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Automated Recommendations for Revising Lecture Slides Using Reading Activity Data

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Abstract: The use of digital textbooks in education provides valuable data on student reading behavior that can help educators refine their course materials and instructional design for future iterations. Previous studies have explored methods for extracting important evidence from this data, but they require manual intervention. By automating these methods, this paper introduces an end-to-end system capable of extracting evidence from e-book data and providing recommendations for slides' content review based on this evidence. Our system incorporates information about reading preferences into the evidence-extraction process and implements Large Language Models (LLMs) for automatic interpretation. Six teachers evaluated our proposed system indicating a promising level of effectiveness, while also highlighting areas for future improvement to ensure a successful classroom implementation. These include considerations for improving the actionability of recommendations, improving the identification of content that needs refinement, and improving the performance of LLMs.

Keywords: e-book, digital textbooks, reading behavior, LAD, LLM

1. Introduction

The accelerated adoption of online and blended learning environments in recent years has led to the increased use of digital textbooks (e-books) in education (Aristovnik et al., 2023; Merkle et al., 2022). E-book platforms not only provide a convenient way to access lecture materials, but also create new opportunities to analyze students' learning behavior through activity data recorded in system logs (Flanagan & Ogata, 2017). A notable example of such platforms is BookRoll, an e-book reader application used in blended classrooms to distribute lecture slides. With BookRoll, students can freely navigate through the pages, highlight text, take notes, etc. For educators, this creates a valuable source of data on students' reading activity within course materials (Ogata et al., 2017).

The reading activity data collected from e-book platforms, such as Bookroll, has several applications in education. For example, it can be used to analyze students' reading strategies (Akcapinar, et al., 2020; Yin et al., 2019), predict low-performing students (Murata et al., 2023), monitor engagement during lectures (Shimada et al., 2018) and guide revisions of lessons and materials (Mori et al., 2018; Sadallah et al., 2020). However, these data alone are limited to describing students' engagement in the system without considering the content they are reading. To address this gap, recent efforts have proposed including information about the content of the lecture slides to better understand students' reading behavior (Wang et al., 2022; Lopez et al., 2023; Takii et al., 2024). With this additional layer of information, future evidence extracted from e-book data could include insights into students' knowledge states and reading preferences.

Although previous studies have proposed methods for extracting useful evidence from reading activity data (Akcapinar, et al., 2020; Yin et al., 2019), these methods often require manual interpretation by experts, making them difficult to implement in real educational settings. In this context, recent advances in Large Language Models (LLMs) offer a promising solution to this challenge. LLMs can summarize and interpret analyses, transforming complex data into simpler explanations that can be delivered directly to final stakeholders (Umerenkov et al., 2023; Wang et al., 2023). This development could improve the usability of e-book data analysis, making it more accessible to educators.

Building on these recent advances, we have developed a dashboard to help teachers refine their lessons and materials using insights from reading activity data. This dashboard summarizes key information about how students engage with the different topics of the lecture materials (reading content-aware evidence). It also provides suggestions in natural language on how instructors can improve their course materials. This approach represents a significant improvement over traditional methods because it automates the data interpretation process. Figure 1 illustrates the key components of our system and shows the two main differences with traditional methods.

