Exploring students’ backtracking behaviors in digital textbooks and its relationship to learning styles

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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. The study was carried out for two 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 the 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, most backtrackers are reflective and visual learners, and the seven backtracking features are good predictors in automatically identifying learning styles. Based on the results of qualitative data analysis, recommendations were made on how to provide prompt backtracking assistants and automatically detect learning styles in digital textbooks.

Keywords: digital textbook, learning style, backtracking, page-turning

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 common and important elements that affect the user experience. Multiple investigations demonstrate the ease of navigation that makes readers find the correct page more easily improves 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 (Smadja et al., 2019). The 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).
A possible reason for the unease of cross-page backtracking is the high cognitive workload caused by page-turning in the digital textbook. On the other hand, students with less working memory are more likely to revisit (Çebi & Güyer, 2019). On the other hand, the hot spots such as icons, gadgets, menus, and toolbars distracted students, especially those with low working memory (Shibata & Omura, 2020b; Xu et al., 2021). This vicious circle leads the students with low working memory to generally have unsatisfactory reading experience. Recent studies reveal that students’ working memory is closely related to their learning styles (Abdul-Rahman & Du Boulay, 2014; Çakiroğlu et al., 2020; Graf et al., 2008). Learning styles is a relatively stable indicator of how people perceive, interact with, and respond to the learning environment. Existing empirical studies have shown that students with different learning styles have different navigation patterns in interactive learning environments (Bousbia et al., 2006; Graf et al., 2010; Hamdaoui et al., 2018; Popescu, 2009). This could be explained by the fact that students’ working memory is limited, they generally prefer to select, organize, and integrate information in digital reading in a way that can best match their 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 the relationship between cross-page backtracking and learning styles. Although there have been studies investigating navigation in digital textbooks, few studies have explored the backtracking behavior. 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? If so, to what extent can cross-page backtracking predict students’ learning styles?

Related work

Digital book has been increasingly used in many reading scenarios, 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 & 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 six-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 & 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, etc. 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, etc. 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.

The unsmooth page-turning in the digital textbook is a specific operational constraint. An earlier study by Marshall & 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 & 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.

From the perspective of psychology, the high cognitive workload caused by backward page-turning may explain the disturbances of concentration in the digital book. Cognitive load is the amount of working memory required to perform a task. Reading in a digital book is a form of multimedia learning and this process could be interpreted by the three-step (selecting-organizing-integrating) cognitive theory of multimedia learning (Mayer, 2014). The learner first selects which information they would like to attend and bring that information into working memory. Then, the learner organizes the visual and verbal information in their working memory into spatial representations and verbal models. Lastly, the learner integrates the spatial and verbal representations and with relevant knowledge activated from long-term memory. In a digital book, these processes are performed under the learners’ working memory limit as well as the operational and physical constraints of digital devices. An ideal reading outcome could be anticipated if learners can appropriately allocate working memory within each step and during the transitions between steps. However, the unease of operation of digital reading system takes readers’ working memory and makes them easy to be distracted, thus readers with low working memory were usually disadvantaged in digital reading (DeStefano & LeFevre, 2007). A more recent empirical study involving 81 university students indicates that the students with high working memory capacity prefer to visit more pages, navigate linearity, and less revisit
Students’ working memory is closely related to their learning styles. The learning style reflects how humans respond to the stimulation in the context of learning and what consistent preferences of behavior may appear. Graf et al. (2008) investigated the relationship between students learning styles and working memory capacity. The results suggest that students with high working memory capacity tend to prefer a reflective, intuitive, and sequential learning style whereas learners with low working memory capacity tend to prefer an active, sensing, visual, and global learning style. Abdul-Rahman & Du Boulay (2014) compared active and reflective learners’ cognitive load and learning performance under three different instructional strategies. The experiment results suggest that learning style may have had a medium-size effect on cognitive load, and thus affect learning outcomes. A more recent also indicated a weak correlation between students’ learning styles and their cognitive load in the multimedia learning environment (Çakiroğlu et al., 2020). As students’ working memory is limited, they generally prefer to select, organize, and integrate information in digital reading in a way that can best match their cognitive traits. For example, Popescu (2009) investigated the relationship between students’ learning styles and behavioral patterns preferences in online learning. Their results showed that sequential learners used the “Next” button more frequently while the global learners tend to backtrack more often on these visited resources. Another early research also showed that students with different learning styles use different strategies to learn and navigate through the online course (Graf et al., 2010). They found that a typical navigation pattern of the active learners is re-submitting an exercise and jumping from content objects to conclusions, but this pattern was not found in reflective learners.
Methodology

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 the co-author Yin et.al., (2019). 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’ 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-test 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 two 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. 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 styles 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 styles questionnaire, only 102 out of 234 participants persevered in using DITeL to preview and review courseware. Therefore, our study is based on the data generated by these 102 participants.

