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AI-enabled adaptive learning using automated topic alignment and doubt detection

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AI-Enabled Adaptive Learning using Automated Topic Alignment and Doubt Detection

Completed Research Paper

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Abstract

Implementing adaptive learning is often a challenging task at higher learning institutions where the students come from diverse backgrounds and disciplines. In this work, we collected informal learning journals from learners. Using the journals, we trained two machine learning models, an automated topic alignment and a doubt detection model to identify areas of adjustment required for teaching and students who require additional attention. The models form the baseline for a quiz recommender tool to dynamically generate personalized quizzes for each learner as practices to reinforce learning. Our pilot deployment of our AI-enabled Adaptive Learning System showed that our approach delivers promising results for learner-centered teaching and personalized learning.

Keywords: Adaptive, Personalized Learning, Learning Analytics, AI in Education

Introduction

Every learner is unique – a statement we often hear in the education industry. The question lies in how we guide according to the specific needs of every individual learner. This becomes more challenging in higher learning institutions where the cohort of students is generally sizeable (Mulryan-Kyne 2010) and students are vastly diverse in their academic ability (Darling-Hammond and Bransford 2007). To identify learning gaps, instructors must collect student feedback to calibrate their teaching strategies and practices. In higher learning institutions, summative feedback in the form of assignments and examinations is widely collected at the end of each term to assess student learning. This poses two major issues, namely the lack of formative feedback for the students to achieve better grades and timely information for the instructors to adapt the teaching to the current cohort's needs.

At Singapore Management University, all classes are small and conducted seminar-style, with an interactive, learner-centred pedagogy instead of a traditional didactic teaching model. We teach an undergraduate-level module on foundational analytics and every week, we collect informal feedback from our students' written entries on what they have learnt or are unclear about in their learning journals to provide personalized responses and guidance to our students. This practice is welcomed by students for its timeliness and effectiveness in addressing their learning needs. However, our manual efforts to analyze the journal entries and translate them to our teaching during the semester are found non-trivial and potentially unsustainable with increasing course enrolment.

Against this backdrop, we propose the use of artificial intelligence (AI) that trains two machine learning models to automate the mining of the qualitative learning journals. Firstly, we developed the Topic Alignment model by using a text similarity mechanism to score the weekly journals against each learning objective. Secondly, we build a Doubt Detection classifier model to predict and classify each student journal with a 'doubt' label (i.e., with doubt or without doubt). A statement with a 'doubt' label is one which may contain a question or simply a statement that requires more clarification of a given topic (Lo et al. 2019).

Both models aided us in evaluating the degree of alignment between what we aimed to teach as defined by the learning objectives (LO) and what was perceived by the students. We could also identify who remained unclear with the concepts and provided targeted coaching promptly. After model training, we built an Adaptive Learning System (ALS) where instructors uploaded the learning journals and the AI models computed the weekly LO alignment score and extracted the doubt labels for each journal. The instructors gain insights into the delivery and progress of students from the ALS dashboard. Finally, the ALS generated personalised quizzes for students based on their doubt profiles, where the adaptive quiz engine selected more questions on topics with doubt labels than those without doubt labels. Hence, ALS provides each student with the opportunity to work on their weaker areas as identified by AI.

This study is novel for information systems educators because it is an AI formative feedback system that focuses on generating usable analytics for students and instructors. Machine learning takes the center stage; it acts as an integral mechanism to support just-in-time teaching and learning activities and opens up possibilities for scalability and translation to other classes, as long as it involves the collection of student responses as formative feedback. By relieving instructors of the reading of voluminous student responses, we hope that more instructors will incline toward learner-centred pedagogy. Coupled with learning journals, ALS empowers personalised learning pathways and meaningful classroom interactions in learner-centred pedagogy via its identification of weaker students for more timely and targeted guidance, while allowing the stronger students to stretch themselves with the personalised quizzes. The students can learn at their own pace, receive timely feedback and make connections in their learning of topics beyond silos and classroom constraints.

Literature Review

There are many published research papers, touching on the different aspects of Learning Analytics (LA). The research approaches of LA in higher education were explored by a paper which analyzed a total of 252 papers between 2012 to 2018 (Viberg et al. 2018). Out of the four propositions on whether LA 1) improve learning support and teaching, 2) improve learning outcomes, 3) are administered ethically and 4) are widely deployed, there was evidence from the research papers showing improvements in learning support and teaching. These results demonstrated much potential for translation to practice in higher education. In this paper (Nguyen et al. 2017), the authors offered a well-structured multi-layered taxonomy of learning analytics applications in education. The taxonomy summarises 9 types of learning analytics applications across objectives (Learner-Centric, Event-Centric, Content-Centric), data (static, dynamic, semi-dynamic data), stakeholders (students, teachers, administrators, departments of education or researchers) and instrument layers (techniques or theories used in learning analytics). Based on the taxonomy, our work falls under the 'Individualized Learning' that applies learning analytics to consume relatively small user-generated data to adjust its content for the learner, also known as adaptive learning. Adaptive learning requires educational experts and high operating complexity. It is commonly executed as part of a learning management system or an AI-enabled tool. While AI-enabled ALS have their potential, it remains unclear how the existing systems are developed. Based on an analysis of 224 articles, this paper (Kabudi 2021) identified 5 design clusters that include a total of 24 design principles of an AI-enabled adaptive learning system which we took reference from.

Another paper on Learning Analytics (Banihashem et al. 2018) evaluated 36 research papers to identify the benefits and challenges for LA. The benefits were listed for different stakeholders including learners, teachers, institutions, researchers, course designers and parents. The paper covers the challenges in the educational aspects (ethics and privacy, scope and quality of data, theoretical and educational foundations). However, most research has not demonstrated the practical implementation of LA in higher educational institutions, which is a notable omission.

To implement learning analytics, we examined two aspects – 1) the feedback mechanism in which the instructors receive cues about students' learning progress and individual needs; and 2) the execution and delivery of the personalized materials. The subsections below provide summaries of existing works that helped us frame our research approach.