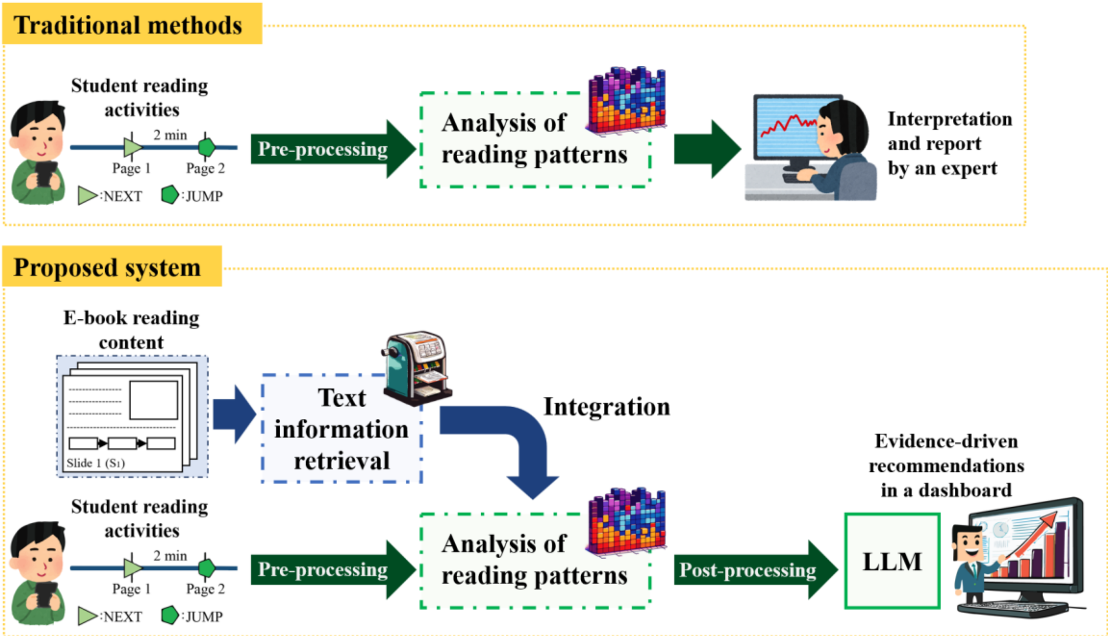

Figure 1. Components of our proposed system compared to traditional methods.

Our main interest is to explore teachers' opinions on the current state of our proposed system and how should it be improved to achieve a practical and useful implementation. Accordingly, the research questions of the present study are as follows:

RQ1. How effectively can our data-driven dashboard provide useful evidence and feedback to help teachers improve lessons and materials?

RQ2. What are the challenges for implementing this dashboard in a real educational environment to support teachers?

2. Related Work

2.1 Extracting evidence of students' reading strategies from BookRoll data

Numerous studies have proposed methods for extracting representative learning strategies from BookRoll activity data. A common approach in these works has been to design a set of data features and group students according to these features using a clustering algorithm. The groups of students reported in this literature were characterized by different levels of reading engagement, receptivity, and responsiveness (Freeman & Saunders, 2016).

For example, Akcapinar et al. (2018) found groups of students with different levels of reading engagement and analyzed the transitions from one group to another across weeks. Their designed features considered the reading time, the number of activities, and the page navigation. Their results indicated that without interventions, students tended to stay in the same group, suggesting a consistency of reading strategies over time.

Yang et al. (2019) considered additional reading activities in their analysis, such as note-taking and searching for specific content. Their findings suggested that increased engagement in all different activities often has a positive correlation with students' final grades. Yin et al. (2019) extended this work by additionally identifying hidden features that do not depend on activity engagement, such as the backtrack reading rate. Accordingly, they identified clusters of students with varying levels of reading engagement and content reexamination. From these results, this study suggested that lecture materials could be personalized to align with students' reading strategies by summarizing or extending the content in the lecture material that they prefer to examine. However, finding this content remains a challenge.

Finally, Akcapinar et al. (2020) proposed a refined set of reading characteristics consisting of reading time in and out of class, along with the frequency of using the highlighting function. The features they selected allowed for a deeper interpretation of reading strategies, identifying three different learning approaches (deep, surface, and strategic). This study made some assumptions to compensate for the lack of information about what content the students were reading. For example, the group of students who had little reading activity outside of class was assumed to be reading only content related to the course exams, which was categorized as a surface approach.

2.2 Teacher-supportive Learning Analytics Dashboards for digital textbooks

Although many Learning Analytics Dashboards (LADs) using data from digital textbooks are designed to support students, some notable studies have also explored how they can support teacher instruction. For example, Mori et al. (2018) implemented a LAD that displays student engagement in different slides uploaded in a Digital Book System to help teachers determine which slides need to be adjusted. This study showed that tracking the engagement in the activities with the "zoom" feature could help teachers identify pages with small text fonts. While the authors acknowledged the value of analyzing other types of reading activities, they did not address how to use this data.

The study by Sadallah et al. (2020) covered this research gap by proposing a set of indicators that can be estimated from reading activity data (stickiness, rereading, navigation, and stopping). Each content block in the course was analyzed according to these indicators to find problems (e.g., very fast speed of reading) and make suggestions for revision (e.g., extend and/or deepen the content). Their results were promising, showing that their LAD often provided teachers with valuable insights for course revision. However, they found mixed opinions about the relevance of their indicators, suggesting their expansion and refinement.

