INTEGRATION OF AI FOR ADAPTIVE LEARNING FOR MCQ SELECTION IN PARAKH

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ABSTRACT

Implementing adaptive learning 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 toidentify 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 de- livers promising results for learner-centred teaching and personalized learning.

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

1. 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 higherlearning institutions where the cohort of students is generally sizeable (Mulryan-Kyne 2010) and studentsare 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' writtenentries 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 effec-tiveness in addressing their learning needs. However, our manual efforts to analyze the journal entries andtranslate 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 Adap- tive 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 personalized 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.

2. PROBLEM STATEMENTS

1. Manual data analysis: Time- consuming, labor intensive, and prone to biases and errors.
2. Subjectivity and bias: Reliance on subjective opinions, experiences, and preferences, leading to suboptimal decision-making.
3. Limited insights: Limited access to comprehensive and up-to-date data, difficulty in processing complex patterns and correlations.
4. Scalability and efficiency: Inefficiency in analysing data for multiple locations, difficulty in keeping up with changing market dynamics.
5. Lack of predictive power: Reliance on intuition or past experiences, which may not accurately forecast future trends and outcomes.

3. LITERATURE SURVEY

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 in- structors 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.

4. 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 stu-dents. The output of the models supports agile teaching where instructors can improve the learning experi- ences 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.

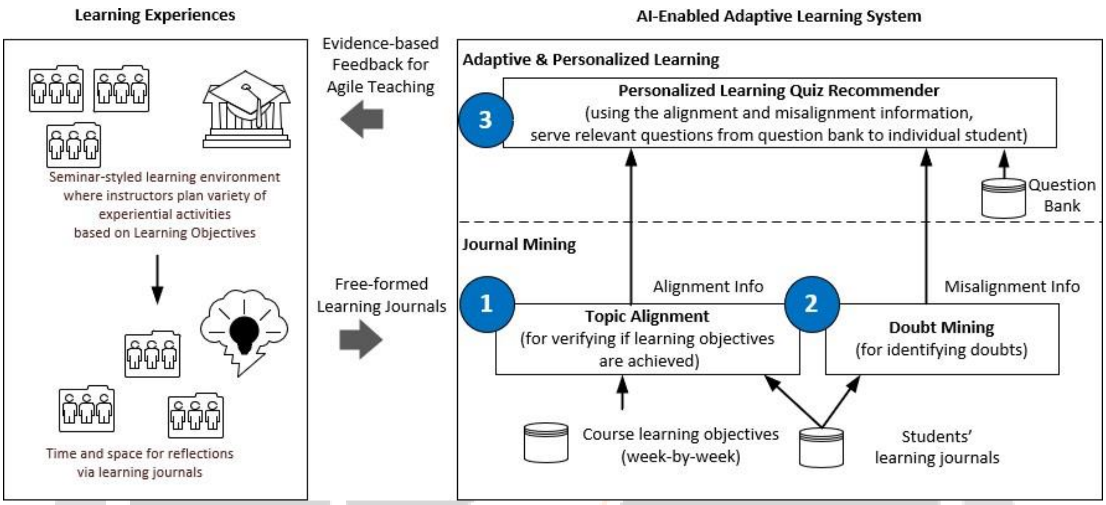


Fig -1: Overview of AI-Enabled Learner- Centered Adaptive Learning

5. METHODOLOGY

To accomplish the objectives, AI is applied in conjunction with the associated methodology. This methodology encompasses the following distinct research tasks: data collection, pre-processing, and transformation.

1. Data Collection: In order to collect, process, and analyze data, as well as present the results, the model's development relies on employing the following research techniques:

a) For primary data: surveys, tests of knowledge about artificial intelligence, self-assessment scales (most of the tools were developed by the authors);

b) For secondary data: data on the success of students from internal records in the high school institution and external data on high school programs of subjects in the field of IT (publicly available data of the Ministry of Education and Ministry of Science Technological Development and Innovation of the Republic of Serbia).