Feedback Mechanism

Feedback has often been considered as a two-way flow where students are at the centre of the learning process (Planar and Moya 2016). Feedback should be provided on a regular and timely basis while focusing primarily on the teaching content. As highlighted in the paper, students favoured individual over group feedback. With an effective feedback system, students can keep track of their performances and align their efforts with the improvements needed; while instructors can monitor the students' learning progress and align teaching content and styles.

There were several research works on analyzing students' feedback. One such study (Nitin et al. 2015) used text mining and opinion mining to extract topics and sentiments from students' qualitative feedback, and fit them into three main categories of teaching, content and learning. Another study (Gottipati et al. 2018) made use of rule-based techniques and four statistical classification methods to extract suggestions found in end-of-term student evaluations to help instructors understand ways to improve students' learning experiences and prioritize the necessary changes. (Hujala et al. 2020), on the other hand, uses a topic-modelling approach to analyse open-ended feedback. The proposed approach helps educators analyse teaching quality at a programme- or institution-wide level, or in single courses with a very large number of students. These studies used student course feedback at the end of the term with the main purpose of providing teaching evaluation. Even though the insights extracted can also be useful for evaluating teaching methods and curriculum, it usually only benefits the next cohort of students and has no direct impact on the current cohort.

Another form of collecting feedback on students' progress is based on assessments and real-time interactions with the course materials. In (Shimada et al. 2018), the feedback was realised through 3 time-loops - yearly, weekly and real-time. Prior to each class, the authors analyzed the students' learning logs which included static data such as attendance and quiz scores to pace their lessons. In real-time, heat maps and visualization charts were used to keep track of whether students were following the class closely. The results showed that the synchronization ratio was higher for the experiment group, as compared to the control group which was not using the feedback system.

On addressing misconceptions among the students, (Gusukuma et al. 2018) investigated the concept of Misconception-Driven Feedback (MDF) where a student's understanding could be inferred from their performance in related learning tasks. Feedback could then be provided to the student to resolve misunderstandings or misconceptions. This was done through an explanation of the misconception and identifying the mistakes made. MDF also helped to reveal new misconceptions and realize how the feedback provided impacts different students.

From the existing literature, we can see that the spectrum of frequency of feedback can be as short as real-time, which is highly dynamic, to as long as yearly. Dynamic real-time feedback allows immediate adjustment of teaching style but is typically unable to address the improvement of teaching materials. Low frequency yearly or semestral feedback does not benefit the students in the immediate semester. Therefore, in this paper, we adopted a balance, using students' journals as a weekly feedback mechanism, where students reflect upon their learning after every lesson. In this way, instructors can better understand students' progress and discover doubts and misconceptions along the learning journey. Implementation of personalized and adaptive learning can also be based on progress and individual needs in a timely manner, benefiting the current cohort of students.

Personalized and adaptive learning implementation

Learning analytics requires effective implementation, via a tool such as personalized and adaptive learning system to benefit students. In (Pardo et al. 2019), instructors used a Learning Management System to prepare a set of feedback messages based on different interaction levels customized to the activities. It provides personalized feedback to a big group of students and the effectiveness was measured by students' level of satisfaction and academic score. Results showed that there was a significant impact on the students' satisfaction level, and a small to medium effect in terms of their academic scores between the control group and experiment group. The effectiveness of the model was evaluated using formal assessment measures which focus on students' performance outcomes rather than learning.

Another paper (Peng et al. 2019) made use of smart technology to monitor in real-time, learners' differences and their individual changes in terms of characteristics, performance and personal development, thus allowing for adaptive adjustment of teaching strategies. A learning path generation recommendation model was created to recommend students a learning list according to their learning states. In the domain of Virtual learning environments (VLEs), (Xu et al. 2014) developed embedded personalization functions within the VLEs to meet learners' differing requirements on an e-Learning platform. The findings suggested that personalized e-learning provides more satisfaction and self-efficacy than without it.

As we frame our concept of personalized and adaptive learning implementation, we want to focus our efforts on encouraging self-directed learning using a software tool that can intelligently discover students' innate abilities and progress, and provide scaffolding means to help them to learn. In a technically and mathematically demanding course in the field of Information Systems, extensive practice is an essential element of learning. This work extends our previous works (Lo et al. 2019; Lo et al. 2021) by fine-tuning the Doubt Detection classification model, including a Topic Alignment model and conducting an empirical study using a pilot Adaptive Learning System which provides a feedback loop by recommending customized practice quizzes for each student. This approach allows students to take charge of their learning, addressing the misalignment through identification of doubts at an individual level.

The Course

In this study, the course concerned covers foundational data analytics concepts including data preparations, visualization, segmentation, regression analysis and some predictive machine learning algorithms. The course is offered at the undergraduate level at the computing school offering Information Systems as a major. The class runs in a seminar-style learning environment with about 45 students in each class over a 15-week semester. There are 12 instructional weeks in the course. Each instructional week consists of three hours of engagement including theory, hands-on activities and discussions. Although offered by the computing school and with a certain degree of programming or use of low-code analytics software as a pre-requisite, the class takes enrolment from students of other disciplines (e.g., business and economics) as long as the pre-requisites are met.

Learning Objectives

The instructors teaching this course carefully curated 3 key learning objectives for each week. They are brief descriptions of the learning points, based on the teaching materials. Examples of the learning objectives for Weeks 1 and 2 are shown in Table 1.

Feedback Process using Learning Journals

Informal feedback, in the form of weekly learning journals was collected by instructors. The journals were submitted by the students through the university's learning management system, where the window of submission was up to a few days after the end of each class.

Table 1. Examples of Learning Objectives (LOs)

Week 1	**Week 2**
1. What is Data Analytics? Data Analytics is about harnessing data into useful insights to help organization make better decisions.	1. What is Exploratory Data Analysis (EDA)? Exploratory Data Analysis is an essential step to clean and present data in a form that makes sense to people.
2. Different levels and types of Analytics. Analytics can be classified by method (descriptive, predictive and prescriptive) or purpose (i.e., field of application such as marketing, finance).	2. Data Analysis Methods, such as handling numeric data, categorical data and data errors. Based on different types of data, there are different statistical measures and analysis techniques that can be applied.
3. Value created by Analytics in action. Analytics can be applied to various industries. Smart cities use data and technology to solve its problems and improve liveability.	3. Ability to apply EDA skills to a scenario. Applying data analysis for model development requires good definition of analytics questions (problem definition) and system approach.