The LAD proposed by Shimada et al. (2018) followed the same approach as Mori et al. (2018), displaying student engagement across reading activities on different pages. However, their LAD was able to display this information in real-time during the lecture. This ability allowed teachers to identify groups of students who were not keeping up with the lecture pace, and to revise content blocks that students were not following correctly (disengagement patterns). These findings suggest that reading activity data can be integrated with additional information (in this case, time information) to better contextualize students' reading strategies and provide more semantic reports for teachers.

2.3 Integrating e-book reading content data into reading activity data

Recent studies have proposed methodologies to integrate reading content information into reading activity data. Wang et al. (2022) introduced a method to transform traditional reading activities into a set of topic-wise activities. They made a list of all the slides on which a topic was written and used it to extract the number of activities for each topic. Although this approach proved effective in improving the quality of traditional analyses, it also raised the issue of optimizing the retrieval of textual information from reading content.

Lopez et al. (2023) addressed this issue by estimating a quantitative relationship between topics and slides using a Language Model. Their model, LECTOR (Lecture slide and topic relationships) outperformed the method proposed by Wang et al. (2022) and other state-of-the-art models for textual information retrieval. This study also complemented the findings of Akcapinar et al. (2020), showing that the inclusion of the reading content information could be used to better extract students' reading strategies. For example, students who had little reading activity outside of class were found to focus on “exercise problems”, demonstrating that they were using a surface learning approach.

Finally, Takii et al. (2024) compared teachers' impressions of two learning visualizations: a knowledge graph extracted from the reading content and the same graph indicating the reading frequency of their nodes (material topics). Teachers indicated a preference for the second condition, remarking the importance of integrating reading content information and reading activities. Since this work did not focus on improving the method of retrieving textual information from e-book slides (they implemented a word co-occurrence algorithm), LECTOR remains the best model for this task (Lopez et al., 2023).

3. Proposed system

Our proposed system consists of three main parts: The extraction of data-driven evidence, the generation of recommendations from this evidence, and the reports in the dashboard. As shown in Figure 2, the first part applies a series of processing modules to extract evidence (two types of evidence) on students' characteristics from the e-book data.

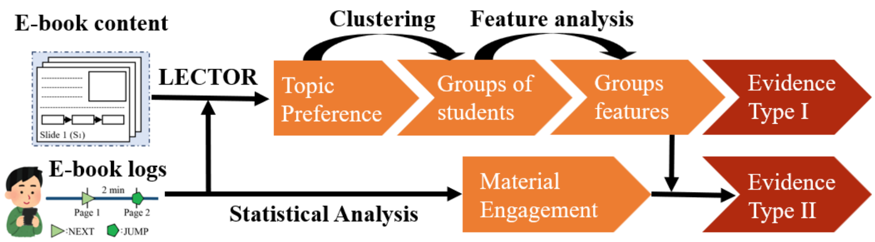

Figure 2. Process flow for extracting e-book data-driven evidence.

First, it uses the language model LECTOR (Lopez et al., 2023) to extract a vector of topic preferences for each student. This vector contains the relative reading time of the different topics in the lecture. The system then applies a clustering algorithm to identify groups of students with similar reading preferences. Since these algorithms are often affected by initial conditions of the model and the number of clusters, we used a consensus clustering approach (Monti et al., 2003). This algorithm selects the most stable clusters (students grouped together in most of the trials) and the most stable number of clusters (the co-occurrence matrix is well defined), thus automating the manual setup of traditional analyses.

Previous studies often employed a heatmap graph to visually understand the main differences between the identified groups. We have emulated this human process with the feature analysis proposed by Lopez et al. (2023). For a given group, our algorithm iteratively selects a feature (topic preference) and applies the Fisher Discriminant Ratio (FDR; Dougherty, 2013) between the samples of this group and the others. It then selects the features with the highest FDR values, as they best separate the group from the others. This information is entered into a text template that generates an “Evidence Type I” describing the characteristics of a particular group (Figure 3).

