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Identifying Student Engagement and Performance from Reading Behaviors in Open eBook Assessment

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Abstract: Digitized learning materials are a core part of modern education and analysis of the use can offer insight into the learning behavior of high and low performing students. The topic of predicting student characteristics has gained a lot of attention in recent years, with applications ranging from affect to performance and at-risk student prediction. In this paper, we examine students reading behavior using a digital textbook system while taking an open ebook test from the perspective of engagement and performance to identify strategies that are used. We create models to predict the performance and engagement of learners before the start of the assessment and extract reading behavior characteristics employed before and after the start of the assessment in a higher education setting. It was found that compared to performance, the prediction of overall engagement has a higher accuracy, and therefore could be more appropriate for identify intervention candidates.

Keywords: Open book; engagement; student performance; reading behavior; online testing

1. Introduction

In the wake of the Covid-19 pandemic, many educators have had to drastically change the way they conduct classes, adapting to online or distance education that has been imposed, and as a consequence to this change in delivery, some traditional methods are difficult to implement. Assessment is often conducted in environments that are tightly controlled including the restriction of reference material. However, it is difficult if not impossible to implement in online and distance education effectively. Open ebook assessments on the other hand can allow the use of reference materials and other sources of information. As assessment is increasingly being performed using LMS and other digital learning systems that are accessed via an internet connection, it is becoming difficult to limit access to external information sources during testing. One argument for open ebook assessment is due to possible information overload of learners. A learner should learn and memorize core knowledge that is key to the domain, while being able to rely on the sourcing of backup or auxiliary knowledge from external references (Heijne-Penninga, 2008). Open ebook testing also can be used to encourage higher cognitive level thinking by reducing the necessity for memorization and rote learning of facts in order to pass a test (Eilertsen & Valdermo, 2000). However, there has been limited work that looks at the actual strategies and information searching through reading behavior that students employ before and during open ebook assessment.

Previously, the authors investigated predicting learner performance from patterns in reading behavior (Flanagan et al., 2020). It was found that reading behavior patterns that occurred during the open book assessment were an important characteristic in predicting low performing learners. In contrast, high performing learners were identified by reading behavior patterns that mainly occurred before the assessment. This indicates the importance of reviewing the lecture materials after class and previewing again before the assessment. While this learning behavior is critical for traditional closed book assessment, previous research suggests that some students view open book assessments differently.

Students might assume that because they will have time during the exam to look at reference materials, prior study is not as crucial to successful performance.

In this paper, we examine the reading behaviors of learners from the first-time topics and concepts are introduced in a lecture, to when they are assessed and the impact of having an open ebook policy assessment. In particular, we are interested in if it is possible to predict problem learners early before the assessment to facilitate possible intervention to improve the learning outcomes. Also, it is beneficial to identify key reading behavior characteristics of high engagement learners when compared to low engagement learners to plan possible effective interventions.

2. Related Work

As the use of digital learning systems is increasing, there are new opportunities to analyze strategies and behaviors of learners from log data that is collected as opposed to more traditional methods of investigation that relied on subjective views and self-reporting from learners. Oi et al. (2015) investigated the preview and review patterns of undergraduate learners by analyzing the usage logs of an ebook reading system. In particular, they examined the aggregate of the number of pages read, the duration of reading and the number of books that were read for a specific time period. It was found that there is a significant difference between the review and preview patterns based on performance in the midterm and term-end examinations.

The problem of predicting low performing students as early as possible has been gaining much attention recently as higher education and MOOCs providers are increasingly examining methods to reduce attrition rates and improve learning outcomes. Okubo et al. (2017) predicted the final academic performance of learners based on their usage of digital learning systems over the course of a 15-week semester. An Recurrent Neural Network (RNN) style model was trained on LMS, e-portfolio and ebook reading events and was able to achieve a high degree of accuracy. Akçapınar et al. (2019; 2019) used features based on aggregates of ebook interaction logs to develop an early-warning system to predict learners that are at-risk of failing the course. 13 different prediction techniques were applied to analyze the data collected over a 14-week semester with promising predictions being made as early as the 3rd week in the semester. Gray & Perkins (2019) demonstrated how at-risk students can be identified within the first 3 weeks by using student attendance/engagement. While Rashid & Asghar (2016) examined the correlation between use of technology/student engagement and academic performance.

