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Effects of artificial Intelligence–Enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom

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ABSTRACT

The flipped classroom approach is aimed at improving learning outcomes by promoting learning motivation and engagement. Recommendation systems can also be used to improve learning outcomes. With the rapid development of artificial intelligence (AI) technology, various systems have been developed to facilitate student learning. Accordingly, we applied AI-enabled personalized video recommendations to stimulate students' learning motivation and engagement during a systems programming course in a flipped classroom setting. We assigned students to control and experimental groups comprising 59 and 43 college students, respectively. The students in both groups received flipped classroom instruction, but only those in the experimental group received AI-enabled personalized video recommendations. We quantitatively measured students' engagement based on their learning profiles in a learning management system. The results revealed that the AI-enabled personalized video recommendations could significantly improve the learning performance and engagement of students with a moderate motivation level.

1. Introduction

Learning motivation is key to successful learning (Maslow, 1981). The literature reveals that learning engagement (Alt, 2015; Hsieh, 2014; Xiong et al., 2015) and learning outcomes (Brooker et al., 2018; Hung et al., 2019) can affect learners' motivation to learn. Xiong et al. (2015) reported that students' learning engagement is a strong predictor of learning motivation (and vice versa). Furthermore, Hung et al. (2019) demonstrated that explicit teaching strategies could improve learning motivation and learning outcomes; these findings imply that learning motivation and learning outcomes are correlated. Educators are increasingly adopting engaging educational approaches such as game-based learning (Molins-Ruano et al., 2014) and mobile learning (Huang et al., 2016) to stimulate students' intrinsic learning motivation and improve their learning outcomes. Such learning tools can increase students' interest in learning, thereby stimulating their intrinsic motivation and improving their academic performance.

Focusing on a commercial context, Zhou et al. (2010) examined the effects of incorporating a video recommendation system into an online video service. They collected data from a university network and observed two major impacts. First, approximately 60% of the video viewers relied on the search and recommendation function for seeking videos. Second, use of the recommendation system reduced the Gini coefficient by 3%, meaning that video viewers were exposed to a wider variety of videos. Both of these results

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demonstrate the importance of recommendation systems in commercial scenarios.

Researchers are also increasingly applying recommendation systems in the educational field (Rivera et al., 2018; Zhong et al., 2019, pp. 12–27); however, two matters have been overlooked in related studies. First,Rivera et al. (2018) conducted a literature review on the application of recommendation systems in educational contexts. They concluded that collaborative filtering is the most common recommendation system algorithm in the educational environment. However, the algorithm used in collaborative filtering recommendation relies on the similarity between students, and the content recommended to the audience is based on group preference. Therefore, because the benefits of personalization are absent, Rivera et al. (2018) highlighted that the use of personalized recommendation systems in educational settings is challenging.

Second, Zhong et al. (2019, pp. 12–27) conducted another literature review related to recommendation system in educational settings, considering research published from 2014 to 2018. They concluded that evaluating students' learning outcomes was the most effective approach to verifying recommendation system performance. However, relevant studies have only focused on students' learning experience and the level of technology acceptance instead of another critical factor: learning motivation. Research has revealed that recommendation systems can improve students' learning performance. However, the impact of recommendation systems on students' learning motivation has received limited research attention. Regarding the study of learning motivation, Rashid and Rana (2019) proposed that students with different levels of learning motivation adopt distinct learning strategies. On this basis, we explored the impact of recommendation systems on groups of students with different motivation levels.

Artificial intelligence (AI) technology can be used to support personalized learning in the classroom. Hwang et al. (2020) proposed that AI systems can assume one of four roles in education: an intelligent tutor, intelligent tutee, intelligent learning tool, and advisor to policy-makers. Intelligent tutoring systems have various forms, such as adaptive learning systems, personalized learning systems, and recommendation systems. Studies have confirmed that intelligent tutoring systems can improve students' learning outcomes (Ma et al., 2014; Steenbergen-Hu & Cooper, 2014). Accordingly, we applied Bayes' theorem and logistic regression classification to implement an AI-enabled personalized recommendation system in a flipped classroom for teaching systems programming. Subsequently, we investigated the influence of this system on students' learning engagement, motivation, and outcomes.

The objective of this study was to stimulate students' intrinsic motivation by providing them with a list of recommended videos for review, thereby improving their learning outcomes. This study was guided by the following research questions (RQs):

RQ1. Can AI-enabled personalized recommendations improve students' learning motivation in a flipped classroom?

RQ2. Can AI-enabled personalized recommendations improve students' learning outcomes in a flipped classroom?

RQ3. Can AI-enabled personalized recommendations improve students' learning engagement in flipped classrooms?

RQ4. How does AI-enabled personalized recommendations improve students' learning outcomes in flipped classrooms?

2. Literature review

2.1. Flipped classroom for improving learning motivation and learning engagement

Because of the importance of learning motivation for successful learning, determining strategies for improving students' learning motivation is crucial in the field of education. A strong learning motivation can drive active and highly engaged learning behaviors, which are crucial prerequisites for effective learning. To increase students' learning motivation and engagement, a flipped classroom can be implemented; this approach involves replacing traditional classroom lectures with interactive learning activities such as teacher–student discussions or collaboration with peers (McLean et al., 2016). The flipped classroom approach is increasingly being integrated into curriculum design in university education (Mortensen & Nicholson, 2015).

In flipped classroom settings, students spend more time on learning tasks than they would in traditional classroom settings (El-Banna et al., 2017; McLean et al., 2016). Studies on flipped classrooms have mainly focused on the effect of this pedagogical approach on students' learning outcomes and engagement. Researchers have also tended to use self-report questionnaires to measure students' engagement in flipped classroom settings. However, students' questionnaire responses are highly subjective, and such questionnaires cannot accurately capture student engagement during the learning process.