A total of 10 learning journals were collected over the semester. Each learning journal consisted of an open-ended question with no limitations on what could be written. A sample question used by one of the instructors of the course to elicit key learning points from students was:

```
Reflect upon the most impressionistic learning point that you have learned in class
this week. Write something specific.
```

In the initial few runs of this course, the instructors noticed interesting journal submissions. Students had not only provided their personal take on the key learning points that they found interesting, but had also included clarification questions based on the topic learned or had indicated their doubts. The following segment provides a few quotes as examples.

- Journals with 'Wisdom' gained but no 'doubts'
  - `I have learnt about the systematic steps during data preparation phase; and the situations where we should use transformation on data, and why we do standardization.`
- Journals showing 'doubts' on a particular concept
  - `I'm confused… It would be good if you can go through [a topic] again.`
  - `I am quite unsure when [an example] is a sample or a population.`
- Journals in which 'Opportunistic' students took the chance to ask questions
  - `How do we check normality?`

Typically, student's expressions in these informal learning journals are open, casual and truthful in their perception of their learning. The reflective statements may not necessarily be aligned with the key learning objective statements laid out by the instructors. Therefore, these reflections became valuable ground truth for instructors in a timely manner. The benefit is two-way. Instructors can adopt agile teaching to adjust their teaching to suit the pace of the learners, and students get their questions and doubts addressed within the week. However, this process is typically manual. The exercise takes a substantial amount of time and effort for the instructors, thus presenting scalability and efficiency issues for larger-scale implementation when the cohort of students gets larger.

The Approach to AI-Enabled Learner-Centred Adaptive Learning

Objectives

The main objective of our approach is to automate the journal mining process using AI-enabled models to minimize the time-consuming manual activities required by instructors to extract useful information from students' learning journals, and eventually translate this into beneficial learning opportunities for the students. The output of the models supports agile teaching where instructors can improve the learning experiences for the current batch of students and provide students with an adaptive and personalized learning tool that suits individual learning progress. An overview of the components of our AI-Enabled Learner-Centred Adaptive Learning approach can be summarized in Figure 1.

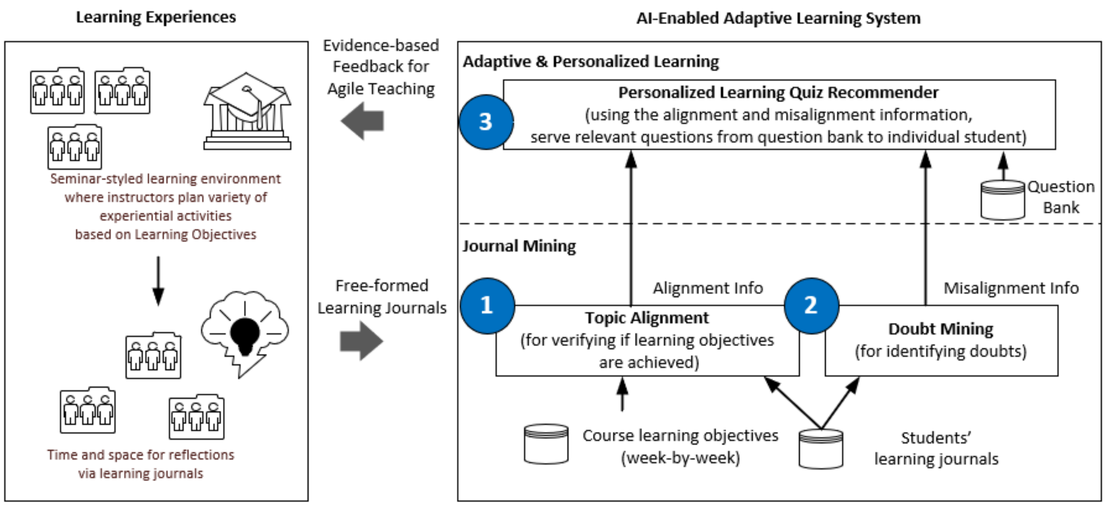


Figure 1. Overview of AI-Enabled Learner-Centred Adaptive Learning

We designed and developed our AI-Enabled Adaptive Learning System with three components – two machine learning models for mining the insights from learning journals and a quiz recommendation engine to serve questions dynamically according to individual needs. They are listed as follows:

1. **Topic Alignment Model:** This is a machine-learning model for assessing if learning objectives are achieved on the weekly basis. This provides information on how well-aligned the execution of the course with the planned objectives was.
2. **Doubt Detection Model:** This is another machine-learning model for identifying doubts among the learning journals and classifying each journal with a doubt label. This provides the misalignment information to evaluate the gap between teaching and learning.
3. **Personalized Quiz Recommender:** This is a matching engine which adaptively serves relevant practice questions to individual students based on the doubt labels in his or her journals.

The Data

The data used for training the machine learning models consisted of a total of 783 journals collected over 10 weeks. Each week contains 63 to 86 journals. Each journal entry was annotated by at least two human annotators with a label 'y' indicating the presence of doubts and 'n' indicating the ones without. The train-test split uses a hold-out ratio of 70:30, stratified by weeks.

Topic Alignment Model

The Topic Alignment Model uses text similarity computations to score the degree of alignment between what had been taught during class (i.e., learning objectives) and what the students had grasped (i.e., the key learning from journals). The overview of the model is shown in Figure 2.

The texts from both LOs and journals were first pre-processed by removing all punctuation characters, special characters and non-alphanumeric characters like emojis, numbers and stop words and retaining only words with more than two characters. Then, all texts were converted to lowercase and tokenized, followed by the WordNetLemmatizer to ensure that the final word is part of the English language. After pre-processing, the text data was converted to Term-Frequency-Inverse-Document-Frequency (TF-IDF) values considering both unigram and bigram representations. Although we attempted to build the model using other unsupervised methods such as Latent Dirichlet Allocation, we found that Cosine Similarity computation was the most effective and consistent despite its simplicity. The results were validated against human interpreters.