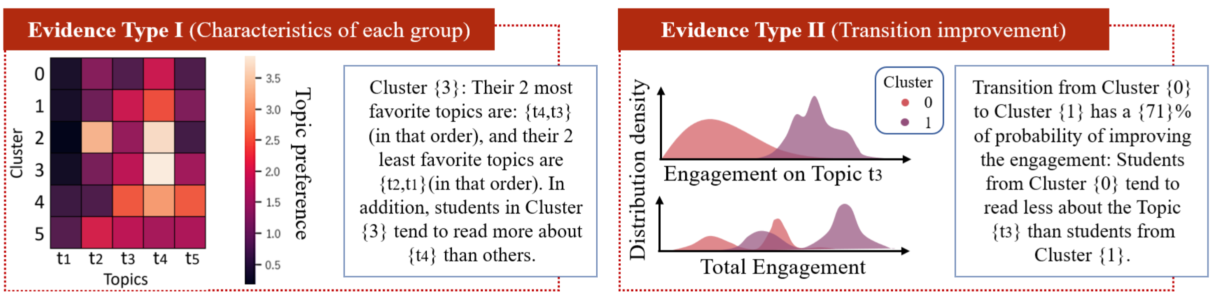

Figure 3. Examples of evidence extracted by the system (Type I and II). Text descriptions are automatically generated using templates.

Simultaneously, our system estimates the reading engagement of all students by applying the method proposed by Boticki et al. (2019). Then, it finds cases where a student from one group is more likely to be engaged in the e-book material than a student from another group. This probability is empirically estimated from the student samples in the groups (Equation 1). When a probability of engagement improvement is higher than 70%, our algorithm uses the FDR to find the most important differences in reading preferences between the groups and enters this information into a text template that generates "Evidence Type II" (Figure 3).

$$Pr\left(E_{G_1} > E_{G_2}\right) = \frac{\sum_{s_i \epsilon G_1} \sum_{s_j \epsilon G_2} \mathbf{1}(e_{si} > e_{sj})}{|G_1| \cdot |G_2|} \tag{1}$$

, where E_n: engagement of a student in group n, G_n: set of student samples in group n, e_{sk}: engagement of the student s_k, $\mathbf{1}(\cdot)$: indicator function, |·|: cardinality function.

The next part of the system processes the text of the extracted evidence with an LLM. As shown in Table 1, a first LLM is prompted to select the most important evidence and to propose "Specific Recommendations" to revise the e-book material. Each "Specific Recommendation" should be based on a specific set of evidence, and the LLM is also requested to provide this reference information. For each e-book material, an additional LLM will then summarize all recommendations into a "General Recommendation" (Table 1).

Table 1. *Used prompts in the generation of Specific and General Recommendations*

	Prompt
Specific	FOUNDATIONAL KNOWLEDGE: When developing and selecting textbooks for teaching, educators should (…) \n CASE OF STUDY: We analyzed the data of our students' reading patterns (…). Now we will show you the patterns we found (...) {Evidence Type I with TAGs} (…) {Evidence Type II with TAGs} \n REPORT OF RESULTS: Let's think step by step. We want to improve the textbooks and the contents explained in class. First, focus on our most important findings ({TAGs of Evidence Type II}) and find general patterns ({TAGs of Evidence Type I}) (…), you MUST add evidence, referencing your statements by using the pattern TAGs.
General	You are a helpful assistant designed to make summaries. Use narrative style. Be concise. {SPECIFIC_RECOMMENDATIONS} Summarize it in less than 75 words.

Finally, the recommendations and the selected evidence are reported into a dashboard. As shown in Figure 4, our system follows the paradigm proposed by Hoffman (2020), providing simple information at a low level of aggregation (General recommendation) and offering the possibility to "unhide" data at higher levels (Specific recommendations and evidence).