Previous research has mainly focused on the analysis of reading behavior for assessment at the semester level or long over the entire span of the course to gain insight to the preview/review patterns or develop early warning prediction models for intervention. In the present research, we focus in particular on the reading behavior of learners in relation to an open ebook assessment. The time frame for intervention in the case that is investigated is also much shorter when compared with previous research and therefore much more fine-grained prediction is required as opposed to prediction at weekly intervals.

3. BookRoll: eBook Reader Log Data

Digitized learning materials are a core part of modern formal education. In addition to serving as a learning material distribution platform, it is also an important source of data for learning analytics into the reading habits of students. The action events of the readers are recorded, such as: turning to the next or previous page, jumping to different pages, memos, comments, bookmarks, and markers indicating parts of the learning materials that are hard to understand or are of importance. The reading behavior of students has previously been used to visualize class preparation and review patterns (Yin et al., 2015; Ogata et al., 2017). The digital textbook system can be used to not only log the actions of students reading reference materials, but also to distribute lecture slides.

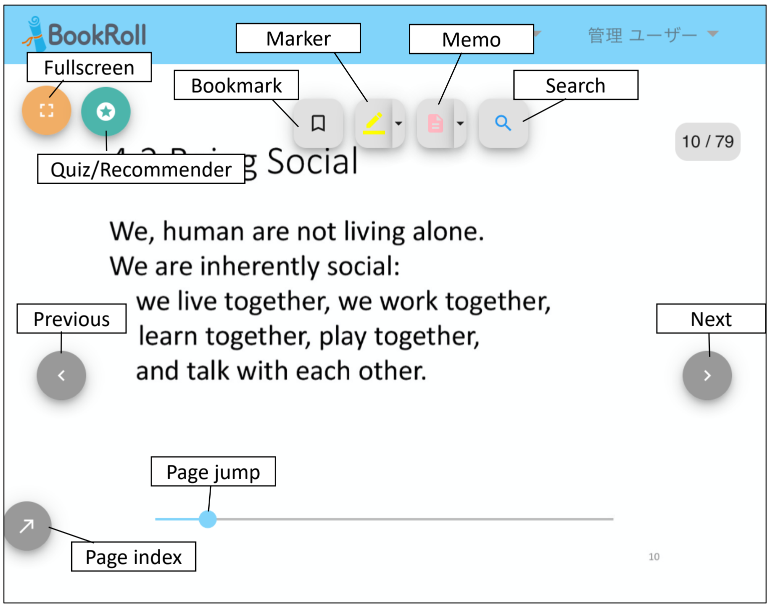

Figure 1. A screenshot of the BookRoll digital learning material reader (Update to include the audio function).

In the present work, the non-proprietary BookRoll digital textbook system was used to serve lecture materials and capture learners reading behavior for analysis. As shown in Figure 1, the user interface supports a variety of functions, such as: moving to the next or previous page, jumping to an arbitrary page, marking sections of reading materials in yellow to indicate sections that were not understood, or red for important sections. Memos can also be created at the page level or with a marker to attach it to a specific section of the page. Users can also bookmark pages or use the full text search function to find the information they are looking for later when revising. Currently, learning material content can be uploaded to BookRoll in PDF format, and it supports a wide range of devices, including: notebook computers, tablets, and smartphones, as it can be accessed through a standard web browser.