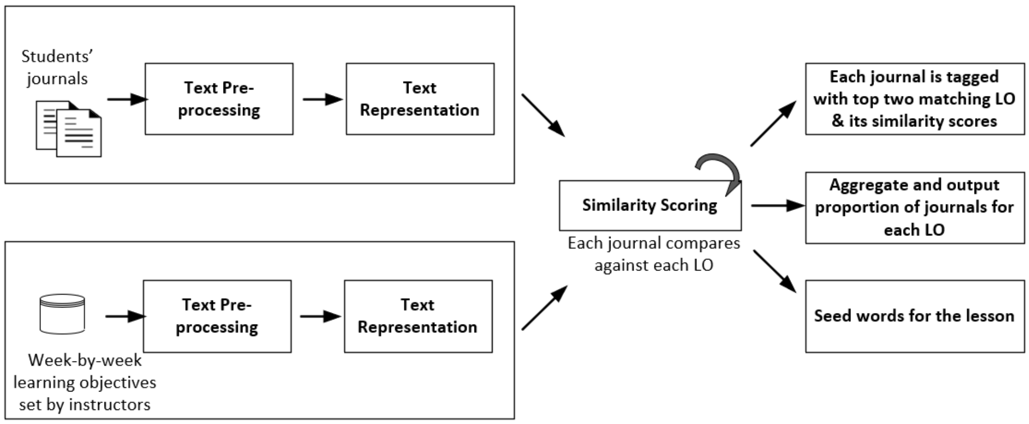


Figure 2. Topic Alignment Model

In the final step, we rank the similarity scores and classified each journal to its top two LOs as a form of soft classification model. The model also provided two other outputs – an aggregate score showing the proportion of journals for each of the LOs for the week and a list of seed words for the week. The seed words are the top n words that are obtained by the summation of the total TF-IDF scores for the same word across every journal in the week. Both the aggregated scores and the seed words can be used either to guide the instructors in adapting their teaching content to fill the learning gap in the same' semester or to serve as additional words for guiding the Topic Alignment model for the future runs of the course.

Doubt Detection Model

While the Topic Alignment aims to understand the alignment of the teaching against the LOs, the Doubt Detection model aims to understand the extent of misalignment among the students on specific weeks by determining the presence of confusion, lack of understanding or simply signs of being uncertain among the journals. These misalignments are then further clarified. The overview of the Doubt Model is shown in Figure 3.

The Doubt Detection model extends our previous works ((Lo et al. 2019; Lo et al. 2021) where we explored a combination of sentiment analysis, questions and negation statements to build doubt classification models. In (Lo et al. 2019), we reported that sentiment analysis alone is not sufficient to detect doubts as there existed journals with positive sentiment but contained doubts; and also journals with negative sentiments which contained no doubts. In (Lo et al. 2021), we reported that specific characters and negation are important in sensing doubts and uncertainty. Instead of removing emoji and punctuation characters, we devised coded words such as *SM1Smile*, *SM2Frown*, *SM3Exclaim* and *SM4Question* to replace expressions such as smiley face, frown face, exclamation mark (!) and question mark (?) respectively among the journal text. Next, for negation, we retained words such as 'not', together with the next word as a set of bigrams to capture expressions such as "not understand", "not easy", which are typical expressions found in journals with doubt.

In this work, we further investigated multiple pretrained models such as GloVe, DistilBERT and Sentence-BERT (Mikolov et al. 2017). With the extracted features, we assigned a 'doubt' label to each learning journal using classification models such as Logistic Regression, Support Vector Machine (SVM) and Gaussian Naive Bayes models. Our models were evaluated against a simple TF-IDF representation with Logistic Regression Model as the baseline for comparison. Detailed analyses were done to compare and determine which model was best suited for the automated doubt-mining.

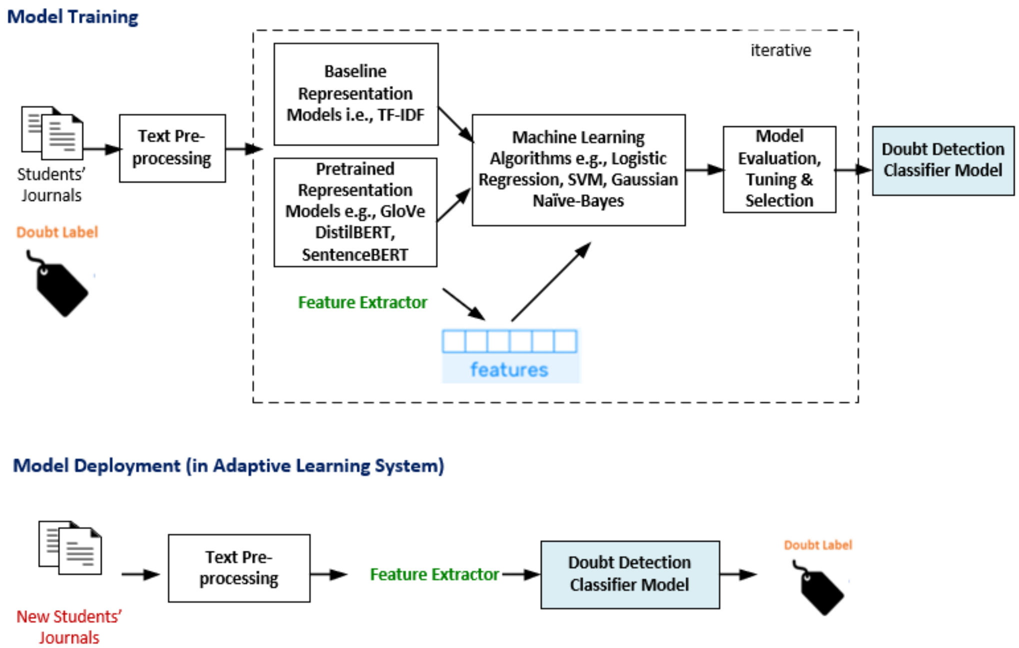


Figure 3. Doubt Detection Model: Training and Deployment

With extensive training and parameter tuning which is beyond the coverage of this paper, we found that the most appropriate model for deployment was DistilBERT-Logistic Regression model. This model provides balanced scores across the performance metrics in terms of precision and recall of doubts among the learning journals.