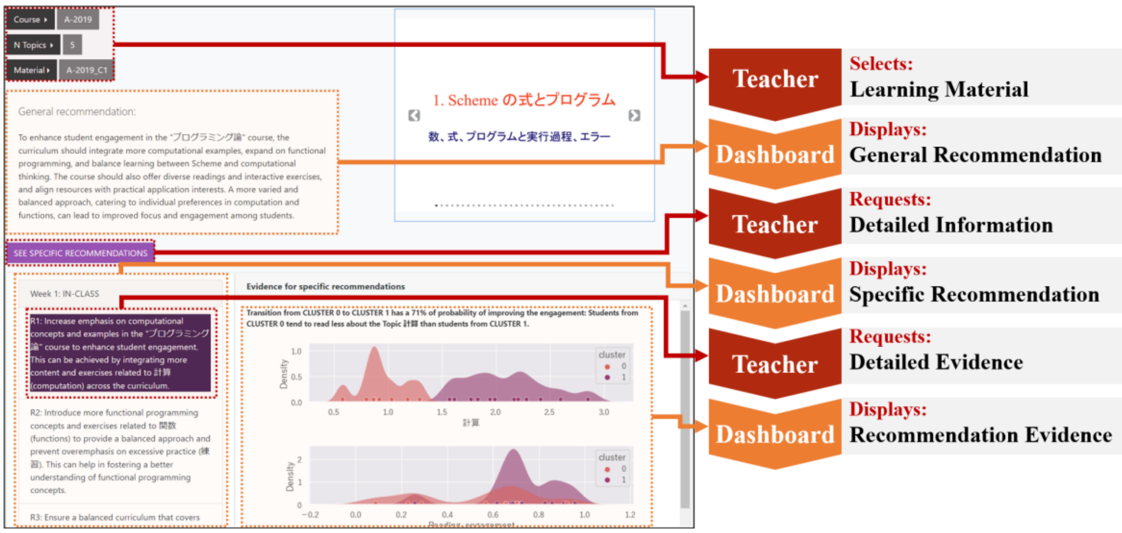

Figure 4. Illustration of the teachers' workflow in the dashboard.

4. Experimental Setting

4.1 Dataset and System Configuration

The information retrieved by our LAD consisted of e-book data from the course "Programming Theory" offered in the year 2019 at Kyushu University (anonymized reading logs from 52 students and reading content from 22 lecture materials). Internally, our system implemented LECTOR with 5, 10, and 15 topics (3 cases), an agglomerative hierarchical clustering model in the consensus algorithm, and OpenAI's "gpt-4-1106-preview" model in the LLM processing.

4.2 Methodology

Teachers were instructed to use the dashboard for at least 30 minutes, carefully examining the recommendations, exploring the supporting evidence, and assessing whether they could use this information in their work. To encourage focus during the evaluation, we asked them to push a "like" button for the most helpful recommendations. Before accessing the dashboard, teachers were provided a manual detailing how to use the system and the purpose of the experiment. Finally, after using the dashboard, they were asked to complete a questionnaire.

This questionnaire was designed to evaluate three dimensions of the LAD: usability, usefulness, and accuracy. The first two dimensions provide an overall assessment of the system (Tables 2 and 3), while accuracy focuses specifically on the outputs (recommendations and data-driven evidence; Table 4). In addition, we included 3 open-ended questions designed to qualitatively assess our technological limitations and explore potential avenues for improvement (Table 5).

Table 2. *Questionnaire items for assessing Usability.*

	Question	**Result**	
		Mean	**STD**
Q1	I think I would like to use the dashboard frequently.	3.33	1.37
Q2	I found the dashboard unnecessarily complex.	3.50	0.76
Q3	I thought the dashboard was easy to use.	3.67	1.25
Q4	I think I would need the support of a technical person to be able to use the dashboard.	3.33	1.70
Q5	I found the various functions in the dashboard (e.g., selecting courses, and displaying the data) were well integrated.	3.83	0.90
Q6	I thought there was too much inconsistency in the dashboard.	3.50	0.96
Q7	I would imagine that most people would learn to use the dashboard very quickly.	3.33	1.70
Q8	I found the dashboard very cumbersome to use.	4.00	1.15
Q9	I felt very confident using the dashboard.	3.00	1.41
Q10	I needed to learn a lot of things before I could get going with the dashboard.	2.50	1.50

Table 3. *Questionnaire items for assessing Usefulness.*

	Question	**Result**	
		Mean	**STD**
Q11	Using the dashboard would improve my work performance.	3.33	0.94
Q12	Using the dashboard would enhance my effectiveness.	3.50	0.76
Q13	I would find the dashboard useful in my work.	3.67	1.11
Q14	The information presented on the dashboard helps me to understand my students' reading preferences.	4.50	0.50
Q15	The dashboard would help me improve the learning materials and the conduction of my classes.	3.50	1.12
Q16	The dashboard presents information that I need to know.	2.83	1.07

The different items of the questionnaire were adapted from 3 widely used evaluation instruments, the System Usability Scale (Brooke, 1996), the Technology Acceptance Model (Davis, 1989), and the LAD success questionnaire (Park & Jo, 2019).