2. Data Pre-processing and Transformation: The sample consists of 400 four-year students of the Vocational Secondary School in Ivanjica, from five educational profiles. The number of students who participated in the study is shown in Table 1, including grade in high school and gender. The data was collected in the high school, from the school secretary, the database and in contact with the students. All relevant data were collected: high school, major, previous knowledge. Students had a test with questions and assignments from programming. For the research composite, a measure of success was established, which includes positive answers to certain questions in the questionnaire and the percentage of familiarity with various tools related to the application of artificial intelligence. Levels of success in knowing artificial intelligence are defined as:

1 – Very successful students (success rate > 70%);

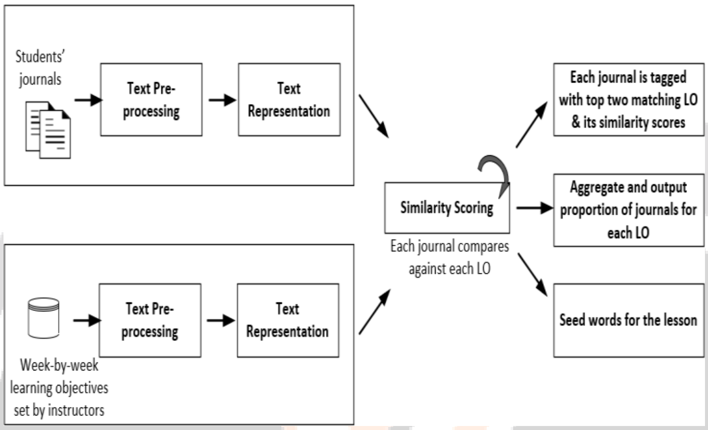
2 – Students with an average level of success (success rate > 40% and ≤ 70%);

3 – Students with low success or failure (success rate ≤ 40%).

Representation of AI in Primary and Secondary Education In this section, the presence of artificial intelligence in primary and secondary education will be discussed. Analyzing curricula and programs on the portal Institute for the Improvement of Education and Training (IET) led to the conclusions shown below. In the eighth grade, artificial intelligence is introduced through the field of Digital Literacy, encompassing two classes. In grammar schools, artificial intelligence is studied through the field of Contemporary Technology with 10 hours of study. However, in secondary vocational education, the inclusion of artificial intelligence in the curriculum is minimal. Only two educational profiles, Electrical Engineering and Informatics, incorporate artificial intelligence in their curriculum through the courses such as Automation of Production and Flexible Technological Systems course as well as the course on Robots. Creating a Model for Improving the Teaching Process The number of students, according to gender and high school grade, who participated in the research is given in Table 1. The path to excellence of Artificial Intelligence in the Improvement of the Teaching Process is through satisfying the standard with the aim of improving the quality of processes and products based on the sources of knowledge standardization of AI requirements.

