in Figure 2, a student read the book page by page from Page 1(P_1) to Page 6 (P_6) by clicking the "*Next*" button on each page. During reading the content in P_6, the student turned pages to P_2 by continuously clicking the "*Prev*" button. After reading the related content in P_2, the student turned back to P_6 again. Here, the process that students turn pages from P_1 to

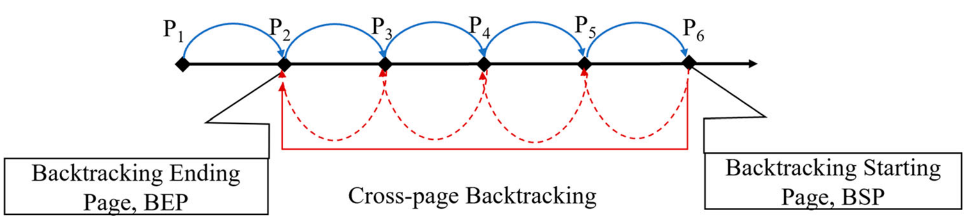

Figure 2. An example of cross-page backtracking in a digital book.

P_6 is a cross-page backtracking behavior. The page where the student clicked the "Prev" button for the first time is the *Backtrack Starting Page* (*BSP*), like P_6 in Figure 2. Likely, the page where students clicked the "Next" button for the first time is the *Backtrack Ending Page* (*BEP*), like P_2 in Figure 2**.**

Using the above-mentioned cross-page backtracking definition, 53,557 backtracking records were extracted from the overall 860,801 log entries. For all backtracking records, we furtherly extracted students' following seven backtracking characteristics to reflect students' learning process during backtracking.

- *backtrackC*: Counts of cross-page backtracking behaviors.
- *backtrackRate*: The backtracking rate is equal to counts of page backward divided by counts of page forward.
- *backtrackSpan*: The backtrackSpan represents how many pages backtracking crossed. It is calculated as the backtracking starting page ID minus ending page ID, i.e. BSP-BEP.
- *backtrackMemo*: Counts of adding memos during the cross-page backtracking.
- *backtrackHighLight*: Counts of adding highlights during the cross-page backtracking.
- *backtrackBookMarker*: Counts of adding bookmarkers during the cross-page backtracking.
- *backtrackSumNotesC*: Total counts of note-taking during the cross-page backtracking.

FSLSM data

The Felder–Silverman learning style model (FSLSM) was used in this study to evaluate students' preference on processing, perceiving, inputting, and understanding material information (Felder & Silverman, 1988). The FSLSM seems to be most appropriate for use in educational research as it distinguishes between preference on four fine-grained dimensions, whereas most other learning style models classify learners in a coarse grain level (Graf et al., 2008). The four dimensions are introduced briefly as follows:

- The dimension of the procession: Learners are divided into active learners and reflective learners by their preference of activities. Active learners prefer to work in groups and do some example-based activities whereas reflective learners prefer to work alone and perform some exercise-based activities.
- The dimension of perception: Learners are classified into sensing learners and intuitive learners by their carefulness degree. Sensing learners tend to be more careful and achieve goals with few trials while intuitive learners show more carelessness for details and a low rate of their goals with several trials.
- The dimension of input: Learners are grouped into visual learners and verbal learners through their inclination upon the types of materials. Visual learners show more interest in picture-based materials whereas verbal learners prefer text-based content.
- The dimension of understanding: Learners are divided into sequential learners and global learners by their interest in learning methodologies. Sequential learners are inclined to look through materials in a manner of knowledge map while global learners prefer to get an overview of outline first.

To evaluate the FSLSM learning style, students were required to fill in the index of learning style (ILS) questionnaire developed by Soloman and Felder (1999). The questionnaire consists of 44 questions and each dimension has 11 questions. Learners' preference in each dimension is expressed by a score between −11 and +11. Take the active–reflective dimension as an example, the score between −11 and −3 means that a learner has a preference for active learning, the score between +3 and +11 means that a learner has a preference for reflective learning, whereas the score between −3 and +3 means that a learner is a balanced learner who has no preference on active–reflective dimension. In this work, 102 participants completed the ILS questionary, and their learning style characteristics are reported in RQ 3.1: Is cross-page backtracking related to students' learning style?.

Analysis method for RQ1: What is the characteristic of students' overall cross-page backtracking behaviors?