One method to assess student engagement in the flipped classroom is measuring frequency characteristics, including quantity-related and time-related features, as derived from the learning management system. Quantity-related features include the number of learning materials viewed (Hsiao et al., 2019; Huang et al., 2020; Lu et al., 2018), the number of messages posted and responded to in forums (Huang et al., 2020; Macfadyen & Dawson, 2010), and the number of specific tasks completed (Hsiao et al., 2019; Lu et al., 2018; Macfadyen & Dawson, 2010). The time-related feature refers mainly to the number of days that the students logged onto the course (Hsiao et al., 2019; Huang et al., 2020; Lu et al., 2018).

A key tenet of learning motivation theory is that intrinsic and extrinsic motivations influence learning outcomes (Ryan & Deci, 2000). Extrinsic motivation mainly encourages students to learn through reward or punishment mechanisms. These mechanisms can only arouse a learner's desire to succeed; they cannot prompt enjoyment of the learning process. However, the enjoyment of learning can be considered a reward. Intrinsic motivation, by contrast, first increases learners' interest in engaging in an activity or enjoying an experience before stimulating learning motivation.

Numerous learning approaches have been applied to improve intrinsic learning motivation; examples include game-based learning (Hwang et al., 2013; Jong et al., 2012; Molins-Ruano et al., 2014) and mobile learning (Huang et al., 2016; Hwang & Chang, 2011). Learning tools can stimulate learners' intrinsic motivation, and considerable research has been conducted on the effect of such tools on learning outcomes. Therefore, in this study, we integrated AI-enabled personalized recommendations into a systems programming flipped classroom to stimulate students' intrinsic motivation and improve their learning performance.

2.2. Personalized recommendations in education

Several researchers have used recommendation systems in learning environments and achieved remarkable learning outcomes (Rivera et al., 2018; Zhong et al., 2019, pp. 12–27). However, our review of the literature revealed that in the field of education, most researchers have focused on e-books as recommended items (Hsu, 2015; Hsu et al., 2013); few studies have examined the utility of recommended video items in education. Research on the effect of recommended videos on learning motivation and outcomes is lacking. Therefore, we explored the effect of personalized video recommendations on the learning motivation and outcomes of learners in a flipped classroom.

Personalized recommendation systems can be divided into three categories: content-based, collaborative, and hybrid recommendations (Adomavicius & Tuzhilin, 2005; Aggarwal, 2016; George & Lal, 2019). Content-based recommendation systems (Pazzani & Billsus, 2007) focus on grouping items according to content similarity, thereafter providing a list of recommendations. Collaborative recommendation systems assume that individuals in the same group have similar requirements (Parvatikar & Joshi, 2015); therefore, they group user attributes and then provide recommendations based on the most commonly chosen items by the group. Hybrid recommendation systems (Mu, 2018) combine the advantage of content-based and collaborative recommendations systems to provide a list that accurately matches user preferences; various recommenders or algorithms are integrated to provide a content-based list of recommendations that accurately matches user preferences. On the basis of these advantages, the present study used a hybrid recommendation system to provide personalized video recommendations.

In the field of e-learning, recommendation systems mainly assist students in their learning by providing suggestions, including for learning materials and objects such as exercises or examples (Rivera et al., 2018; Zhang et al., 2021). A learning path is a sequence of items that includes learning materials, learning objects, or learning activities. On the basis of their review of the literature research, Garcia-Martinez and Hamou-Lhadj (2013) proposed that introducing a recommendation system into the classroom can improve students' learning performance and increase learning motivation. In the aforementioned studies, the impact of recommendation systems on academic performance and motivation was mainly considered for the class as a whole. However, according to Rashid and Rana (2019), students with different motivation levels use distinct learning strategies; that is, they adopt distinct self-regulated learning strategies in the learning process. On the basis of such findings, we explored how recommendation systems affect students with different learning motivation levels.

Mu (2018) proposed that hybrid recommendation systems can be divided into monolithic, parallel, and pipeline hybrid systems. Monolithic systems focus on combining the approaches of several recommenders. Parallel hybrid and pipeline hybrid systems require the use of at least two recommendation algorithms, which are combined to generate a recommendation list. Pipeline hybrid systems connect multiple recommenders in series in a pipeline structure; the output of one recommender is set as the input of another recommender. The parallel hybrid method integrates multiple recommendation lists from independently operated recommenders.

With the rapid development of AI technology, recommendation systems have gradually shifted from using traditional information retrieval methods such as cosine or vector similarity measures to using machine learning algorithms (Mu, 2018; Portugal et al., 2018). Commonly used machine learning–based approaches for constructing recommender systems include Bayesian classification, decision trees, and neural networks. The AI-enabled parallel hybrid recommender system proposed in this study applies Bayes' theorem and logistic regression classification to recommend videos for students' review.

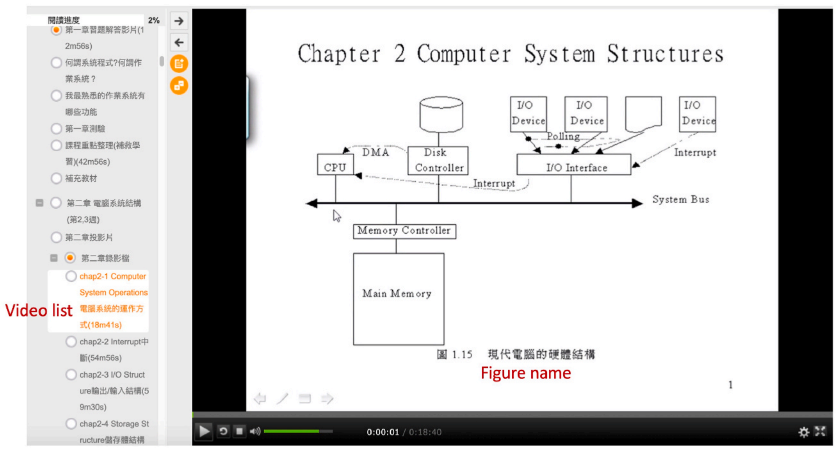

Fig. 1. Screenshot of the online learning environment (iLearning).