**Data Description**

![Figure 2](image-url) An example of cross-page backtracking in a digital book

**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 time, 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 $P_6$ 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.,
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 53557 pieces of backtracking data, we are interested in inferring the causal relationship between backtracking behaviors and course outcomes to figure out to what extent backtracking behaviors affect course 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,

\(^1\) https://github.com/cmu-phil/tetrad
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? If so, to what extent can cross-page backtracking predict students’ learning styles?**

Our third research question is: *Is cross-page backtracking related to students’ learning styles? If so, to what extent can cross-page backtracking predict students’ learning styles?* The characteristic of learning styles of students who have different backtracking pattern via descriptive statistics is first given. Then, the relation between seven backtracking behaviors and learning style scores of four dimensions is explored by Spearman correlation analysis. Finally, the unsupervised machine learning algorithms were applied to students’ learning styles using their cross-page backtracking features. To find out which backtracking feature made the most contribution to learning style identification, one of the feature engineering methods, the Tree algorithm was adopted to automatically sort the importance of features. Then, taking into account results of feature importance ranking, we tried different combinations of the seven backtracking features as an input to five popular classifiers, decision tree, logistic regression, support vector machines, random forests, and Naive Bayes. The final step is to evaluate the model performance. Our study applied stratified k-fold cross-validation by the confusion matrix and use recall, precision, and F-score to evaluate the model performance.
Results

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

![Hierarchical clustering dendrogram](image)

**Figure 3** Hierarchical clustering dendrogram

| Features       | C1(82)          | C2(20)          | $P$-value  |
|----------------|-----------------|-----------------|------------|
| backtrackC     | 141.68/189.84   | 2096.90/1169.31 | .000**     |
| backtrackRate  | 0.44/0.292      | 0.65/0.289      | .004**     |
| backtrackSpan  | 11.09/5.59      | 9.50/2.69       | .221       |
| backtrackMemo  | 1.37/4.79       | 5.70/14.92      | .214       |
| backtrackHighLight | 0.00/0.00 | 0.80/3.58       | .330       |
| backtrackBookMarker | 0.04/0.25 | 2.65/8.16       | .168       |
| backtrackSumNotesC | 1.40/4.79 | 9.15/16.00      | .045*      |

*The symbol ** indicates $P < .01$ and * indicates $P < .05$*

**Table 1** Characteristics of backtracking leaners

**Figure 3** 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 11000 can divide the dendrogram tree into two branches, each of which represents a cluster.
Here, we choose a cut-off distance of 7000 (gray dashed line in Figure 3) to divide the dendrogram into two clusters, which suggests the participants could be divided into two 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, a statistical analysis was conducted and the 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?

![Figure 4](image_url) Comparing the academic performance of backtrackers and average students
We compared the academic performance of students in the two clusters in Figure 4. The violin plot in Figure 4 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 5 depicts the causal relationship between backtracking actions and academic performance. In Figure 5, 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 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 5 indicates direct or indirect causal impacts from pre-test scores, $\text{backtrackC}$, $\text{backtrackRate}$, $\text{backtrackSumNotesC}$ to a higher post-test score. The result also suggests that there is no casual relationship between post-test performance and $\text{backtrackSpan}$, $\text{backtrackMemo}$, $\text{backtrackHighLight}$, and $\text{backtrackBookMarker}$. More specifically, the casual structural in Figure 5 suggests that the times of backtracking ($\text{backtrackC}$) causes a very weakly and direct effect on post-test scores ($\text{coefficient} = .0043$), and $\text{backtrackRate}$, the
proportion of backward page-turning to forward page-turning, has a stronger direct impact on post-test scores (\textit{coefficient}=0.0462). The number of note-takings during backtracking, \textit{backtrackSumNotesC}, has a higher causal influence than the other two backtracking features (\textit{coefficient}=0.0838). Among all factors, students’ pre-test score produces the strongest direct and indirect impact on their post-test score (\textit{coefficient}=0.2293). Also, a higher pre-test can cause a higher backtrack rate (\textit{coefficient}=0.2852) and more note-takings (\textit{coefficient}=0.0550). According to causal analysis results, students’ final academic performance is highly influenced by their initial ability and their backtracking behaviors.

**RQ 3.1: Is cross-page backtracking related to students’ learning style?**

![Figure 6](image-url) The distribution of Felder-Silverman learning style of the 102 participants
Figure 7 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.

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 behavior, here the relationship between students’ learning styles and backtracking behaviors are investigated. The participants completed the ILS questionary and their learning style characteristics are illustrated in Figure 6, where the color of yellow and purple denote two opposite categories in each dimension and the color of 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 7 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 9 (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 10 (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. In contrast, the three understanding styles are evenly distributed in both groups. The above analysis suggests that the two clusters have evident differences in the preference of processing and precepting information.