The first research question is: *What is the characteristic of students' overall cross-page backtracking behaviors?* To answer this question, we first extracted seven backtracking characteristics from cross-page backtracking data and then employed clustering analysis to find the hidden backtracking pattern. The agglomerative hierarchical clustering algorithm was adopted as the number of clusters cannot be determined beforehand. An agglomerative hierarchical clustering algorithm uses a bottom-up approach where first takes all data points as an independent cluster and starts merging them iteratively based on the similarity between clusters. As per the specific similarity metrics, the robust Ward method was used to calculate the similarity between clusters, and the Euclidean Distance was applied to calculate the distance between individuals.

Analysis method for RQ2: does students' cross-page backtracking affect their academic performance?

The second research question is: *Does students' cross-page backtracking affect their academic performance?* With the 53,557 pieces of backtracking log, we are interested in inferring the causal relationship between backtracking behaviors and learning outcomes to figure out to what extent backtracking behaviors affect learning outcomes. *Tetrad*[1] is a widely used software to detect causal relationships from observation data and has been successfully applied in educational data analysis (Jiang et al., 2021; Koedinger et al., 2015, 2018). *Tetrad* implements several popular causal structure search algorithms and enables users to select and configure algorithms interactively and efficiently. It also supports constraints setting, model evaluation, and causal structure visualization. In this study, *Tetrad* was applied to infer the causal relationship between students' pretest scores, backtracking characteristics, and post-test scores. To aid causal structure search, some counterfactual constraints were imposed before searching. These constraints include backtracking behaviors that cannot be the cause of the pretest score, the post-test score cannot influence backtracking variables, and the post-test cannot affect pretest scores. After comparing several available search algorithms in *Tetrad*, we finally choose the *PC algorithm* for causal model construction. Finally, the statistic was used to evaluate the goodness-of-fit of the causal model, and the model with a *P-value* larger than .05 is accepted.

Analysis method for RQ3: Is cross-page backtracking related to students' learning style?

Our third research question is: *Is cross-page backtracking related to students' learning styles?* To begin with, we utilized descriptive statistics to assess the learning styles of students exhibiting different backtracking patterns. Subsequently, employing numerical analysis and significance testing, we examined the relationship between seven types of backtracking behavior and learning style. In the course of numerical analysis, we scrutinized the differing proportions of various learning styles among backtracker and average students, followed by conducting a comprehensive analysis. Likewise, during the significance testing phase, we obtained significant outcomes through chi-square tests and Pearson correlation analyses, thereby facilitating a more profound analysis.

Results

RQ 1: What is the characteristic of students' overall cross-page backtracking behaviors?

First, to cluster different features, we use *Z*-score method to normalize and standardize the backtracking feature data. Then, the sum of the square errors (SSE) based elbow method is used to determine the best cluster number. Finally, the clustering results are obtained through the aggregative hierarchical clustering algorithm.

The statistical information of the original data is shown in Table 1, and it can be seen that the original data follows a normal distribution. We use the *StandardScaler* function in the *sklearn* library to normalize and standardize data. The *StandardScaler* function standardizes features by removing the mean value and reducing it to unit variance. It centers and scales each feature separately by calculating the relevant statistical data for the samples in the training set. Then the "transform" method is used to store the average and standard deviation for future data use. The calculation formula for the normalization method is

$$x_j^{(i)} = \frac{x_j^{(i)} - \mu_j}{\sigma_j},\ \mu_j = \frac{1}{m}\sum_{i=0}^{m-1} x_j^{(i)},\ \sigma_j = \frac{1}{m}\sum_{i=0}^{m-1} (x_j^{(i)} - \mu_j)^2$$

where x represents data, μ represents the average value, σ represents the variance, and m represents the total number of data. After that, we use the SSE analysis method to obtain the "elbow graph" to determine the optimal cluster number, where the SSE calculation method is

$$SSE = \sum_{i=1}^{k} \sum_{p \in C_i} |p - m_i|^2$$

where C_i is the ith cluster, p is the sample point of C_i, m_i is the centroid of C_i, and SSE represents the clustering error of all samples, representing the clustering effect. The graph of *SSE* and *K* will form an elbow shape, and the corresponding *K* value of the elbow is the optimal clustering number for the data.