Adaptive Learning System with Personalized Quiz Recommender

We integrated both the Topic Alignment and the Doubt Detection models, together with a personalized quiz recommender to develop the Adaptive Learning System (ALS). As per any standard system, there are security functionalities such as authentication and securing the data, administration functions such as creating a class and the student list and personalization functions such as customizing own profiles. For executing learning analytics, instructors using this system are presented with three major functions that serve as the inputs, they are 1) upload or enter weekly learning objectives, 2) upload learning journals and 3) create and maintain a question bank. The two AI (machine learning) models are used to analyse the inputs and generate the outputs. i.e., topic alignment results and doubt label for each journal. The doubt labels serve as guiding rules to provide each student with a personalized quiz that is adapted to his or her level of understanding each week. The overview of the system is depicted in Figure 4.

From the instructor's perspective, Figure 5a shows the screen where instructors see the proportion of journals which mentioned the LOs as the top two LOs with highest similarity scores. Instructors can use this insight to better understand if all LOs have been equally covered in class. Should there be a case where one of the LOs is completely unmentioned in learning journals, instructors can revisit the topic in the next lesson. In Figure 5b, it shows that each reflection is given a similarity score to the LO. Instructors can determine to what extent the students attain the LO for the week.

Figure 6a shows the output of the Doubt Detection model where instructors can see at one glance, the proportion of journals which contain doubt for the week. In Figure 6b, this screen enables instructors to view the number of journals with doubt for each student, and to provide the appropriate coaching to students who reflected more doubt.

From the student's perspective, the student can review the number of doubts he or she has across the weeks

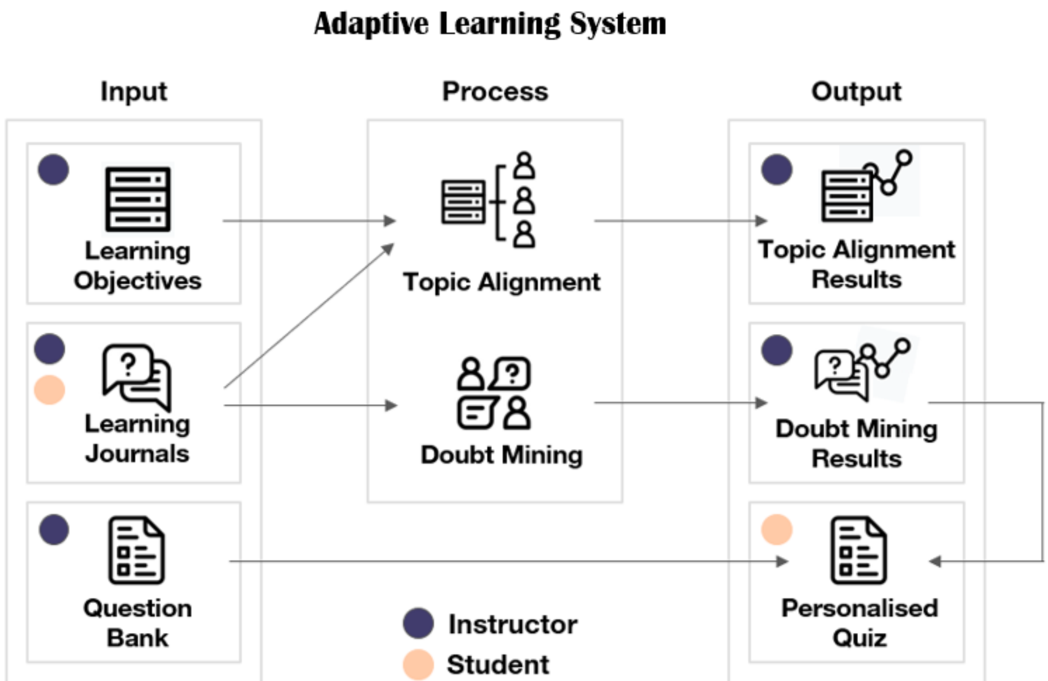


Figure 4. Integrating Topic Alignment and Doubt-Mining Models in Adaptive Learning System

as shown in Figure 7a. The student can also choose to take a personalized quiz as shown in Figure 7b.

With ALS, not only the students can take charge of their learning and work on areas of weakness, but instructors can also now use it as learning analytics to answer questions such as `` `How many students managed to get the key learning points each week?' ``, `` `Who are the students who need more help from week to week?' `` and `` `What guidance to provide to individual learners in a timely manner?' `` In this way, we hope the ALS provides timely guidance to students and allows students to learn at their own pace.

Pilot Study and Results

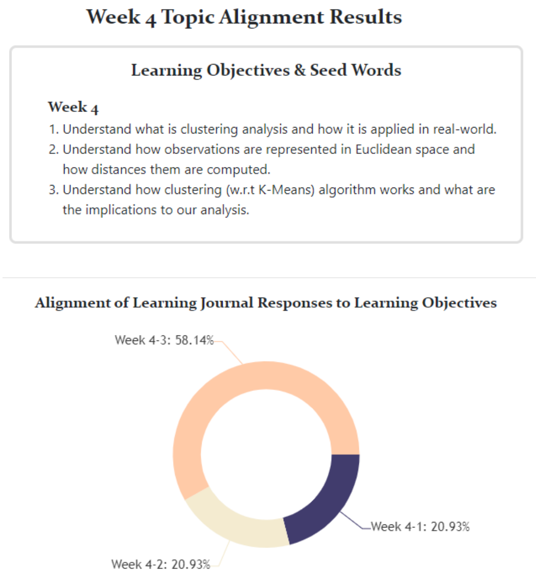
We ran a pilot study using the ALS with a class of 44 students in the autumn semester of academic year 2021 to 2022.