Reading behavior while using the BookRoll system is send using the xAPI standard for pseudonymized learning event logging and collected in an LRS. Table 1 presents a sample of BookRoll's learner behavior logs that have been extracted from an LRS. In the logs there are many types of operations, for example, OPEN means that the student opened the e-book file and NEXT means that he or she clicked the next button to move to the subsequent page. An overview of the types of operations and description of the interaction that is represented is shown in Table 2. The logs that are collected in BookRoll are quantitative education data and can be used to observe various objectives, such as (Ogata et al. 2017):

- Analyze the behavior of "active learners" for use in encouraging students to be more active.
- Observe and analyzing the details of behavior of "active learners" to make the students more active.
- Based on the logs made during a class session, improving
- course designs, which include collaborative learning and flipped classroom approaches.
- Based on the students' patterns of viewing e-books (e.g., understanding which page was frequently viewed), improving teaching materials and the structure of the e-books.

Previous work by Authors (Flanagan & Ogata, 2018) details the learning analytics platform that was used to collected the learner behavior data analyzed in the present paper.

Table 1

A sample of events recorded from user interaction with BookRoll.

Contents id	Memo text	Operation date	Operation name	Page no	User id
EBOOK_341		2018/01/22 18:10	REGIST CONTENTS	0	t1
EBOOK_341		2018/01/23 9:16	OPEN	1	s1
EBOOK_341		2018/01/23 9:20	NEXT	2	s1
EBOOK_341		2018/01/23 9:21	OPEN	1	s2
EBOOK_341	Sample memo	2018/01/23 9:22	ADD MEMO	2	s1

Table 2

Operation names and descriptions for learning behavior interactions captured with BookRoll.

Operation Name	Description
OPEN	opened the book
CLOSE	closed the book
NEXT	went to the next page
PREV	went to the previous page
PAGE_JUMP	jumped to a particular page
ADD BOOKMARK	added a bookmark to current page
ADD MARKER	added a marker to current page
ADD MEMO	added a memo to current page
CHANGE MEMO	edited an existing memo
DELETE BOOKMARK	deleted a bookmark on current page
DELETE MARKER	deleted a marker on current page
DELETE_MEMO	deleted a memo on current page

4. Data Collection and Pre-processing

The data examined in the present paper was collected from an undergraduate Introduction to Informatics course which is a core first year second semester subject at Kyoto University. There were 233 students enrolled in the class. The data was collected for one open ebook assessment that was held at the start of a class for 30min. This was to assess knowledge learnt in a previous lecture. The assessment was provided using the standard testing features on the University's Sakai LMS. In the weeks leading up to the lecture and assessment, the use of the digital textbook system and testing features in the LMS were introduced and actively used. This ensured that students had good working knowledge of the systems, and were not impaired by using unfamiliar systems. The learning materials for the course were only made available through BookRoll, which has been intentionally designed to restrict offline study by making it difficult to download and print reading materials. The assessment makes up part of the overall final grade of the course. This along with the schedule and focus of the assessments was announced to students at the start and end of each lecture to reinforce the significance of the assessment for learners. As the assessment only focused on one ebook which contained the slides of one lecture, the log data from other learning materials that are not relevant to the assessment were excluded from this study. A total of 164 learners submitted all the questions in the test and were graded.

The lecture which contained the learning material relevant to the assessment was uploaded before being explained to the students. The assessment was given 7 weeks after the lecture, and 5 lectures that focused on a different topic were given during the period until the assessment. The lecture slides were mainly text based with figures and graphs being used sparingly where necessary to assist in explaining models and concepts. The assessment contained questions that involved the simple processing of data or calculation of models which were described in the lecture material that was shared on BookRoll. A short essay was also given at the end of the assessment which asked students to think critically about the possible applications of methods that were introduced during class.