3. Methods and experiments

3.1. Participants and measurement

This study included a total of 102 students enrolled in a systems programming course at a university in northern Taiwan. The goal of the systems programming course is to increase students' knowledge of the relationship between computer hardware architecture and system software and to cultivate students' ability to design and implement system software. The students were assigned to an experimental group ($n = 43$) and a control group ($n = 59$). The experimental period was from September to November 2020. Both groups learned in a flipped classroom setting, with the only difference being that the experimental group received AI-enabled personalized video recommendations. The iLearning online learning environment, which enables students to learn independently anytime and anywhere, was adopted in this course (Fig. 1).

In this study, we applied a pretest, posttest, and learning motivation questionnaire for measurement. The pretest and posttest were used to evaluate students' knowledge of systems programming. The learning motivation questionnaire applied herein was developed by Hwang et al. (2013; additional details are provided in the appendix), and questions were answered on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). The questionnaire contains seven items designed to evaluate students' learning motivation toward systems programming; the Cronbach's α for the questionnaire items was 0.92.

Student learning engagement is typically measured through questionnaires. However, because of the useful data collected automatically in learning management systems (LMSs), students' learning engagement can be measured through their LMS profiles. Henrie et al. (2015) proposed a mechanism for measuring students' cognitive, emotional, and behavioral engagement from their LMS profiles. Using this approach, we quantitatively measured students' engagement in the proposed flipped classroom through their LMS profiles.

3.2. AI-enabled personalized recommendations

In this study, AI-enabled personalized recommendations were provided to students to adjust their learning approaches and thus improve their learning performance. The recommendations were based on a self-administered sequential probability ratio test (SPRT) as well as students' learning profiles on iLearning. Fig. 2 presents the architecture of the proposed recommendation system. In the SPRT, Bayes' theorem was used to evaluate students' mastery of pertinent concepts. Wald (2004) proposed an SPRT approach based on Bayes' theorem and applied it to manage armament production quality. An SPRT can be used to construct a test module by using Bayes' theorem to evaluate testers' probability of mastering a concept. To determine whether a student has thoroughly mastered a concept, some researchers (Jong et al., 2006; Lai et al., 2014; Luo et al., 2013) have developed SPRTs for educational purposes, and their equation is as follows:

$$\mathrm{PR} = \frac{P_{om} \times P_m^r (1 - P_m)^w}{P_{on} \times P_n^r (1 - P_n)^w} \quad (1)$$

where Pom and Pon represent the probability of concepts being familiar and unfamiliar, respectively, to the student, with the initial values set to 0.5. *Pm* is the probability of a learner being familiar with the concept and answering the question correctly. By contrast, Pn is the probability of the learner being unfamiliar with the concept but answering the question correctly. The initial values of *Pm* and Pn are set to 0.6 and 0.4, respectively. The values of r and w are set to the number of consecutive correct and consecutively incorrect

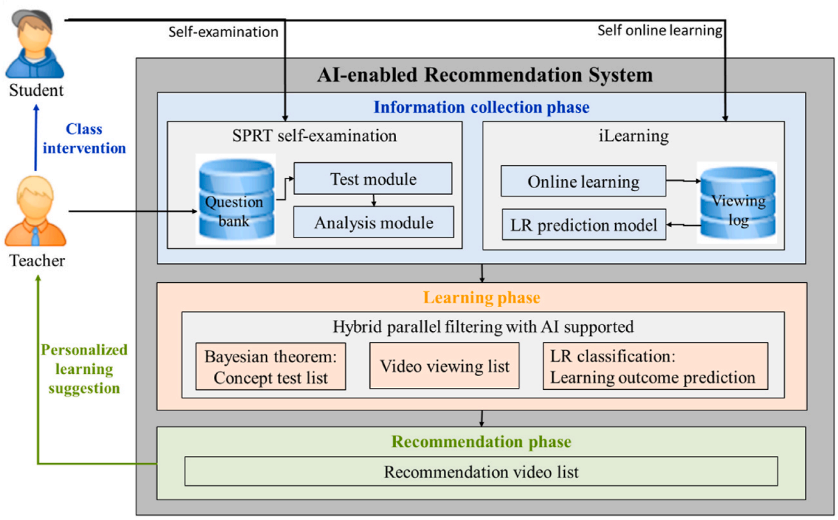

Fig. 2. Architecture of the AI-enabled personalized recommendation system.

answers, respectively. The symbol PR indicates the student's familiarity ratio for a particular concept. The PR value is used to determine whether students need to answer further questions. The following three situations are used to judge the students' learning status: (1) A PR value greater than or equal to $(1-\beta)/\alpha$ indicates that the students are familiar with a given concept; that is, the students have mastered a given concept and need not continue answering questions. (2) A PR value less than or equal to $\beta/(1-\alpha)$ indicates that students are unfamiliar with a given concept, meaning they need to review the learning materials first and then conduct another self-assessment. (3) Finally, a PR value between $(1-\beta)/\alpha$ and $\beta/(1-\alpha)$ indicates that the students' familiarity with a given concept cannot be accurately determined; therefore, further testing is necessary for a final determination. The parameter α represents the probability of the student being unfamiliar with the concept but judged as being familiar with it, whereas the parameter β represents the probability of the student being familiar with the concept but judged as being unfamiliar with it. The parameters α and β are initially set to 0.25 and dynamically adjusted according to the students' ratio of incorrect answers.