We administered a survey to evaluate the student's learning effectiveness and learning experiences after using the tool. The questionnaire contained 32 questions with three background information, 24 seven-point Likert questions classified into four sub-scales, 1 ten-point Likert item named 'Net Promoter Score' and 4 open-ended qualitative questions. A total of 32 (Male: 12, Female: 20) students responded to the questionnaire. Most of the students (29) were from the School of Computing and Information Systems. The rest were from the School of Economics (2) and School of Social Sciences (1). The questionnaire evaluates the ALS' two main areas – (1) Learning Effectiveness and (2) Learning Experiences. Institutional Review Board (IRB) approval was obtained from our university for the above study design.

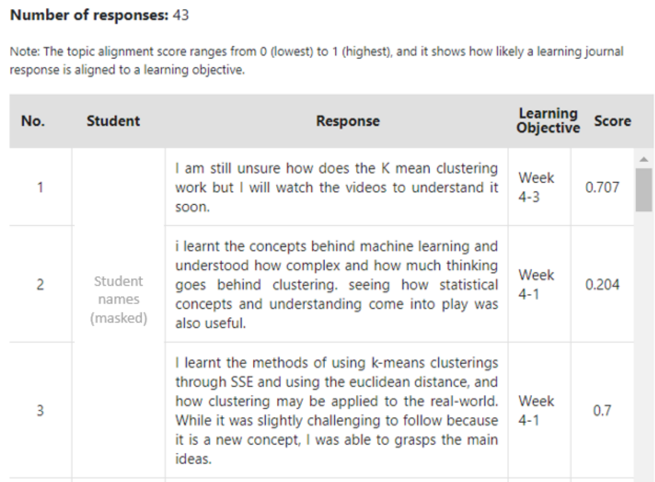
Learning Effectiveness Evaluation

To understand the learning effectiveness of the ALS, descriptive statistics, paired-sample t-test and reliability analyses of the sub-scales were executed to find out students' perceptions of the different items, indicating their learning gains and the internal consistency of the tool.

For learning gains, the questionnaire investigated the **change in knowledge** before and after using the

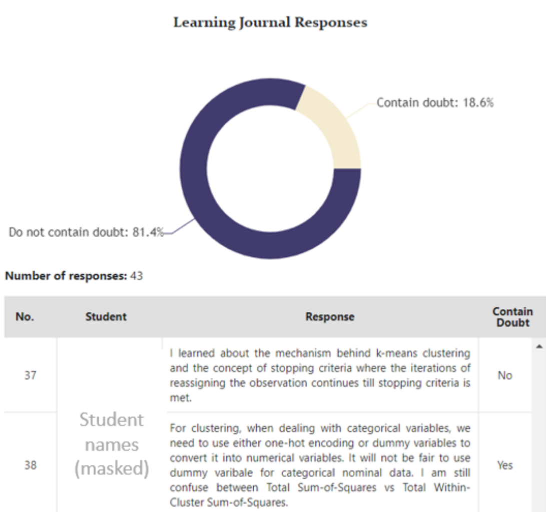


(a) Summary of the Proportion of LOs in the Learning Journals

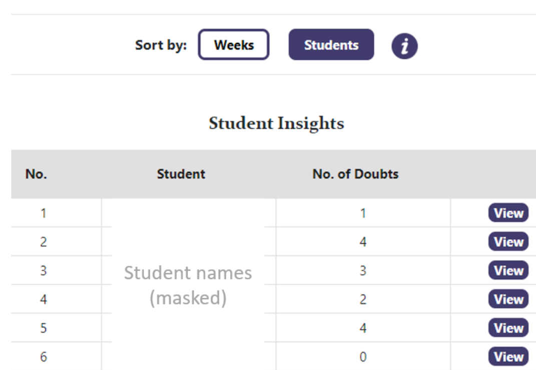


(b) Topic Alignment Scores Assigned to Each Journal Entry

Figure 5. Analyses Generated Using the Topic Alignment Model

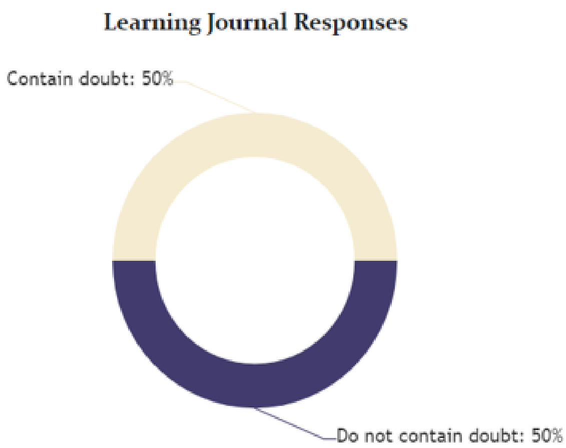


(a) Weekly Summary of Doubts Among the Learning Journals)

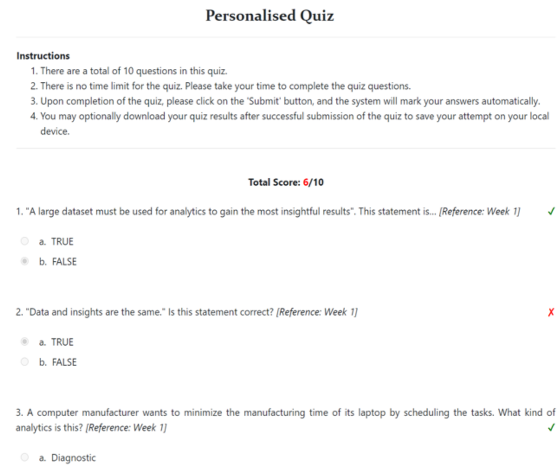


(b) Doubt Analysis for Each Student Across the Weeks

Figure 6. Analyses Generated Using the Doubt Detection Model



(a) Summary of Doubts Among Individual's Learning Journals)



(b) Topic Alignment Scores Assigned to Each Journal Entry

Figure 7. Analysis and Personalized Quiz Tool for the Students

ALS. Students were asked to rate their perceived knowledge about the course using a 7-point Likert scale (1 = Very Low to 7 =Very High). They reported an increase in perceived knowledge after using the ALS ($\mu = 5.31, \sigma = 0.998$) versus before using it ($\mu = 3.91, \sigma = 1.489$). Using a paired samples t-test, we compare both sets of ratings and the results showed a statistically significant difference ($t_{31} = 5.159$, $p < 0.0005$). This suggests that ALS was effective in improving students' knowledge about the concepts in the course.