Table 4. *Questionnaire items for assessing Accuracy.*

Question \ Results		5 Topics		10 Topics		15 Topics	
		Mean	STD	Mean	STD	Mean	STD
A1	The recommendations use human-like, simple, and coherent language.	3.83	1.47	3.83	1.17	3.67	1.21
A2	The recommendations reflect correctly the data shown in the evidence.	3.67	0.52	3.83	0.41	3.33	0.52
A3	The recommendations are actionable and relevant.	3.33	1.51	2.83	1.17	2.67	1.21
A4	The evidence is easy to interpret	3.33	1.03	3.17	0.98	3.17	0.98
A5	The evidence contains relevant information about students.	4.17	0.75	4.17	0.75	4.17	0.98

Table 5. *Open-ended items in the questionnaire.*

	Question
O1	A current limitation of the dashboard is that it does not include specific pages of the learning materials that teachers may improve. Do you think that having information about specific pages would be useful to assist teachers in designing classes and improving materials? If your response is affirmative, how do you think having this information could assist teachers?
O2	The dashboard uses information from the actions of students in the e-book reader system. The current version only uses information on the reading time on the different pages to find useful evidence. Do you think you can benefit from this kind of data to revise your materials and design classes? What other sources of information would you use for this purpose?
O3	What specific suggestions do you have for improving the dashboard? Please share your thoughts on the potential benefits, challenges, and any additional suggestions you may have for implementing these improvements.

Six teachers from the Faculty of Information Science and Electrical Engineering at Kyushu University participated in the experiment (N=6). Their teaching experience ranged from 1 to 15 years, with an average of 5 years. Five of the participants specialized in engineering and science, and one specialized in education. In addition, one of the participants had been responsible for teaching the course “Programming Theory” for the past 5 years and authored the materials that were revised in the experiment.

5. Results

The results of the questionnaire items are summarized in Tables 2, 3, and 4 (Usability, Usefulness, and Accuracy, respectively). These items were scored on a scale of 1 to 5, where larger values are better. In Table 2, however, the final scores of the even items were calculated as module 5 of their raw scores, since they were code-reversed.

Table 2 shows an average usability score of 3.4, indicating a moderately satisfactory level with high reliability (Cronbach's alpha score of 0.92). However, item Q10 received a relatively low score, indicating challenges with the onboarding process. Some comments in the open-ended responses (Table 5) indicate that learning to interpret the data evidence prior to using the dashboard was challenging.

Table 3 shows a slightly higher average score of 3.6 supported by a good reliability (Cronbach's alpha score of 0.88). This indicates that the system is generally considered to be moderately useful. However, the relatively low score of Q16 suggests potential issues with the relevance or completeness of the dashboard information. Feedback from the open-ended responses (Table 5) indicates that the recommendations were often overly broad, reducing actionability. While teachers recognized the importance of the information provided, they struggled to translate it into actionable changes in the lecture materials.

Finally, Table 4 shows moderately good accuracy levels for recommendations (average of 3.44, Cronbach's alpha score = 0.81) and evidence (average of 3.69, Cronbach's alpha score = 0.82). Notably, the accuracy of recommendations improves as the number of topics decreases. We attribute this trend to a limitation of LLMs in information processing. Despite their ability to retrieve information from large amounts of text, LLMs have limited ability to reason about the facts listed in the text. Consequently, analyzing fewer topic preferences may lead to more natural and actionable recommendations.

As described in the previous section, we implemented a “like” button, designed to encourage teachers to focus on the evaluation. Accordingly, the recommendations with more “likes” describe teachers' preferences. In Table 6, we show 3 examples of these choices. These examples complement the teachers' comments about the actionability of the recommendations. For example, recommendation R1 does not only specify the topics “calculation” and “Scheme”, but also links them with an action: adding exercises (programming tasks) about calculation. Since this combination of topics corresponds to a specific pair of slides, teachers do not have much difficulty in deciding which changes to make. In contrast, a recommendation such as “Increase the quantity and quality of content related to Scheme language and expressions to improve engagement for clusters showing high interaction with these topics.” (an actual system recommendation) includes the topics “Scheme” and “expressions” that are covered largely in the lecture material (a broad recommendation), without specifying an action, which is difficult to translate into a review of the material.