For personalized recommendations, Isinkaye et al. (2015) proposed that the recommendation process should include three phases: information collection, learning, and recommendation. Accordingly, the proposed AI-enabled personalized recommendation system was implemented in the three aforementioned phases, details of which are described as follows:

- Information collection phase

This phase primarily involved the collection of students' learning profiles, which could provide information relevant to personalized recommendations. This information was gleaned from the students' video-viewing logs on iLearning and their self-administered SPRT results. The lecturer uploaded educational videos related to each learning concept before class, allowing students to study online at their convenience using the iLearning system; the students' video-viewing logs on iLearning were subsequently recorded and used to calculate how long each student spent viewing each video. A set of video-viewing lists can be presented as follows: $T = \{t_{i1}, t_{i2}, \ldots, t_{in}\}$, where t_{ij} represents the time student s_i spends watching videos v_j. Machine learning methods can be used to construct learning outcome prediction models that provide early warnings to students likely to have insufficient learning outcomes. We used logistic regression to develop a model for predicting students' learning outcomes. The students' video-viewing logs from September to November 2019 and from the same period the next year were used as the training and test data sets, respectively. Then, we generated a list of video-viewing times (set T) and constructed a learning outcome prediction model for providing personalized recommendations.

The proposed self-administered SPRT was implemented using a test module and analysis module (based on Bayes' theorem) to determine students' mastery of learning concepts. For each learning concept, the test module randomly selected questions from a question bank to test the students' conceptual mastery. As students' mastery of a particular concept progressed, the module minimized the number of related test questions. In the systems programming flipped classroom, four concepts were taught, namely introduction to systems programming (c_1), assembling (c_2), compiling (c_3), and software engineering (c_4). Hence, the probability ratio set $PR_i = \{PR_{i1}, PR_{i2}, PR_{i3}, PR_{i4}\}$ was used to determine the familiarity of student s_i with concepts c_1 to c_4. Each concept has three mastery levels: mastery, nonmastery, and partial mastery.

- Learning phase

This phase involved designing an integrated process for filtering personalized recommendations collected from the students' learning profiles in the information collection phase. The filtering process comprised two steps: first the learning profile is extracted and then the recommended video list is generated. According to information on students' learning profiles collected in the previous phase, the first step was executed to collect data on the students' self-administered test results and video-viewing behavior; the

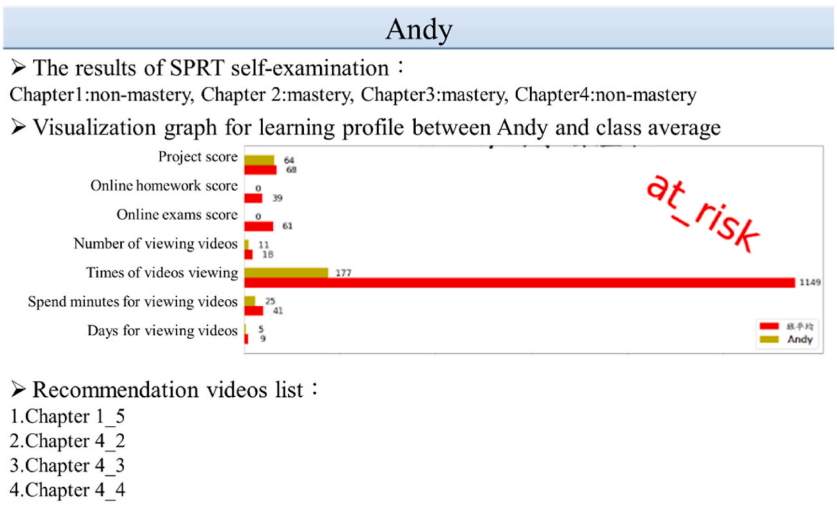

Fig. 3. Example of a recommended video list for an at-risk student.

collected data were used to predict learning outcomes. The test results and video-viewing lists revealed the students' mastery of each concept (extracted from the probability ratio set *PR*) and each student's single video-viewing time (extracted from the video-viewing log), respectively. Student learning outcome predictions were obtained using the logistic regression–based prediction model constructed in the information collection phase. In the second step, for concepts that students had not yet mastered or only partially mastered, they received recommendations to rewatch videos they spent the shortest time on. Students who had mastered all concepts received recommendations to view three videos that they had spent the shortest time viewing. According to the importance of each concept, the maximum number of recommended videos for c_1, c_2, c_3, and c_4 was set to 1, 2, 3, and 4, respectively.

- Recommendation phase

The recommendation phase involved providing the students with a personalized list of recommended videos to guide them in reviewing videos about concepts they had not mastered or only partially mastered, thus improving their learning outcomes. Fig. 3 presents an example of the learning status summary available for each student, including a list of recommended videos; the following information is provided (from top to bottom): (1) self-administered SPRT results, (2) a graph visualizing the student's learning profiles, (3) the student's learning outcome prediction results, and (4) the recommended videos.

The self-administered SPRT results provide the students with information on their learning progress. The graph for student learning profiles enables the students to compare their online learning performance with the class average; the aim of providing this graph was to promote students' engagement in online learning. The students' learning outcome predictions were conducted using logistic regression classification according to their learning progress. Student learning profiles from the systems programming course for a 9-week period (from September to November 2019) were used as the training data set, and learning profiles from September to November 2020 were used as the test data set. The labels used in logistic regression classification were "at risk" and "safe." The recommended video list was based on students' learning profiles.

3.3. Experimental procedure

The systems programming course considered in this study involves 1 h of online self-learning and 2 h of face-to-face teaching in the classroom every week for 9 weeks. Fig. 4 presents the following learning activities: (1) video viewing, (2) topic discussion and quiz, and (3) self-examination and video review. In this study, the only difference between the experimental and control groups was the video content viewed in the after-class activities. The students in the experimental group received a personalized list of recommended videos based on their video-viewing logs and SPRT results. The three learning activities in the flipped classroom for this course are as follows:

- Video viewing (before class): The lecturer uploads learning videos to iLearning before class, enabling the students to engage in preclass self-learning.
- Topic discussion and quiz (in class): The lecturer prompts the students to engage in interactive discussions on topics related to the video content. The students are required to write an essay on a given learning topic every 2 weeks.
- Self-examination and video review (after class): The self-administered SPRT is implemented to enable the students to examine their knowledge of systems programming after class. Moreover, the students can review videos after class to recollect the concepts they had learned. The video content provided to the control and experimental groups was the same, but the students in the experimental group also received a personalized video recommendation list (Fig. 3).