The elbow graph (Figure 3) shows that the optimal number of clusters is 2. Also, Figure 4 demonstrates the output dendrogram produced by the agglomerative hierarchical clustering algorithm with Ward linkage. It can be seen that a cut-off distance between 6000 and 11,000 can divide the dendrogram tree into two branches, each of which represents a cluster. Here, according to the best number of clusters obtained from the elbow graph, we choose a cut-off distance of 7000

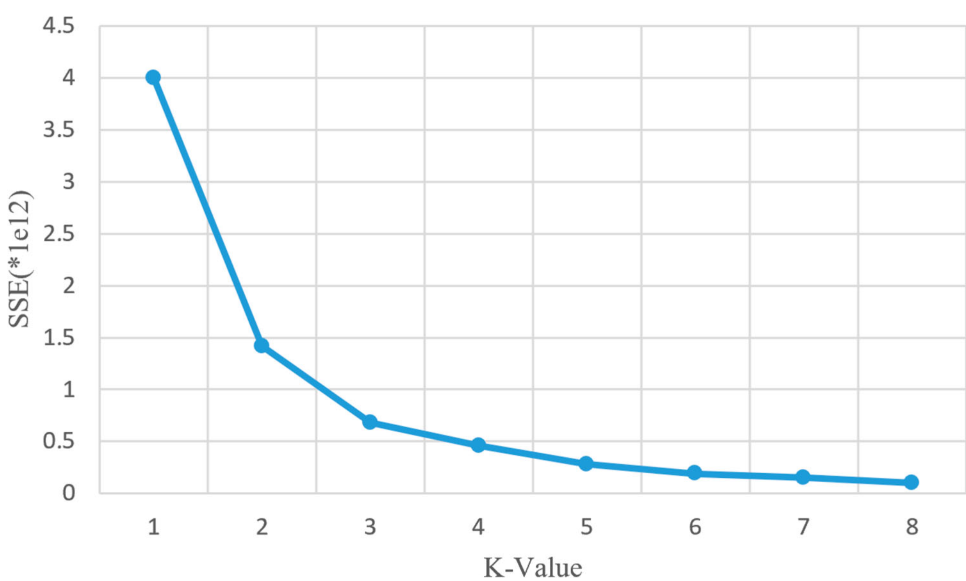

Figure 3. Cluster elbow method diagram.

Table 1. Characteristics of backtracking leaners.

Features	C1(82)Average reader			C2(20)Backtracker			
	Mean/SD	Skewness/SE Skewness	Kurtosis/SE Kurtosis	Mean/SD	Skewness/SE Skewness	Kurtosis/SE Kurtosis	*P*-value
backtrackC	141.68/189.84	0.0486/0.1538	0.2611/0.8258	2096.90/1169.31	−0.0239/0.0757	0.0305/0.0965	.000**
backtrackRate	0.44/0.292	−0.0326/0.1032	0.2102/0.6648	0.65/0.289	0.1124/0.1463	0.1463/0.4628	.004**
backtrackSpan	11.09/5.59	−0.0127/0.0404	0.0778/0.2462	9.50/2.69	−0.0268/0.227	0.2270/0.7179	0.221
backtrackMemo	1.37/4.79	−0.2278/0.7205	0.2081/0.6581	5.70/14.92	0.0993/0.1092	0.1092/0.3455	0.214
backtrackHighLight	0.00/0.00	–	–	0.80/3.58	0.0951/0.3007	0.0025/0.0079	0.33
backtrackBookMarker	0.04/0.25	0.0324/0.1027	0.1181/0.3736	2.65/8.16	0.0368/0.1165	0.1024/0.3240	0.168
backtrackSumNotesC	1.40/4.79	−0.0152/0.0481	0.1876/0.5934	9.15/16.00	0.0896/0.2834	0.1647/0.5210	.045*

** $P < .01$; * $P < .05$

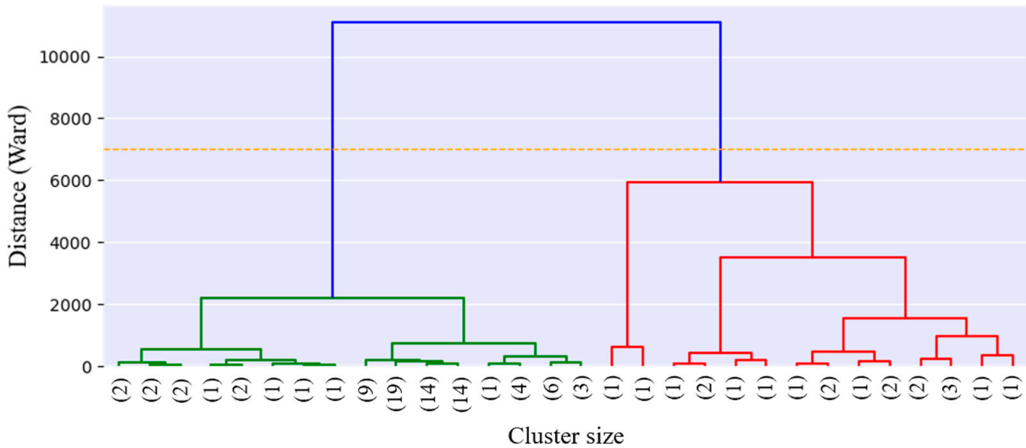

Figure 4. Hierarchical clustering dendrogram.