The learning behavior logs were preprocessed to calculate the amount of time a learner spent on each event by comparing the timestamp of neighboring logs. We then removed logs where the learner spent less than 3 seconds on a page as this is indicative of surfing behavior where learners quickly transition from page to page while looking for specific information. Features for training a model were then generated from the filtered raw event logs by concatenating the operation name of four adjacent logs to create a 5-gram feature that represents a sub-segment of the time series of interactions by the learner. This type of feature is also often used in NLP and sequence mining (Flanagan et al., 2014). For example, "NEXT_PREV_NEXT_NEXT_CLOSE" was used when a learner had gone to the next page in the ebook and then returned to the previous page to re-read before reading two the following two pages and finally closing the ebook. In addition, the features were marked with a suffix of "b" or "a" to denote whether the event took place before or after the open ebook assessment had started. The exact time that the learner began the assessment on the LMS was used to account for variations throughout the class. Learners were divided into two groups based on their performance in the assessment: high and low. The assessment had a maximum score of 17 points, so the groups were divided as follows: low < 8.5 < high. It was confirmed that no learner achieved a score of 8.5 so there weren't any discrepancies. The groups were nearly balanced, with n=86 for the low group, and n=78 for the high group.

We used the method proposed by Akçapınar et al. (2019; 2019) to measure learner reading engagement from the aggregate frequency of the following reading behavior logs: the total number of reading logs, the number of reading sessions, the total reading time, the number of weeks of reading, the number of days spent reading, the amount of reading events longer and shorter than 3 seconds, how many times the learner went to the next or previous page, number of page jump events, number of red or yellow markers drawn, memo written, and bookmark placed in the learning material. These frequencies were then aggregated using the percentile rank equation as below. It should be noted that the features that were used to calculate the engagement score were not used in the training or evaluation of the prediction models.

$$PR = \frac{f_b + 0.5 f_w}{N}$$

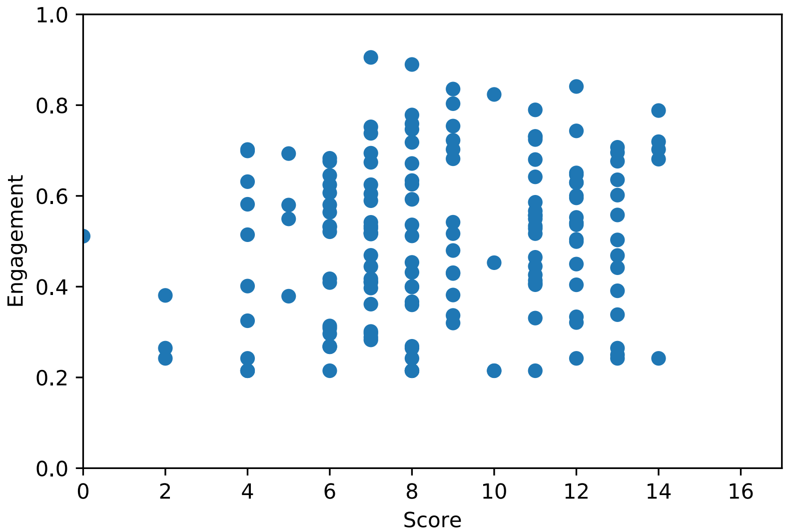

Figure 2. A plot showing the relation between a learners' score and their level of engagement.

A plot of the learner performance score that was achieved on the open ebook assessment and the overall engagement that was calculated based on the frequency of different types of reading behavior is shown in Figure 2. The correlation between the score that the learner achieved on the open book test and the level of engagement was measured, and it was found that there is a weak correlation of 0.18. This is in contradiction to the results reported by Akçapınar et al. (2019; 2019) and Rashid & Asghar (2016), where it was found that learner performance had a stronger correlation with learner engagement. It can be seen that some students have low overall engagement levels, but have achieved relatively high scores on the test, while other students have high engagement but low scores on the test.

In addition to predicting the score of the student for interventions for at-risk students, the early prediction of a student's overall engagement could be used to trigger an intervention to increase engagement in the reading task.