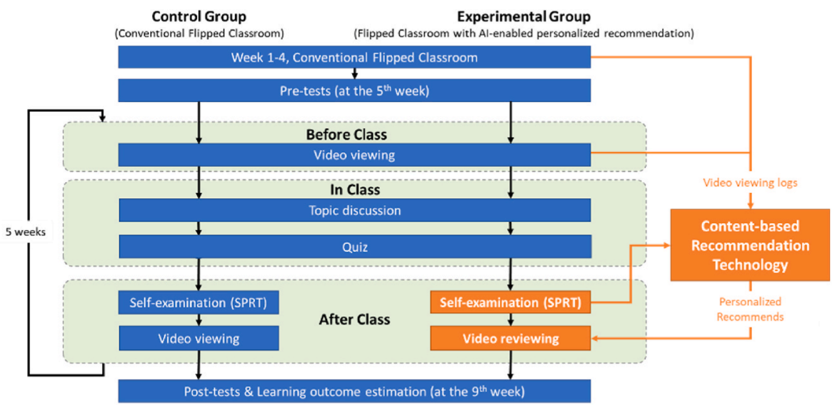

Fig. 4. Learning activities of the control and experimental groups.

4. Results and discussion

4.1. Influence of AI-enabled personalized recommendations on students' learning motivation in a flipped classroom

To explore the influence of AI-enabled personalized recommendations on the students' learning motivation, we compared the pretest and posttest motivation scores. We divided students into two subgroups according to the extent of motivation improvement (posttest–pretest scores): students with a motivation improvement equal to or greater than zero were assigned to the increased motivation (G_{M+}) subgroup, and the others were assigned to the decreased motivation (G_{M-}) subgroup. We used an independent *t*-test to determine differences in learning motivation improvement between the control and experimental groups; the results are provided in Table 1.

The numbers (proportions) of students in the G_{M+} subgroups of the control and experimental groups were 31 (53%) and 28 (65%), respectively (Table 1). The numbers (proportions) of students in the G_{M-} subgroups of the control and experimental groups were 28 (47%) and 15 (35%), respectively. Therefore, relative to the control group, the experimental group had a higher proportion of students with improved learning motivation and a lower proportion of students with reduced learning motivation. Thus, although no significant difference was observed in motivation improvement between the two groups, the proportion of students with improved motivation in the experimental group was higher than that in the control group. This indicates that students' learning motivation could be enhanced through the use of the proposed AI-enabled personalized recommendation system.

To identify learning categories, previous studies (Berland et al., 2013; Fincham et al., 2018; Jovanovic et al., 2017; Pardo et al., 2018) have used the clustering method to separate students into different groups. Berland et al. (2013) used the clustering method to identify categories of program states for novice programmers. Jovanovic et al.,2017 identified students' learning strategies by using sequence mining and clustering methods. In a flipped classroom in Australian higher education institutions, Fincham et al. (2018) used a clustering method to identify students' self-regulated learning strategies based on their video browsing records in engineering courses. Finally, Rashid and Rana (2019) explored the use of self-regulated learning strategies by different groups of students according to distinct motivation levels. Consistent with the approach of the aforementioned studies, we grouped students according to their learning motivation through k-means clustering to further explore the effect of the proposed AI-enabled personalized recommendation system on learning motivation in a flipped classroom. K-means clustering, one of the most common clustering methods, was applied to group the students on the basis of their pretest responses to the 7-item learning motivation questionnaire. In k-means clustering, the optimal number of clusters can be determined through the elbow method. We adopted this method and determined the optimal number to be 3. Therefore, the students were divided into three subgroups: those with high, moderate, and low levels of learning motivation were assigned to the G_H (n = 19), G_M (n = 48), and G_L (n = 35) subgroups, respectively.

Table 2 presents the numbers and proportions of students in the G_H, G_M, and G_L groups in the G_{M+} and G_{M-} subgroups. Independent *t* tests revealed no significant differences in learning motivation improvements for the students in the G_H group between the G_{M+} and G_{M-} subgroups of the experimental and control groups ($t = .70$, $p > .05$ for G_{M+}; $t = -1.5$, $p > .05$ for G_{M-}). Moreover, the improvement in learning motivation for the G_M ($t = -0.21$, $p > .05$ for G_{M+}; $t = 0.33$, $p > .05$ for G_{M-}) and G_L groups ($t = 1.71$, $p > .05$ for G_{M+}; $t = -1.61$, $p > .05$ for G_{M-}) in the G_{M+} and G_{M-} subgroups was the same as that of the students in the G_H subgroup; that is, the G_H, G_M, and G_L subgroups exhibited no significant differences in learning motivation improvement between the G_{M+} and G_{M-} subgroups. These results indicate that the students in the G_M, G_M, and G_L subgroups of the control and experimental groups had similar improvements and reductions in learning motivation.

In the control and experimental groups, the proportions of students with improved motivation in the G_H subgroups were 50% and 44%, respectively, those in the G_M subgroups were 39% and 60%, respectively, and those in the G_L subgroups were 71% and 85%, respectively (Table 2). According to these results, the proportions of students with improved motivation in the G_M and G_L subgroups of the experimental group were 21% and 14% higher than those in the G_M and G_L subgroups of the control group, respectively. The proportion of students with improved motivation in the G_H subgroup of the experimental group was 6% lower than that in the G_H subgroup of the control group by.

In summary, although the experimental and control groups did not differ significantly in terms of motivation improvement, the experimental group had a higher proportion of students with improved learning motivation, especially in the G_M subgroup. In response to **RQ1**, these results indicate that the proposed AI-enabled personalized recommendation system did not result in significant improvements in students' motivation but prompted an increase in the proportions of students with improved motivation, especially among students with a moderate motivation level.

Table 1
Numbers and proportions of students in the experimental and control groups who exhibited increased and decreased learning motivation.