(orange dashed line in Figure 4) to divide the dendrogram into 2 clusters, which suggests the participants could be divided into 2 distinct groups based on their backtracking features. There are 82 students in cluster 1 (*C1*, in blue color) and 20 in cluster 2 (*C2*, in red color). To investigate the characteristic of students in each cluster, we conducted a statistical analysis. Before that, the homogeneity of the variance of the data was tested using *Levene* test. The *Levene* test suggests $P = 0.01629 < 0.05$, which means we can use the independent-samples *t*-test as follow to compare the two groups.

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

where S_1^2 and S_2^2 represent the variance of the two samples, and n_1 and n_2 represent the two sample sizes. Then we set the original hypothesis H_0: there is no significant difference between the mean values of the two samples in the review group and the average group.

The *t*-test results are reported in Table 1. The significant difference between the two groups on *backtrackC* ($P = .000$) and *backtrackRate* ($P = .004$) reveal that students in *C2* backtracked more frequently than students in *C1*. Therefore, we call students in *C1* as average students and ones in *C2* as backtrackers. Moreover, the backtrackers prefer to do more memos, highlights, book-markers, and notes during the backtracking process than average students. In particular, the backtrackers took significantly more notes than average students during backtracking ($P = .045$).

RQ 2: Does students' cross-page backtracking affect their academic performance?

We compared the academic performance of students in the two clusters in Figure 5. The violin plot in Figure 5 shows that there is no evident difference in their pre-test score ($P = .578$ in *t*-test), but the backtracker achieved a significantly higher post-test performance than the average students ($P = .013$ in *t*-test). We are very interested in whether the cross-page backtracking improved students' learning. To answer this question, the causal relationship between students' backtracking behaviors and academic performance was investigated using *Tetrad*. Figure 6 depicts the causal relationship between backtracking actions and academic performance. In Figure 6, each node represents a variable, and "$A \rightarrow B$" represents variable A is a cause of variable B. It may be a direct or indirect cause that may include other measured variables. The coefficient on each edge represents the strength of

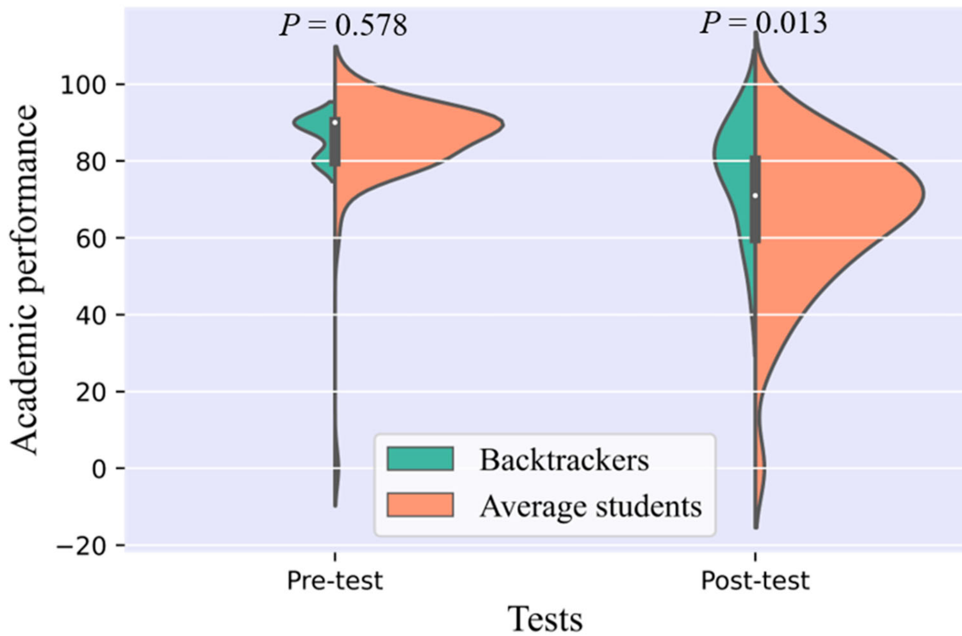

Figure 5. Comparing the academic performance of backtrackers and average students.

the relationship. The model is a good one in that a chi-square (*df* = 2) test shows its predictions are not statistically different from the data (*P* = .889).