The change in learner engagement over time is shown in Figure 3, where at each point in time the engagement of the learner is calculated in relation to their reading behavior up until that point. During the period of the lecture on the left of the x-axis and the open book assessment on the right, there are fluctuations in learner engagement. This could be attributed to learner self-regulation and different learning behavior types, such as: procrastination, learning habit, random, diminished drive, early bird, chevron, and catch-up as described by Goda et al. (2015), and early completers, late completers, early dropouts, and late dropouts as described by Li et al. (2018). Therefore, a learner's engagement at any point in time up until the end of the period under examination is not necessarily indicative of the engagement of the learner over the whole period.

Once again, we divided learners into two groups based on their reading engagement: high and low. As the percentile rank is between 0 to 1 the groups were divided as follows: low < 0.5 < high. It was confirmed that no learner achieved an engagement level of of 0.5 so there weren't any discrepancies, with n=74 for the low group, and n=91 for the high group.

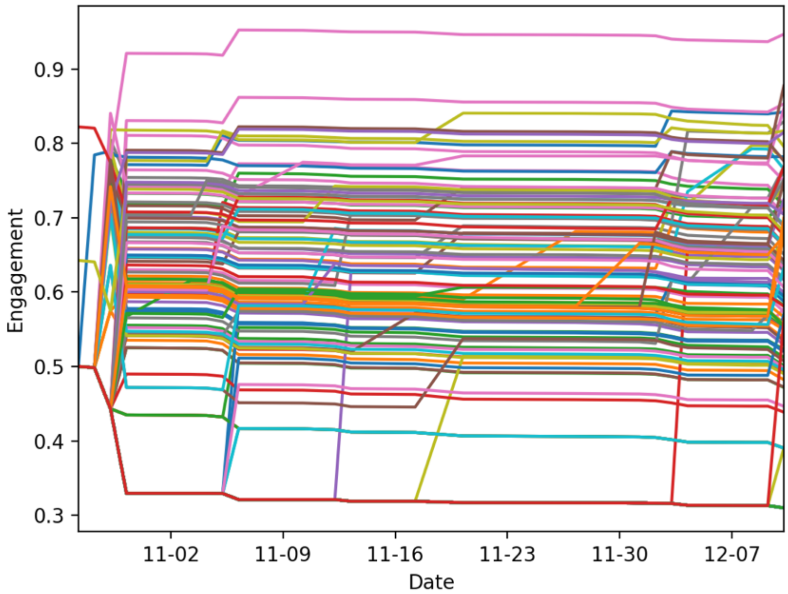

Figure 3. A plot showing the changes in learner engagement over time.

5. Modeling and Analysis of Reading Behavior Characteristics

To model the performance of the learners based on their reading behavior, we approached the analysis as a 2-class classification problem, where the high and low groups were positive and negative class labels respectively. The learners' raw reading behavior logs were vectorized in the form of the occurrence frequency of 5-gram reading behavior sequence features that are described in the previous section. The vectors were then normalized using the z-score (Kreyszig, 2009), where each dimension in the vector is normalized relative to the sample mean and standard deviation.

First, we examine the problem of early warning prediction. The aim is to identify learners who will have low engagement or performance in the assessment as early as possible before the assessment. The warning could be an intervention that is mediated by the teacher, or an automated intervention, however investigation into this is beyond the scope of this paper and should be addressed in future work. We approach the early prediction problem by training, testing, and evaluating a model for each day between the initial lecture and the start of the assessment where a learner used the digital textbook system to read about the contents of the lecture. Each model was trained on cumulative data up until the day where the prediction is being made, and therefore models are progressively trained on a greater amount of data as the assessment day is closer. At each point, we train a linear-SVM model using weight guided feature selection as proposed by Flanagan, et al. (2014) to select an optimal subset of characteristic features that describe high and low engaged and performing learners' reading behavior. The performance of the model was evaluated using 5-fold stratified cross validation. These evaluations were then conducted for 30 randomized trials and the average is reported to reduce the possibility of the results being biased due to selective cross validation.