Table 6. Examples of recommendations liked by teachers.

Tag	System Recommendation
R1	Integrate calculation with Scheme: Develop exercises that incorporate “calculation” within Scheme programming tasks to improve engagement with calculations
R2	Balance Error Learning: Avoid overemphasis on “error” and “syntax error”. Include more success-based examples and structured debugging exercises
R3	Rethink the presentation format of practical exercises and incorporate more examples related to “conversion” topics to increase engagement

6. Discussion

In response to RQ1, our experiment showed a moderate level of effectiveness in providing useful evidence and recommendations. The results of the dashboard’s usability, usefulness, and accuracy are promising, but the challenges of system onboarding and recommendations actionability highlight the need to refine the current system. Considering the teachers' feedback about the current limitations of the system (results from Table 5), we will next discuss the main challenges in designing an effective dashboard to be implemented in a real educational environment (RQ2).

First, it is essential to ensure that system recommendations are actionable. Five evaluators indicated that recommending specific actions for specific pages would increase actionability. To this end, new systems should perform their evidence extraction in single blocks of content (a single slide or a set of slides with similar contents), similar to the approach proposed by Sadallah et al. (2020). This task requires a deeper multimodal integration of information. New models should estimate slide-to-slide relationships to identify sets of slides providing a single unit of knowledge. In addition, using slide-to-slide transitions can contextualize internal relationships within content blocks (e.g., one slide is often read after another, only one slide is read), while slide-focused activities can identify issues (e.g., very fast speed of reading may require content expansion or merging).

This approach would also improve the performance of LLMs. In our system, LLMs were tasked with a complex interpretation of the data, requiring them to both understand the evidence and design actionable recommendations. By identifying actions during evidence extraction, LLMs can focus on rephrasing this information in human-like language. Moreover, LLMs could play an additional role in future dashboards. While the presentation of evidence is critical to ensuring system trustworthiness, evaluators found visual interpretation of evidence challenging. Accordingly, evidence could be presented as a short text description, allowing teachers to get a deeper explanation from a chat agent LLM.

Next, future systems should integrate additional sources of information to extract evidence. Teachers mentioned the importance of considering other reading activities, such as adding/deleting highlights and making annotations, as they reflect students' cognitive reading strategies. For example, reading receptivity and responsiveness can be estimated from these activities (Freeman & Saunders, 2016). In addition, three evaluators mentioned the importance of using information from learning performance (grades) and learning reflections. For example, the system could identify hard-to-understand knowledge units from students' learning reflections and prioritize the analysis of the corresponding content blocks.

Regarding the use of learning performance indicators, courses that use weekly quizzes can implement a variation of our proposed Evidence type II. Instead of estimated engagement, they can use the quiz scores to identify performance differences between groups of students with different content preferences. In addition, they can define new indicators that integrate both engagement and performance to reduce the influence of students' personal characteristics such as Deep Effortlessly Concentration (DEC), which affects engagement and performance regardless of the reading materials involved (Smith et al., 2023). In cases where an assessment is not available, the systems can implement models for early prediction of final grades (Murata et al., 2023) to estimate the expected learning performances.

7. Conclusions

The evidence extracted from e-book reading logs can help educators refine their instruction, including the refinement of their materials. Accordingly, several works have proposed methods for extracting this type of evidence. Our study extends these efforts by automating their processes, integrating content-aware data, and using LLMs to interpret the extracted evidence, culminating in an end-to-end system. This system was implemented in a dashboard and represents a significant advancement in the use of e-book data for educational support.

To assess the practical utility of our enhancement, six teachers evaluated our dashboard and provided feedback for further improvement. While this sample size meets minimum reliability standards, it limits the generalizability of the findings (Sadallah et al., 2020). Therefore, conducting future evaluations in different settings is recommended.

Our dashboard results indicate a promising moderate level of effectiveness in providing useful and accurate recommendations to educators. The main limitations of our current dashboard highlight the importance of ensuring actionable recommendations and intuitive presentation of evidence. Based on teachers' feedback, future efforts should focus on extracting actionable evidence for individual content blocks, integrating LLMs to facilitate evidence interpretation, and incorporating additional data sources that can help identify parts of the materials that need improvement.

Acknowledgments

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