The model in Figure 6 indicates direct or indirect causal impacts from pre-test scores, *backtrackC*, *backtrackRate*, *backtrackSumNotesC* to a higher post-test score. The result also suggests that there is

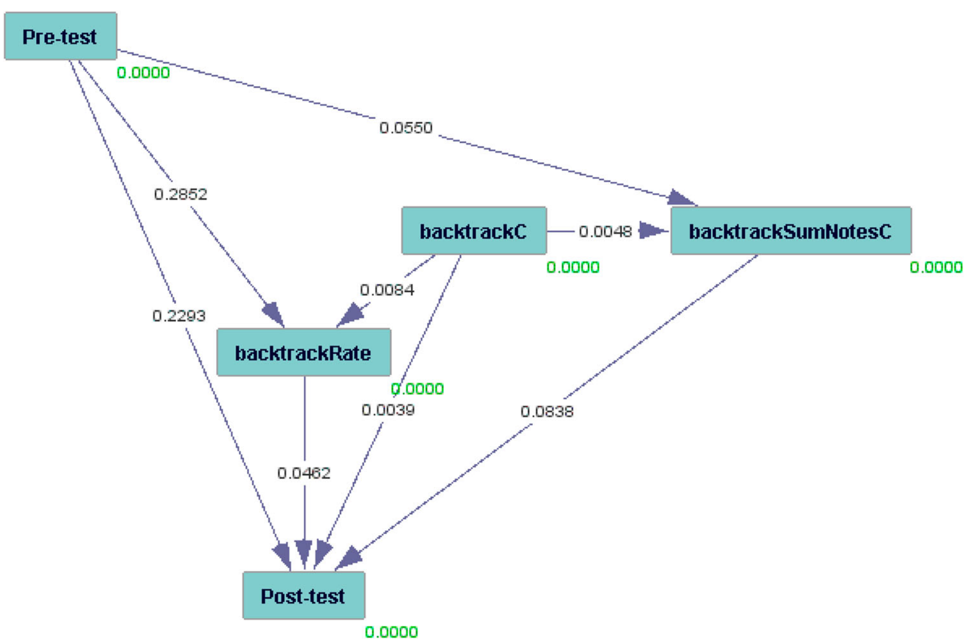

Figure 6. Tetrad inference of causal relationships between backtracking behaviors and academic performances (*alpha* = *.450, df* = *2, Chi Square* = *0.236, P* = *.889*).

no casual relationship between post-test performance and *backtrackSpan, backtrackMemo, backtrackHighLight, and backtrackBookMarker*. More specifically, the casual structural in Figure 6 suggests that the times of backtracking (*backtrackC*) causes a very weakly and direct effect on post-test scores (*coefficient* = *.0043*), and *backtrackRate*, the proportion of backward page-turning to forward page-turning, has a stronger direct impact on post-test scores (*coefficient* = *.0462*). The number of note-takings during backtracking, *backtrackSumNotesC*, has a higher causal influence than the other two backtracking features (*coefficient* = *.0838*). Among all factors, students' pre-test score produces the strongest direct and indirect impact on their post-test score (*coefficient* = *.2293*). Also, a higher pre-test can cause a higher backtrack rate (*coefficient* = *.2852*) and more note-takings (*coefficient* = *.0550*). According to causal analysis results, students' final academic performance is highly influenced by their initial ability and their backtracking behaviors.

RQ 3: Is cross-page backtracking related to students' learning style?