To evaluate the internal consistency of the tool, the questionnaire investigates learning effectiveness based on 4 sub-scales as follows:

1. **Quality of Content:** The alignment of the content to the course learning objectives, organisation and delivery of content, making connections to real-life issues andor concepts taught in class.
2. **Support for Learning:** The extent to which the tool provides learning at the student's own pace, providing timely feedback and enhancing learning.
3. **Cognitive Task Engagement:** The extent to which the tool trains student's persistence at the task, stimulates curiosity in the topic, motivation, challenging, focused and forget about everything else when working on the learning activity.
4. **Affective Task Engagement:** The extent to which the tool provides enjoyment, energising, feel-good emotions or whether it is making the students feel frustrated or bored during the learning activity.

For all categories, the sub-scales were evaluated using questions with a 7-point Likert scale (1 = Strongly disagree to 7 = Strongly agree). The 32 respondents indicated the option that best represented how they felt most of the time when using the ALS.

Quality of Content

The quality of content was evaluated using 7 questions in the questionnaire and the result is shown in Table 2.

From the results, the students indicated strong agreement that the learning activity using the content in the ALS was aligned to the course learning objectives. It was well-organised, delivered in a clear manner, allowed them to build on their knowledge on this course, enhanced their ability to make connections to real-life issues; allowed them to make meaningful connections to the concepts taught in class; and made sense to them. The Cronbach's Alpha reliability coefficient for all 7 items was 0.884 ($\alpha \geq 0.8$), indicating very good internal consistency. The skewness value was -1.167, suggesting an opposite direction skew, which impact on Cronbach's Alpha index is considered as slight to moderate reduction (Greer et al. 2006).

Table 2. Learning Effectiveness Sub-Scale: Quality of Content

No.	Question	Min.	Max.	Mean(μ)	Stdev(σ)
1	Alignment to learning objectives	5	7	6.28	0.581
2	Well-organised	3	7	6.09	0.928
3	Deliver in a clear manner	2	7	6.19	0.998
4	Allow building of knowledge	5	7	6.38	0.554
5	Enhance making connections to real-life issues	2	7	5.91	1.058
6	Make meaningful connections to concepts taught	2	7	6.28	0.924
7	Make sense to student	4	7	6.34	0.653

Support for Learning

Support for learning was evaluated using 3 questions in the questionnaire and the result is shown in Table 3.

Table 3. Learning Effectiveness Sub-Scale: Support for Learning

No.	Question	Min.	Max.	Mean(μ)	Stdev(σ)
1	Allow learning at own pace	4	7	6.38	0.707
2	Provide timely feedback	3	7	6.03	0.861
3	Enhance student learning	5	7	6.41	0.560

The students provided strong indications with scores more than 6 on the average indicating agreement that the ALS allowed them to learn at their own pace; provided them with timely feedback for their learning; and enhanced their learning. The Cronbach's Alpha reliability coefficient for all 3 items was 0.797 ($\alpha \approx 0.8$), suggesting very good internal consistency. The skewness value was -1.411, suggesting an opposite direction skew, which impact on Cronbach's Alpha index is considered as slight to moderate reduction (Greer et al. 2006).

Cognitive Task Engagement

The cognitive task engagement was evaluated using 7 questions in the questionnaire and the result is shown in Table 4. In this segment we use the term *The Task* to indicate the adaptive and personalized quiz on the ALS.

Table 4. Learning Effectiveness Sub-Scale: Cognitive Task Engagement

No.	Question	Min.	Max.	Mean(μ)	Stdev(σ)
1	Work on *The Task* until it is completed	6	7	6.38	0.492
2	Stimulate curiosity in the topic	4	7	6.03	0.647
3	Motivate student to explore further	3	7	6.06	0.801
4	*The Task* is challenging	3	7	5.69	0.896
5	Focused when working on *The Task*	5	7	6.22	0.659
6	Forgot about everything during *The Task*	2	7	4.94	1.413
7	Do not wish to do something else during *The Task*	1	7	4.25	1.646

From the results, students agreed that the ALS stimulates their curiosity and motivates them to explore further. Students also agreed that they find the task challenging, keeping them focused until completion. However, they have also indicated that the tool engages them to the extent of 'forgetting everything' or 'do not wish to do something else' while working on the task. The Cronbach's Alpha reliability coefficient for all 7 items was 0.422, suggesting poor internal consistency. However, if question 7 were to be removed from the analysis, it would increase the alpha score to 0.654 which indicates the acceptable internal consistency. This implies that question 7 provides the heterogeneous examination of cognitive task engagement as the question represents an extreme view of the tool. For future surveys, we will consider removing this question in the questionnaire. The skewness value was -0.140, suggesting that the distribution was symmetrical and no impact on Cronbach's Alpha coefficient.

Affective Task Engagement

The affective task engagement was evaluated using 5 questions in the questionnaire and the result is shown in Table 5.

Table 5. Learning Effectiveness Sub-Scale: Affective Task Engagement

No.	Question	Min.	Max.	Mean(μ)	Stdev(σ)
1	Enjoy using ALS for learning	4	7	6.13	0.660
2	Feel energised using ALS	3	7	5.41	0.979
3	Feel good using ALS	4	7	5.62	0.793
4	Do not feel frustrated when using ALS	1	7	5.22	1.809
5	Do not feel bored when using ALS	1	7	4.75	1.586

The students reported that they enjoyed using the ALS for learning and felt good using it. However, we recognized that a minority of the students felt that the tool was not able to capture the feeling of 'affection' and may result in negative feelings of frustration and boredom. The Cronbach's Alpha reliability coefficient for all 5 items was 0.626 ($\alpha \geq 0.6$), suggesting acceptable internal consistency. The skewness value was -0.382, suggesting the distribution was symmetrical and no impact on Cronbach's Alpha coefficient.