Second, we examine the characteristic reading behaviors of learners from the perspective of high and low engagement and performance before and after the start of the assessment to identify possible differences in strategies that the groups of learners employ for open ebook assessment. In this case, we create an SVM model using all of the available reading behavior data, and add suffixes to identify which events took place before and after the start of the assessment as described in the previous section. Once again, the weight guided feature selection method is used to select a subset of characteristic features of the two groups, and evaluated with 5-fold stratified cross validation over 30 randomized trials. Further, a test of the feature selection is also conducted to verify the significance of the identified characteristic features.

6. Results

Firstly, we will report the results of the early warning prediction. The evaluation of the SVM model by Area Under Curve (AUC) over time is shown in Figure 4.

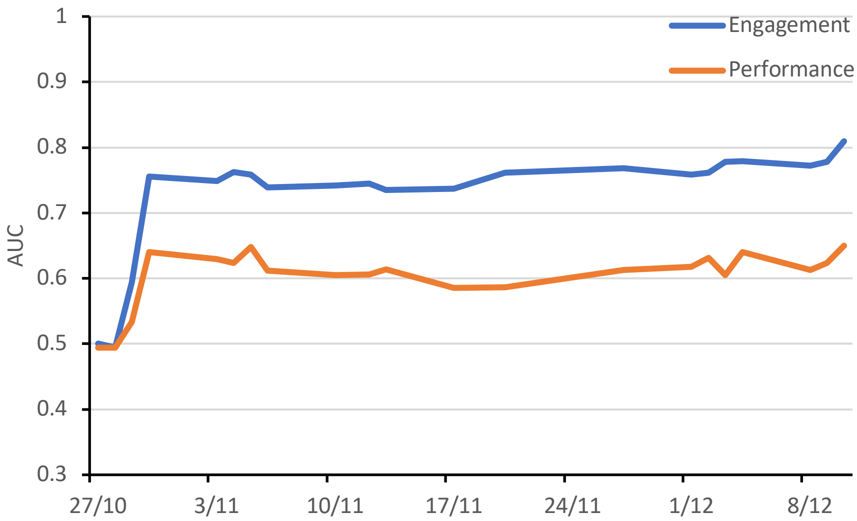

Figure 4. Evaluation of early warning prediction of Engagement and Performance over time by AUC.

The left side of the graph is the day of the lecture where all of the concepts in the assessment are introduced and the learners start reading the lecture materials using the digital textbook system. We can see initially the model cannot predict the engagement or performance of learners with AUC of around 0.5. The first peak in prediction performance is at 30/10 which is the day after the first lecture, with an AUC of 0.7559 for engagement and 0.6405 for performance. Even at this early stage in the prediction, the engagement model is outperforming the performance model by more than 10% AUC. At this point in time the optimal model was trained using only 6 characteristic features for engagement and 80 for performance. The next peak in prediction performance is in the week following the initial lecture with an AUC of 0.7626 for engagement and 0.6475 for performance with 30 and 70 optimal features respectively on around 4-5/11. This could be due to revising by high performing students a week after the initial lecture leading up to the next lecture. The next peak in model performance is the week before the assessment on 4/12, with an AUC of 0.7792 for engagement and 0.6405 for performance with 40 and 30 optimal features respectively. It is possible that this is due to review/preview strategies before the assessment. Finally, the last peak is on 10/12 which is a model trained with all of the data leading up to the assessment that took place on the same day. The final peak was an AUC of 0.8094 for engagement and 0.6499 for performance with both 60 optimal features. It should be noted that the peak in model performance the week after the initial lecture and on the day of the assessment are close, which indicates that in this case predictions and warnings of low performance could be made as early as a week after the initial lecture.