Another interesting finding from the above causal analysis is that a higher pre-test also causes a higher frequency of backtracking, which means students with high initial ability are more likely to backtrack. As students' learning behavior is closely related to their learning style, here the relationship between students' learning styles and backtracking behaviors is investigated. The participants completed the ILS questionary and their learning style characteristics are illustrated in Figure 7, where yellow and purple denote two opposite categories in each dimension and orange represents a balanced one. Using the active-reflective dimension as an example, the ILS suggest that 19 participants are active learner, 42 participants are reflective learner, whereas 41 out of the 102 participants have no preference on either active learning or reflective learning. We are interested in the characteristics of the learning style of students in different clusters. Figure 8 illustrates the proportion of learning styles of backtrackers and average students. In the dimension of the procession, the active learner dominates the others in backtrackers, according to Figure 8(a) nearly 65% of backtrackers are reflective learners, but the distribution is more flattened in average students. In other words, compared to average students, backtrackers may prefer a reflective way of processing information, they learn best by thinking about and reflecting on the material in the digital textbook. As depicted in Figure 8(b), in the dimension of perception, more than half of backtrackers are balance learners, more than half average students are sensing learners and only very few students in both groups are intuitive (about 10%). This result suggests that though nearly 90% of backtrackers and average students are sensing and balanced students, the average students are more prefer to learn facts and concrete learning material. According to Figure 8(c) and (d), both groups have a similar distribution in the dimension of input and understanding. In both groups, visual learner dominates others in the dimension of input. To further explore whether there is a correlation, we conducted a significance experiment (Figure 9 and Table 2).

Chi-square test and *Pearson* correlation coefficient were used for significance analysis and correlation analysis. The results showed that only Procession class had significant differences, and

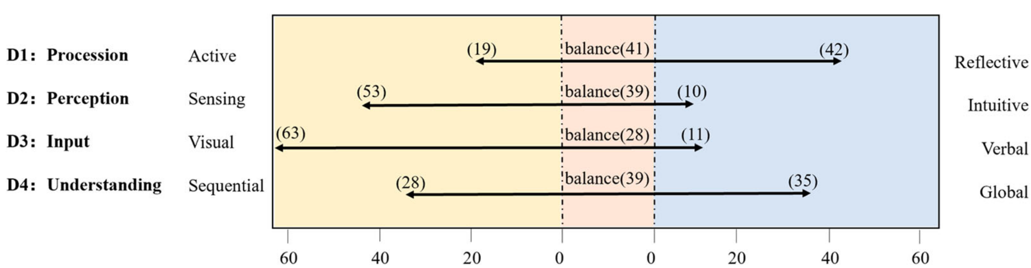

Figure 7. The distribution of Felder–Silverman learning style of the 102 participants.