Learning Experiences Evaluation

To understand learning experiences with ALS, a quantitative scoring approach and qualitative method were used. The net promoter score was calculated to find out how satisfying the experience was. Qualitatively, four open-ended questions were used to learn how the students described their learning experiences.

Net Promoter Score (NPS)

The Net Promoter Score (Reichheld 2003) is an index ranging from -100 to 100 that measures the willingness of students to recommend a learning activity or intervention to others. It is used as a proxy for gauging the student's overall satisfaction with the learning activity. NPS is computed by the percentage of promoters minus the percentage of detractors (those who will not recommend the tool to others). A NPS index below zero indicates that the activity needs an improvement. An index of 0 to 30 indicates it is *'Good'*, index of 30 to 70 indicates *'Great'* and index above 70 indicates an *'Excellent'* activity.

Among the response collected for ALS, there were 29 students who responded to this question, out of which there were 15 promoters, 10 being passive (standing on fence) and 4 detractors. The Net Promoter Score of ALS is computed to be $(\frac{15}{29}$ - $\frac{4}{29}) * 100 \approx 38$, which indicates being **'Great'**. This means students were willing to recommend the tool as a learning activity to others.

Qualitative Open-Ended Questions

Four qualitative questions based on the usage of ALS were posed to the students. The first open-ended question asked the students to describe how ALS has helped them to understand or apply the concepts learnt. The second question asked for what they like best about ALS. The third question asked students to provide suggestions to improve it. The final question was an unguided question for students to input any other feedback based on their experiences with the tool. For the interest of this paper, we will be sharing the responses from the first two open-ended questions as the last two questions gathered more information about how to improve the system such as the size of the question bank, explanations for the questions and the user interface.

Open-ended Question 1: Describe how ALS helps you understand/apply the concepts learnt? We analysed the responses to the question on how ALS has helped them, and grouped the comments into two key benefits.

Firstly, the students get targeted learning through **personalized quizzes**. Students reported that ALS allowed them to focus on areas which they have doubts with, which was very helpful for the students. Some related quotes were:

- `It provides more practices targeted at concepts I am less familiar with.`
- `Able to refresh concepts and identify areas that needs clarification again.`
- `It directly tackles the doubts that you are facing by allowing us to think through concepts again.`
- `The personalised quiz is an interesting tool, it has great potential for me to test and validate my own knowledge especially on areas I am weak in.`
- `It allows me to see which areas and concepts I need to further study on.`
- `I think quizzes like this helps to stimulate my learning. Lecture notes are of course important but to be able to practice somewhere using this resource, it would be great[,] especially to test where I stand and know which topic I am weaker at and needs more improvement.`

Secondly, the students reported that the ALS reinforced their learning of concepts by providing *more practices*, as illustrated by the quotes below:

- `It helps me reflect on every chapters on a weekly basis so I can have a good big picture of each topic.`
- `It gives us questions to work on, and let us know where we can learn about it if we get it wrong.`
- `Recaps the topics learnt in class, provides us with more deep scenario questions for us to apply our concepts learnt.`
- `It allows to draw in concepts from across chapters all at once. [It's] a helpful way in promoting active recall from across chapters.`
- `It helps me reinforce my understanding of topics taught in class.`
- `[It] provides questions that reinforce the foundations taught in class.`

Open-ended Question 2: What do you like best about the ALS?

From the students' comments, we found 3 distinct themes. Predominantly, the students opined that what they liked most about ALS was that it truly enabled personalized learning by providing (1) personalized quizzes, (2) more practices, and access to (3) access to learning at any time as illustrated by the following quotes.

1. Personalized quizzes
    - `The personalized quizzes`

    - `I like how it gives us a personalised quiz depending on our weaknesses according to the our reflections [i.e., learning journals].`
    - `Personalized quizzes`

2. More practices
    - `More practice`
    - `Multiple-choice questions`
    - `More questions to practice on`
3. Learning at any time
    - `Own time own target`
    - `It is available 24/7, at any timing we are doing our revision.`
    - `Accessible anywhere`
    - `Enjoy that it allows me to revise at my own time.`

The students also complimented ALS as a **user-friendly and well-organised** system. They liked ALS because it made learning focused and efficient, with clean user interface (UI) and the downloadable data spreadsheet which contain the quiz questions for offline learning.

- `Efficient way to for revision and identify my weakness.`
- `Simple and easy to use.`
- `Easy to use, fast, friction free and clean UI. Focused on the task at hand.`
- `Well organised system.`
- `The downloaded data excel sheet.`
- `It [is] online and automated.`

In summary, many students indicated that the quiz recommender tool in ALS was effective for targeted and personalized learning. The system also helped students identify their weaker topics and reinforced their concepts by providing them with more practices.

Conclusion and Future Work

In this paper, we presented an approach where informal free-formed learning journals were deployed in the class as a learner-centered mechanism to provide learning guidance for the students. We designed and developed a topic alignment model that allows instructors to ensure that their delivery is consistent with learning objectives; and an automated doubt-mining model, coupled with a personalized learning tool which identifies the needs of an individual learner. Integrating all the components into an adaptive learning system and piloting it in a class, the results from the survey reported that the AI-enabled adaptive learning system provided students with higher learning effectiveness and experiences. It confirms that this structured and evidence-based approach using learning journals promotes effective learning as it allows learners to learn according to their needs and pace.

We recognize some limitations in our pilot study which involves deployment of ALS to only one class which resulted in a small sample size of the questionnaire responses. Hence, we identified the following areas of improvements which we plan to address in our future work. To increase generalization of our results, we seek to extend our approach to evaluate more runs of the same course or to other courses involving more students. Another area is to further enhance our evaluation of learning effectiveness. We can conduct an experiment whereby the same cohort be presented with a mock assessment paper on a specific topic (without ALS) and then compared to a treatment condition with another mock assessment paper on another topic of similar difficulty (using ALS) to evaluate the efficacy to achieve their learning outcomes by using the result of both assessment papers.

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