Group	Number		Proportion		Mean (S.D.): Improvement of learning motivation		t value
	GC	GE	GC	GE	GC	GE	
G_{M+}	31	28	.53	.65	.41 (.42)	.29 (.31)	−1.22
G_{M-}	28	15	.47	.35	−.64 (.47)	−.62 (.38)	−1.7

The results revealed that the number of students with learning motivation improvements in the experimental and control groups did not differ significantly ($t = -1.22$, $p > .05$ for G_{M+}; $t = -1.7$, $p > .05$ for G_{M-}). The results also indicated that the experimental and control groups had similar levels of motivation. Accordingly, we investigated the proportions of students in the G_{M+} and G_{M-} subgroups of the experimental and control groups.

Table 2
Numbers and proportions of students in the G_H, G_M, and G_L groups in the G_{M+} and G_{M-} subgroups.

Group		Number		Proportion		Mean (S.D.): Improvement of learning motivation		t value
		GC	GE	GC	GE	GC	GE	
G_H	G_{M+}	5	4	.50	.44	.09 (.13)	.04 (.071)	.70
	G_{M-}	5	5	.50	**.56**	−1.11 (.79)	−.51 (.41)	−1.5
G_M	G_{M+}	11	12	.39	**.60**	.36 (.27)	.39 (.37)	−.21
	G_{M-}	17	8	.61	.40	−.60 (.31)	−.64 (.37)	.33
G_L	G_{M+}	15	12	.71	**.85**	.55 (.51)	.27 (.25)	1.71
	G_{M-}	6	2	.29	.15	−.38 (.25)	−.79 (.51)	−1.61

4.2. Influence of AI-enabled personalized recommendations on improving students' learning outcomes in a flipped classroom

To investigate the influence of the proposed AI-enabled personalized recommendations on students' learning outcome in the flipped classroom, an independent *t*-test was used. A pretest and posttest were administered in Weeks 4 and 9, respectively, to determine students' learning outcomes. The results indicated that the pretest, posttest, and improvement scores (posttest −pretest scores) did not differ significantly between the students in the experimental and control groups ($t = 0.16$, $p > .05$ for pretest scores; $t = -1.01$, $p > .05$ for posttest scores; $t = -1.12$, $p > .05$ for improvement scores; Table 3).

The pretest and posttest scores revealed that the students in the experimental and control groups had equivalent knowledge of systems programming both at the outset and end of the course. Moreover, the students in the experimental group did not exhibit higher improvement scores than the students in the control group. Therefore, the use of the proposed recommendation system did not result in an improvement in scores for students.

As indicated in Table 2, the AI-enabled personalized recommendations increased the learning motivation of some students. The proportions of students with improved learning motivation in the G_M and G_L subgroups of the experimental group were 60% and 85%, respectively. Because no differences were noted in learning outcome improvements between the experimental and control groups (Table 3), we applied an independent *t*-test to compare the learning outcome improvements between the G_H, G_M, and G_L subgroups of the control and experimental groups (see Table 4).

The numbers of students in the G_H, G_M, G_L subgroups were 10, 28, and 21 in the control group and 9, 20, and 14 in the experimental group. Our analysis revealed no significant difference between the G_H and G_L subgroups in the control and experimental groups in terms of learning outcome improvement ($t = 0.119$, $p > .05$ for G_H; $t = 0.224$, $p > .05$ for G_L). However, the G_M subgroup of the experimental group had a significantly higher improvement in learning outcomes than did the corresponding subgroup of the control group ($t = -2.441$, $p < .05$). In response to **RQ2**, the proposed AI-enabled personalized recommendations had a significant positive effect on improving the learning outcomes of students with moderate motivation levels; this effect was not observed for students with high or low motivation levels.

4.3. Influence of AI-enabled personalized recommendations on student engagement in a flipped classroom

We collected data on frequency-type indicators from iLearning to evaluate students' engagement in online learning. Eleven features were extracted; these are described in Table 5. Regarding f_8 (number of videos not watched), lower values were considered to indicate higher engagement in online learning. For the other 10 features, higher values were considered to indicate higher engagement in online learning. Apart from f_8, the values of the other features had a positive relationship with students' engagement in online learning. Two features, f1 and f3, are time-related features, whereas the other nine are quantity-related features. Most quantity-related features focus only on accounting for the number of operations on the learning resource. We extracted features f2, f4, f8, f10, and f11 as quantity-related features. Previous studies have tended to consider the number of days students logged in to courses for time-related features. Because of this, we extracted the number of unique days videos were watched (f1) and accumulated the time spent watching videos (f3). Moreover, we considered information regarding online learning resource usage for the key periods of the course: before, in, and after class. Features f5 and f6 are related to the before-class and in-class periods, respectively. Features f7 and f9 are related to the after-class period.

To examine changes in the students' learning engagement prompted by the AI-enabled personalized recommendations (**RQ3**), we

Table 3
Independent *t*-test results for the improvement scores of the control and experimental groups.

Variable	Group	N	Mean	S.D.	t value
Pretest	GC	59	42.915	15.346	0.16
	GE	43	42.419	14.791	
Posttest	GC	59	50.69	23.0	−1.01
	GE	43	55.0	19.76	
Improvement score (posttest – pretest)	GC	59	8.677	21.082	−1.12
	GE	43	12.581	20.309	

Table 4
Independent *t*-test results and descriptive statistics for differences in learning outcome improvements between the G_H, G_M, and G_L subgroups.

Group	N	N_{GC}/N_{GE}	Mean (S.D.) of learning motivation	Mean (S.D.) of improvement score (posttest – pretest)		t value
				Control	Experimental	
G_H	19	10/9	5.84 (.21)	14.7 (19.39)	3.88 (20.17)	1.190
G_M	48	28/20	4.88 (.22)	4.142 (20.304)	18.2 (18.715)	−2.441*
G_L	35	21/14	4.05 (.40)	11.85 (22.48)	10.14 (21.51)	0.224

Note : N_{GC} and N_{GE}, the numbers of students in the G_H, G_M, and G_L subgroups of the control and experimental groups, respectively.