6. ARCHITECTURE

Fig- 2: Topic Alignment Model



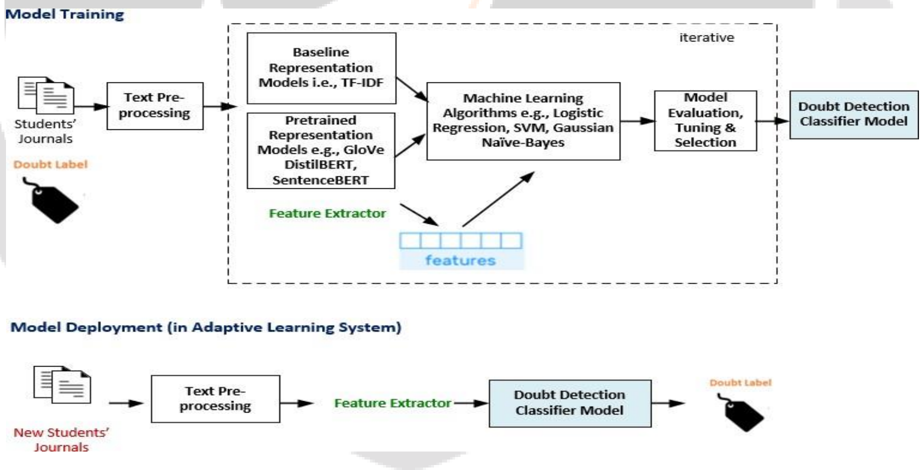


Fig -3: Doubt detection model-Training and Deployment

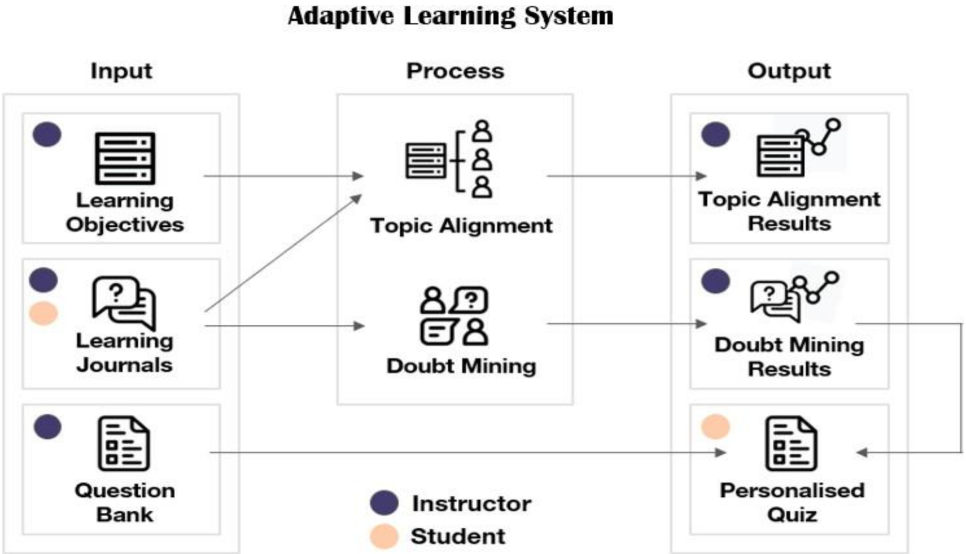


Fig-4: Integrating Topic Alignment and doubt mining models in Adaptive Learning System

7. 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. Therest 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.

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 ALS.

Number of responses: 43

Note: The topic alignment score ranges from 0 (lowest) to 1 (highest), and it shows how likely a learning journal response is aligned to a learning objective.

No.	Student	Response	Learning Objective	Score
1	Student names (masked)	I am still unsure how does the K mean clustering work but I will watch the videos to understand it soon.	Week 4-3	0.707
2		i learnt the concepts behind machine learning and understood how complex and how much thinking goes behind clustering. seeing how statistical concepts and understanding come into play was also useful.	Week 4-1	0.204
3		I learnt the methods of using k-means clusterings through SSE and using the euclidean distance, and how clustering may be applied to the real-world. While it was slightly challenging to follow because it is a new concept, I was able to grasps the main ideas.	Week 4-1	0.7