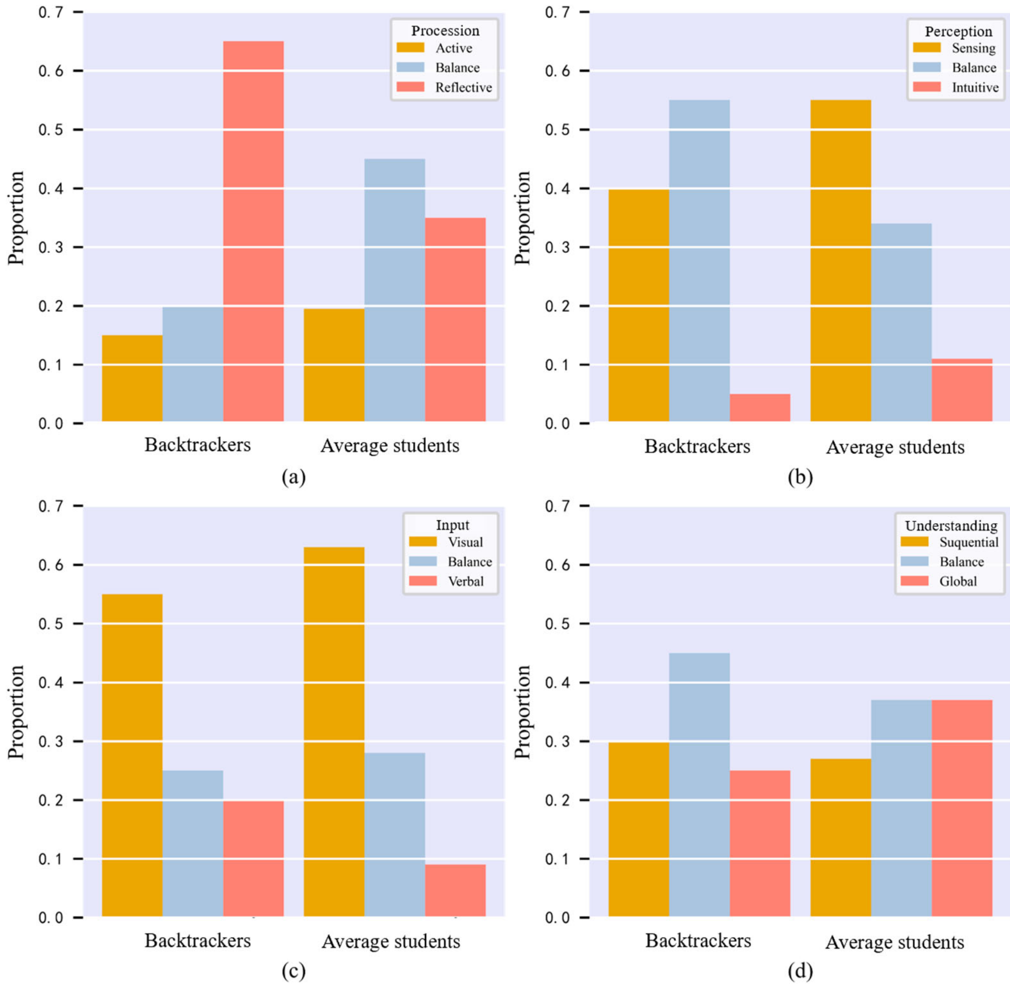

Figure 8. The learning styles of students in the two produced clusters: (a) dimension of procession, (b) dimension of perception, (c) dimension of input, and (d) dimension of understanding.

correlation analysis showed no correlation. This suggests that different learning styles may not directly affect whether students have backtracking reading behavior.

Discussion and conclusion

The aim of this study is to uncover the relationship between students' backtracking behavior and their learning performance. Additionally, we seek to explore the potential association between students' backtracking behavior and their learning style. As for the backtracking pattern, the clustering analysis suggests dividing the participants into two groups, backtrackers, and average students. The

Table 2. Characteristics of backtracking leaners.

When the significance level was set to 0.05, Critical Value: 5.9914				
	Procession	Perception	Input	Understanding
Chi-square	6.1292	3.0992	2.1979	0.9855
p-value	0.0466	0.2123	0.3332	0.6109

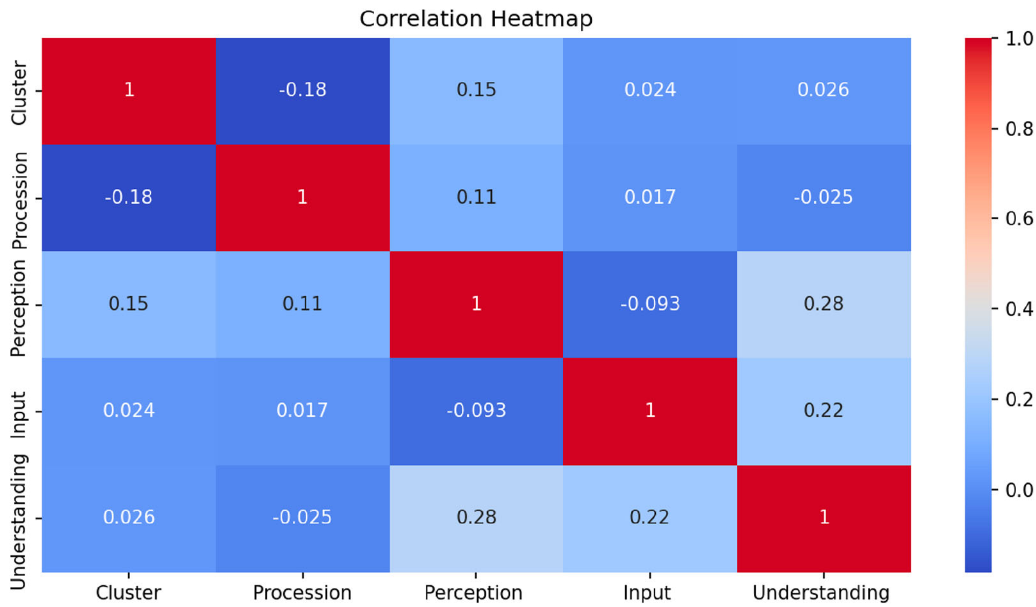

Figure 9. The distribution of Felder–Silverman learning style of the 102 participants.

further statistical analysis shows that the backtrackers generally flipped back more frequently than the average students. In addition, the backtrackers also prefer to memo, highlight, bookmark, and take notes during the revisiting.