To investigate the strategies that are employed by high and low engagement students, we created a model using all of the available data and tagged the features with a suffix to indicate if the event occurred before or after the assessment had started. A comparison of the 30 trial results for the model using all of the features and the optimized model are shown in Figure 5, where the x-axis is the number of features used to train the model plotted using log scale. The baseline AUC is shown as a dotted horizontal line. We can see that precision initially increases with few features; however, the Accuracy and AUC performance is still low. The model performs best at around 100 optimal features, before declining as additional features are used to train the model.

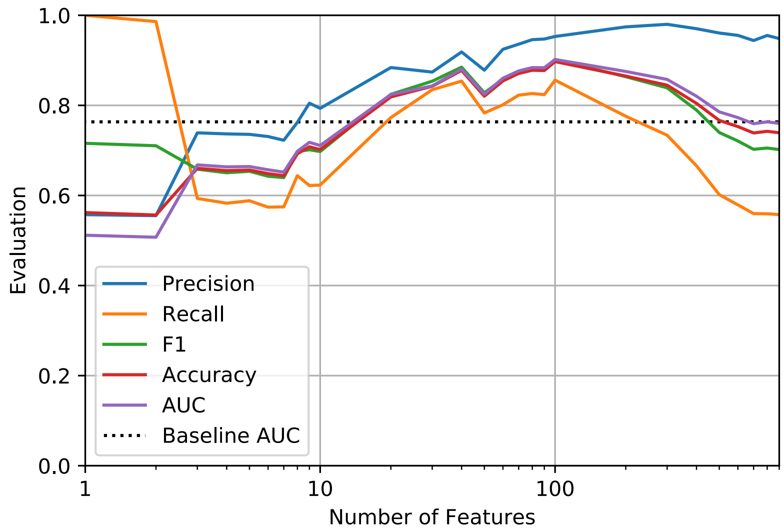

Figure 5. A comparison of the engagement performance of the baseline model vs feature optimized model.

Figure 6 shows a candlestick plot of the AUC prediction results from the baseline and optimized model. The Shapiro-Wilk test was used to confirm if the 30 trial results for both the original and optimized model are normally distributed ($W = 0.9656$, $p = 0.4267$). This indicates that the sample of the trial evaluations had normal distribution in both model results. The Students t-test was employed to determine the significance of the trial results. It was found that the prediction performance measured by AUC of the optimized model was significantly better than that of the original model with $p < 0.02$.

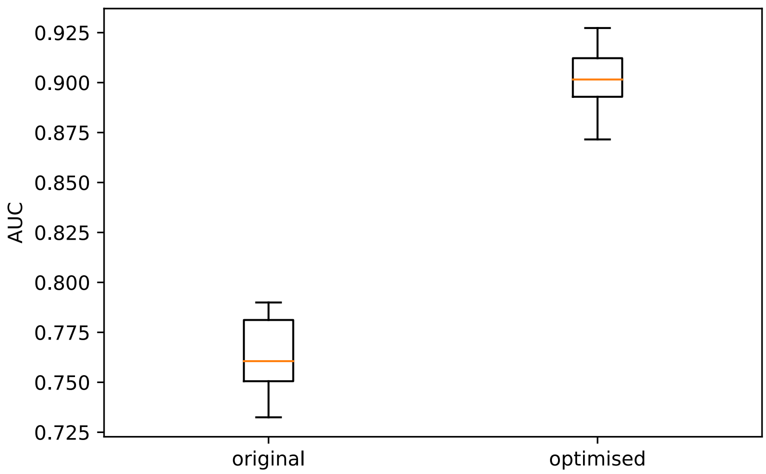

Figure 6. A box plot of the 30-trial evaluation by AUC.

Table 3 contains the detailed precision, recall, F1, accuracy and AUC evaluation metrics of the optimal performing model. The significance of the F1, accuracy, and AUC were tested using the Students t-test, and all had $p < 0.02$ indicating that there is a significant difference in the performance of the original and optimal feature model.