Table 5
Features extracted from the online learning environment.

	Feature name	Description
f_1	Days watched	Number of days on which a student watched videos per week
f_2	Watching sessions	Number of times a student watched videos per week
f_3	Total watching time	Total time spent (minutes) watching videos per week
f_4	Videos watched	Number of videos that a student watched per week
f_5	Previewed videos watched	Number of videos that a student watched in preparation for class (according to course progress)
f_6	On-track videos watch	Number of on-track videos that a student watched (according to course progress)
f_7	Rewatched videos	Number of videos that a student rewatched
f_8	Videos not watched	The number of videos that a student has not watched (according to course progress)
f_9	Makeup videos	The number of videos watched to make up for missed learning opportunities
f_{10}	Forum post days	Number of days a student posted on forums
f_{11}	Forum post times	Number of times a student posted on forums

evaluated the 11 features in Weeks 6 and 8—before and after the students received the video recommendations. We applied Spearman's correlation analysis (Table 6) and the Mann–Whitney *U* test (Tables 7 and 8).

According to the Spearman correlation coefficients (Table 6), eight features (f_1, f_2, f_3, f_4, f_5, f_6, f_7, and f_8) were significantly correlated with improved student scores in Week 6. To investigate the difference between the control and experimental groups in terms of online learning engagement before the provision of the AI-enabled personalized recommendations, we derived the values of the 11 features in Week 6. The values of the features did not differ significantly between the control and experimental groups in Week 6 (Table 7). This indicates that the students in the experimental and control groups had the same level of online learning engagement before the provision of the personalized video recommendations.

Regarding changes in the values of the 11 features after the provision of the AI-enabled personalized recommendations (Week 8), six features (f_1, f_2, f_3, f_4, f_6, and f_9) were significantly positively correlated with improvement scores (*$p < .05$ for f_6, and f_9; **$p < .01$ for f_1, f_2, and f_3; ***$p < .001$ for f_4), and the corresponding correlation coefficients ranged from 0.21 to 0.37; similarly, f_8 was significantly negatively correlated with improvement scores (*$p < .05$), and the corresponding correlation coefficient was −0.22 (Table 6). Finally, the values of four features ($U = 907$, $p < .01$ for f_2; $U = 908$, $p < .01$ for f_3; $U = 906$, $p < .01$ for f_4; $U = 772$, $p < .001$ for f_9) were significantly higher in the experimental group than in the control group (Table 8). These four features (f_2, f_3, f_4, and f_9) were significantly related to learning performance; therefore, the experimental group had a significantly higher level of online learning engagement than did the control group in Week 8. This result indicates that the students in the experimental group watched videos more times, spent more time watching videos, watched more videos, and watched more videos to compensate for missed learning opportunities compared with those in the control group. These results can be attributed to the fact that the recommended videos focused on concepts that were unclear to the students, as determined by their SPRT results and video-viewing logs. We can infer that the students in the experimental group sought to enhance their knowledge of unclear concepts by watching the recommended videos.

In response to **RQ3**, our results suggest that AI-enabled personalized recommendations can improve students' learning engagement in flipped classroom settings. After the students in the experimental group received video recommendations for a few weeks (Week 8), their online learning engagement improved. Furthermore, their improved online learning engagement (based on extracted features) was related to their learning performance.

4.4. *Improved learning outcomes of students in different motivation groups given AI-enabled personalized recommendations*

To answer **RQ4**, we compared the engagement of the students in the G_H, G_M, and G_L subgroups between the experimental and control groups in Weeks 6 and 8 by using the Mann–Whitney *U* test (Tables 9 and 10).

Table 6
Spearman's correlation between students' improvement scores and the extracted features in Weeks 6 and 8.

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
Week 6	.26**	.279**	.239*	.226*	.224*	.247*	.216*	−.247*	.178	−.057	−.056
Week 8	.302**	.361**	.276**	.37***	n.a	.219*	.108	−.219*	.214*	−.168	−.168

Table 7
Mann–Whitney *U* test results for online learning engagement (f_1–f_{11}) in the experimental and control groups in Week 6.

	F_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
Mean of GC	1.881	8.034	190	3.593	0.271	0.22	0.085	2.78	1.034	0.203	0.525
Mean of GE	2.07	8.116	152	3.605	0.047	0.372	0.093	2.628	1.209	0.302	0.302
Mann-Whitney *U* Test	1219	1260.5	1218	1253	1169	1213	1238	1213	1184	1266	1261

Table 8
Results of a Mann–Whitney *U* test regarding the online learning engagement (f_1–f_{11}) of the experimental and control groups in Week 8.

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
Mean of GC	1.46	6.73	229	4.09	0	0.76	0.19	3.24	1.48	0.10	0.15
Mean of GE	1.84	10.33	341	5.95	0	0.65	0.21	3.35	2.67	0.21	0.23
Mann-Whitney *U* Test	1034	906**	907**	906**	n.a	1216	1236	1216	771***	1231	1232

Table 9
Mann–Whitney *U* test results for online learning engagement (f_1–f_{11}) in the experimental and control groups in Week 6.

	F_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
	G_H Group										
Mean of GC	1.88	8.03	190	3.59	0.27	0.22	0.09	2.8	1.03	0.20	0.53
Mean of GE	2.07	8.12	152	3.61	0.05	0.37	0.09	2.63	1.21	0.30	0.30
Mann-Whitney *U* Test	1219	1261	1218	1253	1169	1213	1238	1213	1184	1266	1261
	G_M Group										
Mean of GC	1.96	9.18	193	3.82	0.39	0.21	0.07	2.79	1.11	0.18	0.21
Mean of GE	2.15	7.25	211	3.4	0.1	0.2	0.1	2.8	1.05	0.35	0.35
Mann-Whitney *U* Test	180	185	181	191	175	164	196	164	194	189	189
	G_L Group										
Mean of GC	1.86	7.76	184	3.62	0.24	0.24	0.14	2.76	1.14	0.33	1.19
Mean of GE	2.07	10.07	108	3.86	0	0.64	0.07	2.36	1.21	0.43	0.43
Mann-Whitney *U* Test	130	121	131	132	126	128	143	128	138	145	143

Table 10
Mann–Whitney *U* test results for online learning engagement (f_1–f_{11}) in the experimental and control groups in Week 8.