We furtherly found that the two groups of students' initial abilities in this course are similar, but the backtrackers significantly outperformed the average students in the final exam. The causal inference analysis reveals that a higher pre-test score can directly cause a higher frequency of backtracking, thus affecting the post-test score. Also, a higher backtracking frequency, counts of backtracking, counts of note takings during backtracking slightly cause a higher post-test score. Therefore, we can conclude that backtracking in digital textbooks benefits students reading and comprehension. Similar to backtracking in browsing webpage, backtracking in the digital textbook is also a fine-grained signal of engagement that can reflect readers' understanding of the reading material (Smadja et al., 2019). Also, readers' backtracking reflects their interest in the reading material, and readers with high interest would flip the pages backward and forward more frequently (Badi et al., 2006). Therefore, the frequent backtracking may reflect students' strong interest in the academic material and active involvement in a reading activity, both of which would cause a better learning outcome.

Our findings reveal that backtrackers only exhibit distinct preferences in information processing and selection. Regarding information processing, most backtrackers demonstrate a reflective learning style, indicating a preference for contemplating and reflecting upon the reading material. On the other hand, average students do not show a noticeable preference for information processing, aligning with the study conducted by Graf et al. (2010). They discovered that active learners typically navigate from content objects to the conclusion section, a pattern that is absent in reflective learners. In terms of information selection, average students tend to prefer learning factual and concrete material, while backtrackers do not exhibit a specific preference in this dimension. In terms of the perception dimension, both groups predominantly consist of visual learners. However, in the understanding dimension, we did not observe a particular inclination among backtrackers towards global comprehension of materials. This finding differs from the study conducted by Popescu (2009), who found that sequential learners more frequently used the "Next" button, whereas global learners tended to backtrack more often on previously visited resources. Notably, several recent studies support the notion that reflective learning enhances students' performance in digital learning environments (Chang & Lin, 2014; Guo, 2022; Zhan et al., 2011). According to Abdul-Rahman and Du Boulay (2014), reflective learners generally outperformed active learners in various learning tasks due to the medium-sized effect of information perception on cognitive load and subsequent learning outcomes.

There is no significant relationship between backtracking and learning style from the results of significance analysis and correlation. The results of the experimental analysis show that only information processing has a significant difference, which is related to the working memory mentioned above. Backtracking behavior involves the size of students' working memory capacity. In addition, learning style is the performance of students to effectively perceive, process, store, and recall what they have learned in a complex way under certain conditions, which also involves the capacity of working memory. The size of the working memory directly affects the level of information processing, which causes a significant difference between the backtracker and average student information processing.

Our research provides some insights into the future use of electronic books. On the one hand, as backtracking benefits students' comprehension but operating in a digital book is not very efficient, the digital textbook should be designed to promote backtracking and eliminate the existing operation constraints. For example, the digital textbook could detect readers' page-turning patterns and provide additional reading assistants for backtrackers to make them backtracking more efficient. The system can link the two pages that contain prerequisite concepts to make readers backtrack more easily. Also, the system can analyze readers' page-turning logs using associate rule mining to identify the most associated pages, and thus recommend the potential pages the readers may want to revisit. On the other hand, automatic learning style detection overcomes the uncertainty problem of the conventional questionnaire-based method. The proposed learning style detection model can be embedded into any digital textbook system to identify readers' learning styles automatically and seamlessly. With it, the digital textbook system could provide several personalized reading services for readers. For example, if the prediction model suggests a reader with poor academic performance is an active learner, the system can provide some reflective interventions such as a prompt question or hint to promote reflective learning.

Limitations, contributions, and future work

It needs to consider that the results should be interpreted with caution because of the following two limitations. The first limitation of this work comes from the low number of participants. Although more than 200 students were recruited to participate in this study, only about half of them persisted in using our digital textbook system as the reading tool. This throws a threat to the validity of causal analysis results as the insufficient data makes the output of the causality algorithm less reliable. Another threat comes from students' reading data. Although there are 102 participants persisted in using the digital textbook, the most backtracking happened in the first half of this course. The relatively low engagement of participates in the second half of learning brought difficulties in exploring the statistical correlations between learning style and backtracking behavior.

Although the above two limitations throw threats to the validity of this work, we still make three important contributions to the growing body of research on digital textbook. First, this study focuses on backtracking, an under-explored learning behavior, and found the two hidden backtracking patterns and identified the positive impact of backtracking on the learning outcomes. This study provides new insights into students' reading behaviors analysis in the digital textbook. Then, we found no significant correlation between backtracking and learning style. In the future, we would like to furtherly explore the factor that affects students' backtracking behavior by questionary investigation. In addition, we are planning to automatically link the backtracking starting page and ending page in the DITeL platform using data generated by others, and thus recommend the possible target page students may flip back to.

Note

1. https://github.com/cmu-phil/tetrad

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