Table 3

Comparison of the Evaluation of Baseline and Optimized Model Performance.

Model	**Precision**	**Recall**	**F1**	**Accuracy**	**AUC**
Baseline	0.9483	0.5652	0.7078	0.7430	0.7634
Optimized	0.9529	0.8560	0.9017**	0.8971**	0.9018**

*$p < 0.05$, **$p < 0.02$

Table 4

Characteristic Reading Behaviors of High Engagement Learners.

Reading Behavior Sequence	**Weight**
NEXTb_CLOSEb_OPENb_CLOSEb_OPENa	0.0742
OPENa_NEXTa_NEXTa_NEXTa_NEXTa	0.0708
CLOSEa_OPENa_NEXTa_NEXTa_NEXTa	0.0637
NEXTa_CLOSEa_CLOSEa_OPENa_NEXTa	0.0616
CLOSEa_CLOSEa_OPENa_NEXTa_NEXTa	0.0569
NEXTa_NEXTa_CLOSEa_OPENa_NEXTa	0.0552
NEXTa_PREVa_NEXTa_NEXTa_NEXTa	0.0543
CLOSEb_OPENb_CLOSEb_OPENa_NEXTa	0.0539
OPENb_CLOSEb_OPENa_NEXTa_NEXTa	0.0539
NEXTa_NEXTa_CLOSEa_CLOSEa_OPENa	0.0535

Finally, we interpreted the features that were used to train the optimal model and the weight that was assigned, which indicates the importance of the feature in predicting high and low engagement learners. The top 10 characteristic reading behaviors of high engagement students is shown in Table 4. It should be pointed out that there are not markedly more features that occur before the start of the assessment as was identify in previous work by Flanagan et al. (2020), and instead all features contain some behaviors that occurred after the assessment started. The characteristic reading behaviors of low engagement students is shown in Table 5.

Table 5

Characteristic Reading Behaviors of Low Engagement Learners.

Reading Behavior Sequence	**Weight**
NEXTb_CLOSEb_NEXTa_NEXTa_CLOSEa	-0.0429
NEXTa_NEXTa_NEXTa_NEXTa_OPENa	-0.0330
NEXTa_NEXTa_NEXTa_OPENa_NEXTa	-0.0330
NEXTa_NEXTa_OPENa_NEXTa_NEXTa	-0.0330
NEXTa_OPENa_NEXTa_NEXTa_NEXTa	-0.0330
CLOSEb_NEXTa_NEXTa_CLOSEa_NEXTa	-0.0286
PREVa_CLOSEa_NEXTa_CLOSEa_CLOSEa	-0.0262
OPENb_NEXTb_CLOSEb_NEXTa	-0.0253
OPENb_NEXTb_CLOSEb_CLOSEb_NEXTb	-0.0241
OPENb_NEXTb_NEXTb_NEXTa_NEXTa	-0.0239

7. Discussion and Conclusion

In the present study, we propose and evaluate a method for early warning prediction of high and low engagement students on open ebook assessment. In addition, we also investigate what reading behavior strategies are employed by high and low engagement students. It was found that strategies, such as: revising and previewing are indicators of how a learner will perform and their overall engagement in an open ebook assessment. We anticipate that the use of both early warning prediction of overall engagement and performance could be effective in providing timely interventions to nudge learners to action at key periods.

There are several limitations to the study presented in this paper that should be noted. The number of learners that were observed in this study was restricted to one class, and might be limited for general application. While the features analyzed in this research are not content specific as page numbers and domain information was not part of the feature set, other content level limitations, such as number of pages could impact on the usefulness of the method for other classes or materials.

In future work, we plan to integrate a knowledge map that will provide concept level features of reading behavior to see if it can increase the discrimination of the model and also provide insight into the relationship of assessment items and lecture materials.

Acknowledgements

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