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
G_H Group											
Mean of GC	1.4	6.5	208	3.9	0	0.6	0.1	3.4	1.7	0	0
Mean of GE	1.56	6.44	290	3.67	0	0	0	4	2	0.22	0.3
Mann-Whitney *U* Test	58	49.5	55	46.5	n.a	59	56.5	59	43	65	65
G_M Group											
Mean of GC	1.25	4.79	172	3.04	0	0.75	0.18	3.25	0.93	0.21	0.32
Mean of GE	2	11.4	369	6.5	0	0.65	0.2	3.35	2.95	0	0
Mann-Whitney *U* Test	148	110*	123*	101**	n.a	169	168	169	79***	188	189
G_L Group											
Mean of GC	1.76	9.43	317	5.57	0	0.86	0.24	3.14	2.1	0	0
Mean of GE	1.79	11.27	334	6.64	0	1.07	0.36	2.93	2.71	0.5	0.5
Mann-Whitney *U* Test	136	114	109	113	n.a	144	129	144	104	137	137

The values of all features did not differ significantly between the G_H, G_M, and G_L subgroups of the control and experimental groups in Week 6 (Table 9). This means that students with high, moderate, and low learning motivation levels in the control and experimental groups had equivalent online learning engagement before the provision of the recommended video lists.

The values of all features did not differ significantly between the G_H and G_L subgroups of the control and experimental groups in Week 8 (Table 10); however, the values of four features were significantly higher in the G_M subgroup of the experimental group than in the corresponding subgroup of the control group ($U = 110.5$, $p < .05$ for f_2; $U = 123.0$, $p < .05$ for f_3; $U = 101.5$, $p < .01$ for f_4, $U = 79.5$, $p < .001$ for f_9). These results indicate that students with a moderate motivation level in the experimental group had higher levels of online learning engagement in Week 8 than did those in the control group. This is because the students in the experimental group received a list of personalized video recommendations in Week 7. However, students with high and low levels of learning motivation had the same levels of online engagement in Week 8. This result is consistent with that provided in Section 4.2 for RQ2; for students with moderate motivation levels, the improvement scores of the experimental group were significantly higher than those of the control group. In the experimental group, students with a moderate level of motivation exhibited improved learning outcomes following their use of personalized video recommendation lists.

Our analysis in Week 8 revealed that the AI-enabled personalized recommendations had a significant and positive effect on the online learning engagement of students with a moderate level of motivation. However, the same effect was not observed for the online learning engagement of students with high or low motivation levels. The proposed recommendation system mainly recommends relevant videos to guide students to review according to their conceptual proficiency and helps students review the course content before examinations. The results in Table 10 indicate that our AI-enabled personalized recommendation system can improve the learning engagement of students with moderate motivation levels but does not affect high and low motivation groups. This result is consistent with the finding of a related study (Rashid & Rana, 2019) on help-seeking learning strategies, which revealed that only students with moderate motivation levels, not those with high or low motivation, use help-seeking learning strategies. We interviewed some teachers to understand the aforementioned results; the teachers argued that students with high learning motivation generally have a high self-review ability. By contrast, those with low learning motivation tend to exhibit low learning engagement. Therefore, we speculate that students with high motivation do not need AI-enabled personalized recommendations to aid in their review. By contrast, students with low motivation may become discouraged regarding their studies, leaving them unwilling to review through AI-enabled personalized recommendations.

Concerning **RQ4**, our results suggest that the AI-enabled personalized recommendation system only effectively promotes the online learning engagement of students with a moderate level of motivation. The recommendations aided students with moderate learning motivation (i.e., those in the G_M subgroup) to review learning content; these students watched videos more often, spent more time watching videos, watched more videos, and watched more videos to compensate for missed learning opportunities. Therefore, the learning outcomes of students with moderate learning motivation can be improved by increasing their online learning engagement.

5. Conclusions

We designed an AI-enabled personalized recommendation system for a flipped classroom and explored its effect on three factors related to learning success, namely motivation, engagement, and outcomes. Our results reveal that the proposed system could increase students' learning motivation. We observed that improvements in students with moderate motivation levels were significantly higher than those in students with high and low levels of motivation. This disparity can be attributed to highly motivated students having already mastered related concepts; therefore, they rarely followed the recommendations of the AI-based system. The range of learning outcome improvement for students with high learning motivation was minimal. Moreover, students with low-level motivation did not benefit noticeably from the proposed system because of their poor willingness to use the learning management system. We also analyzed learning engagement and learning outcomes because these two indicators are highly related to learning motivation. Our results demonstrate that learning engagement and learning outcomes increased with motivation. Therefore, personalized video recommendation systems constitute a useful learning tool for individuals with a moderate level of learning motivation.

Credit author statement

Anna Y.Q. Huang: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, **Owen H.T. Lu**: Validation, Visualization, Resources, Data curation, Writing – review & editing, **Stephen J.H. Yang**: Writing - Review & Editing, Supervision, Project administration, Funding acquisition

Data availability

No data was used for the research described in the article.

Appendix. Learning Motivation Questionnaire

1. I think learning natural science is interesting and valuable.
2. I would like to learn more and observe more in the natural science course.
3. It is worth learning those things about natural science.
4. It is important for me to learn the natural science course well.
5. It is important to know the natural science knowledge related to our living environment.
6. I will actively search for more information and learn about natural science.
7. It is important for everyone to take the natural science course.

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