Fig-5: Summary of proportion of LOs in the learning Journal

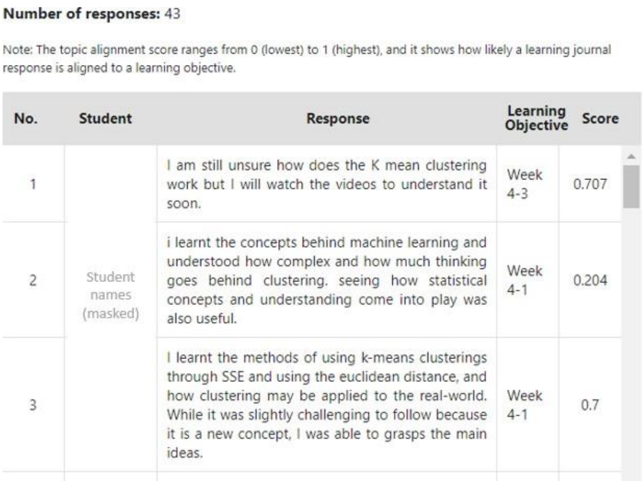


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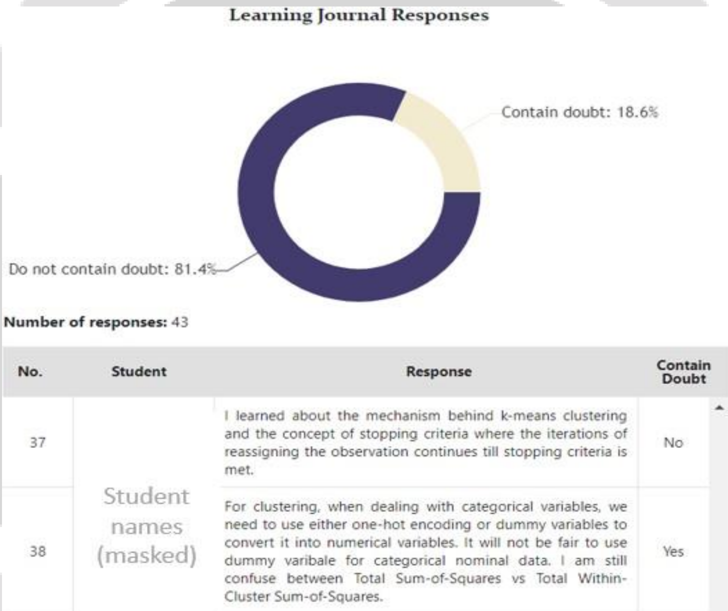
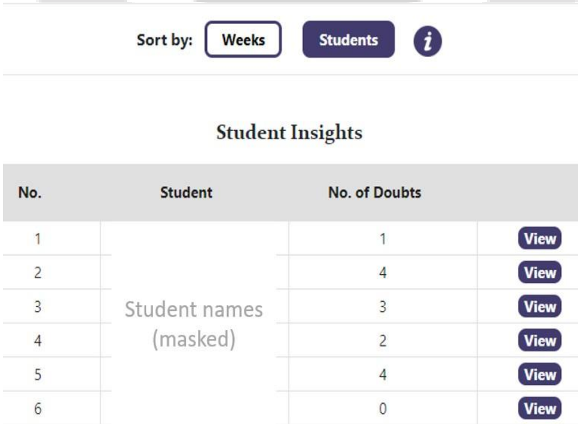
Fig- 6: Topic Alignment Score attached to each journal entry



Number of responses: 43

No.	Student	Response	Contain Doubt
37	Student names (masked)	I learned about the mechanism behind k-means clustering and the concept of stopping criteria where the iterations of reassigning the observation continues till stopping criteria is met.	No
38		For clustering, when dealing with categorical variables, we need to use either one-hot encoding or dummy variables to convert it into numerical variables. It will not be fair to use dummy varibale for categorical nominal data. I am still confuse between Total Sum-of-Squares vs Total Within-Cluster Sum-of-Squares.	Yes

Fig -7: Weekly summary of doubts among Learning journals



Student Insights

No.	Student	No. of Doubts	
1	Student names (masked)	1	View
2		4	View
3		3	View
4		2	View
5		4	View
6		0	View

Fig -8: Doubt analysis for each student across the weeks

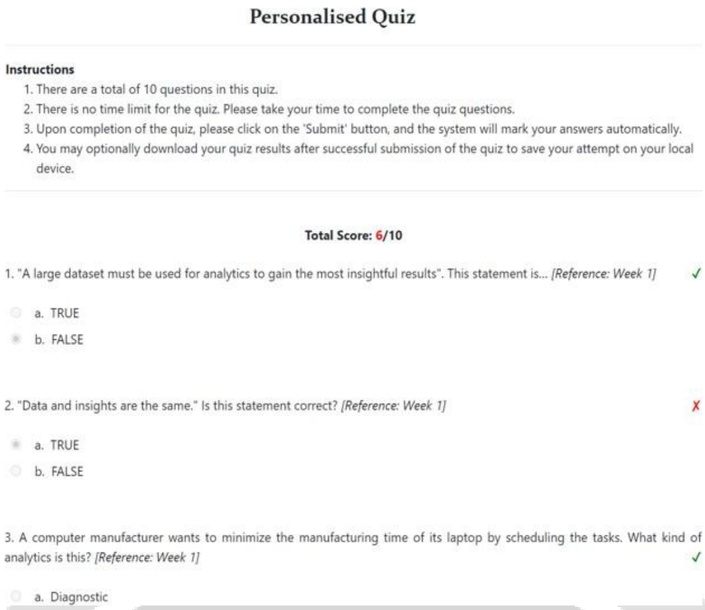


Fig- 9: Analysis and personalized quiz tool for the students

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, organization and delivery of content, making connections to real-life issues and/or 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, energizing, 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 feltmost of the time when using 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 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-organized 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 organized 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.

8. CONCLUSION

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 ofsimilar difficulty (using ALS) to evaluate the efficacy to achieve their learning outcomes by using the resultof both assessment papers.

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