RQ 3.2: To what extent can cross-page backtracking predict students’ learning styles?

To identify learner learning styles automatically, we fed the seven backtracking features into five popular classification models for predicting learning styles in a k-fold cross validation manner. The five classifiers are decision tree, logistic regression, support vector machines, random forests, and Naive Bayes. The results showed that the random forest algorithm performed best. Therefore, the random forest was finally selected as the classifier in this work. The questions we are interested in are how these backtracker features contribute to the learning styles prediction task. Figure 12 shows the contribution of seven backtracking features. It can be seen that backtrackRate, backtrackC, and backtrackBookMarker are the top three features that contributed to the learning style prediction. They overall contributed nearly 90% of overall feature importance to the prediction task. More specifically, the individual feature importance of backtrackRate, backtrackC, and backtrackBookMarker are 0.35, 0.34, and 0.17, respectively. Figure 13 compares the learning style prediction performance generated by random forest
algorithms that use different backtracking feature groups. Surprisingly, according to Figure 13 (a)-(c), it can be seen that the prediction performance of different predictors on the dimension of procession, perception, and input are generally high. More specifically, these algorithms produced at least 80% level on all the four performance indicators, i.e., accuracy, precision, recall, and F1. On the most reliable indicator F1, the random forest algorithm with the full feature reached nearly 90% level in all three prediction tasks. In contrast, according to Figure 13 (d), all backtracking feature combinations performed poorly in predicting students’ preference on the dimension of understanding. The poor prediction performance on the understanding dimension might be interpreted by the nearly uniform distribution of understanding preference in the participants. According to Figure 11 (d), it can be seen that no matter the backtrackers or the average students, they don’t have an obvious preference in information understanding approach, which implies that the backtracking behavior can not depict the difference between them. Finally, in each dimension, an algorithm that used the full features outperformed the one that uses feature subgroups, which indicates that all backtracking features contributed to the prediction task. In all the four prediction tasks, algorithms just using the backtrackRate feature performed very well, which may be explained by its high feature importance that is shown in Figure 12.

![Figure 12 Feature importance of backtracking behaviors](image)

(BR: backtrackRate; BC: backtrackC; BBM: backtrackBookMarker; BHL: backtrackHighLight; BMM: backtrackMemo; BS: backtrackSpan; BSNC: backtrackSumNotesC)
Figure 13 Feature selection and prediction performances for learning style prediction

(BR: backtrackRate; BC: backtrackC; BBM: backtrackBookMarker)

Discussion and conclusions

This study aims to reveal students’ backtracking behavior patterns and investigate the potential relationship between students’ backtracking behaviors and learning styles. As for the backtracking pattern, the clustering analysis suggests dividing the participates into two groups, backtrackers, and average students. The 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.

For RQ3, we found the backtrackers have distinct preferences in information processing and information selection. In the dimension of processing, most backtrackers are reflective learners, and they prefer to think about and reflect on the reading material, but there is no obvious preference in information procession for average students. This finding consists of the study of (Graf et al., 2010). They found that a typical navigation pattern of the active learners is jumping from content objects to the conclusion part, but this pattern was not found in reflective learners. In the dimension of perception, the average students are more prefer to learn facts and concrete learning material, but the backtrackers have no preference in information selection. In the dimension of input, most students in both groups are visual learners. In the dimension of understanding, we didn’t find backtrackers prefer to understand materials globally, while Popescu (2009) found that sequential learners used the “Next” button more frequently while the global learners tend to backtrack more often on these visited resources. In summary, we may conclude from this work that the main difference between backtrackers and the other students in learning style is that most of the backtrackers are reflective learners. Connecting to the high post-test scores of backtrackers, we may conclude that the reflective learning style is positively related to students’ learning outcomes. Indeed, several recent studies support that reflective learning benefits students’ learning in the digital learning environment (Chang & Lin, 2014; Guo, 2022; Zhan et al., 2011). According to Abdul-Rahman & Du Boulay (2014), the reflective learner generally outperformed active learners in several learning tasks because information perception had a medium-size effect on cognitive load, and thus affect learning outcomes.

As for the learning style prediction, the experimental results demonstrated that the seven fine-grained backtracking behaviors are good predictors to predict students’ learning styles, especially in the dimensions of procession, perception, and input. The feature importance analysis demonstrates that the backtracking frequency and the total number of backtrackings are the two most important features in learning style prediction. This finding provides a novel
approach to automatically predict students’ learning styles using fine-grained reading behavior data.

There are at least two implications from our findings. 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 three 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 participate 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. Secondly, the connection between students’ backtracking behaviors and learning styles is identified, which poses a possible lens to explain why someone prefers to backtracking and others do not. Lastly, we propose a well-performed prediction model that is able to detect students’ learning styles using just the seven fine-grained backtracking features. This backtracking feature-based model provides a new approach to automatic learning style detection. 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.

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