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An Online Personalized Learning System with Ongoing Learning Experience Adaptation: A Prototype System for STEM Discipline

Charoenchai WONGWATKIT[a,b*], Patcharin PANJABUREE[c] & Sasithorn CHOOKAEW[d]

[a]*School of Information Technology, Mae Fah Luang University, Thailand*
[b]*Innovation for Quality of Life Development with Information Technology Research Group, Mae Fah Luang University, Thailand*
[c]*Institute for Innovative Learning, Mahidol University, Thailand*
[d]*Department of Teacher Training in Mechanical Engineering, Faculty of Technical Education, King Mongkut's University of Technology North Bangkok, Thailand*
*wongwatkit.c@gmail.com

Abstract: In personalized learning systems, personal information and learning information are usually analyzed for providing proper instruction for individuals. On the other hand, scholars have indicated the challenge of proposing models owing the lack of taking various data types into account. Several previous studies have indicated that without properly incorporating learning behavior into the personalized learning systems might fail to help students learn with proper learning process. To address this issue, this study proposes a model for analyzing ongoing learning data and adapting personalized learning experience. Besides, this study presents an overall structure of a personalized learning system that can work with the proposed mechanism. In comparison with other models, the proposed model performed the best with high accuracy; consequently, it can be deployed in the presented learning system. The findings of this study not only address the significance of ongoing learning experience in the personalized learning system but also enable a practical example to increase learning motivation in the online learning world, in particular STEM-related courses.

Keywords: Educational data mining, artificial intelligence in education, applications for STEM education

1. Introduction

Learning experience is recognized by scholars as a significance component of learning. In online learning environment, ongoing learning experience plays a crucial role in learning success. Not only the students have strong determination and learning discipline, but also the systems must respond to their learning capability in order to drive learning motivation continuously and give them positive in learning attitude (Fonseca, Martí, Redondo, Navarro, & Sánchez, 2014; Rosenberg, 2001). To avoid dropout rate in online learning, scholars have suggested preparing learning experience in order to respond with dynamic change of individual's capability (Panjaburee, Triampo, Hwang, Chuedoung, & Triampo, 2013; Chookaew, Wanichsan, Hwang, & Panjaburee, 2015; Srisawasdi & Panjaburee, 2015; Kuo, Tsai, & Wang, 2017; Wongwatkit, Srisawasdi, Hwang, & Panjaburee, 2017). Even though the existing personalized learning systems have an adaptive feature, the analysis of students characteristics is performed before actual learning as well as learning recommendation system (Hung, Chang, & Lin, 2016; Hwang, Chu, & Yin, 2017). This has some limitations in taking ongoing learning data and students' capability into account of making learning adaptation because there are a large amount of data and different data in the different learning units.

To address these shortcomings, this study proposes a mechanism for adapting ongoing learning experience based on educational data mining technique. The proposed mechanism can take the learning data to learn and eventually to develop an algorithm to be deployed in the personalized learning environment. The results of this study shed light of enhancing the learning experience and quality of students, and research advancement in the personalized learning environment, in particular an application of this system on STEM-related courses. This study was directed with two objectives: 1) to propose a mechanism for ongoing learning experience adaptation, and 2) to present an overall structure of the personalized learning system that can work with the proposed mechanism.

2. Related Study

2.1 Educational Data Mining and Methodology

Educational Data Mining (EDM) is a method to find insights of data in different perspectives of education, including policy, operation, and learning (Dutt, Ismail, & Herawan, 2017). Regarding policy, EDM can help analyze data from different departments/functions in institutions for amending policy or strategy in responding with current need or situation. In operation, EDM can take data of personnel, students, and classrooms in providing the trend or reducing the process. Moreover, in learning, EDM can use data generated during the learning process to analyze and segment students by their performance or to predict a trend of students who are likely to fail (Calvet Liñán & Juan Pérez, 2015; Guruler & Istanbullu, 2014). It is certain that data mining is very beneficial in various perspectives of education.

One of the well-known techniques in EDM is machine learning. It is the learning of machine or computer by learning from the historical data to analyze and find the pattern, trend or association, and explain the phenomena, or predict the possibility of the new data. Machine learning can be categorized in three groups. 1) clustering: it can cluster or segment data by similar characteristic (unsupervised learning), e.g., K-Means clustering, EM Clustering, Affinity Propagation, 2) classification: it can learn from a big data with identified class/answer (supervised learning) and develop a model/algorithm to predict the answer of unknown data, e.g., kNN, Naïve Bayes, SVM, Decision Tree, Random Forest, Deep Learning, and 3) association: it can analyze for the relationship among data that meet the condition set. However, different techniques have different process of preparing data and the results can be different. It is necessary to evaluate their performance with suggested metrics (Baradwaj & Pal, 2012; Jamal et al., 2016; Vaessen et al., 2014).

In the past ten years, many studies have applied EDM in different domains: 1) students' performance prediction. For example, evaluating students' performance from end-semester examination in university (Baradwaj & Pal, 2012), predicting academic achievement at the end of program (Asif, Merceron, Ali, & Haider, 2017), and final performance prediction based on participation (Xing, Guo, Petakovic, & Goggins, 2015), 2) Early prediction of academic failure, e.g., detect failure in computer course (Costa, Fonseca, Santana, de Araújo, & Rego, 2017), and 3) completion rate, e.g., predicting completion rate from discussion forum in language course on MOOCs (Crossley et al., 2015). Moreover, many researches applied EDM in adaptive and interactive learning platforms (Colchester, Hagras, Alghazzawi, & Aldabbagh, 2017; Bannert, Molenar, Azevedo, Järvelä, & Gašević, 2017; Udupi, Sharma, & Jha, 2016). In this study, EDM process is used as a method in developing a classification model for analyzing the learning experience.

2.2 Personalized Learning System and Ongoing Learning Experience

Personalized learning system is the online learning system that consider the students' data into analysis for adapting and recommending the learning activities for individual students. This system can help improve learning motivation, which plays an important role in better learning performance (Nedungadi & Raman, 2012). There are three types of students' data used in the system. 1) Personal data, e.g., gender, age, personality, 2) learning background, e.g., pre-test score, exercise results, and 3) learning preference, e.g., learning style, learning format, learning feedback. Some systems integrate this data for enhancement, called learning profile (Hwang, Sung, Hung, & Huang, 2013). Besides, the learning strategy behind this system can be different, e.g., formative assessment, inquiry learning, collaborative learning or game-based learning, which can be applied in different learning topics that require more learning motivation (Srisawasdi & Panjaburee, 2015).

In the past years, learning data generated while learning is considered important for personalized learning system since each student can have different learning experience (Wongwatkit &

Prommool, 2018) and different patterns. Learning intention can consider from duration of learning, doing exercises, taking exams. Learning performance or capability is widely used as it is easy to assess and calculate (Fonseca et al., 2014). Next is the learning sequence, which can be used as learning behavior. More importantly, learning interaction is quite difficult in storing as it has more complexity for analysis, and different in formats, e.g., scrolling the mouse, pinching on the mobile, eye blinking (Wongta et al., 2016). To say, such data is very beneficial in making learning more meaningful, since they are the real learning experience of the students.

In the past decade, there is a range of research studies related to adaptive/personalized learning. For example, many studies on taking students' scores or students' characteristics, e.g., gender, age to analyze and present learning recommendation (Sasithorn Chookaew, Panjaburee, Wanichsan, & Laosinchai, 2014; Wongwatkit, Chookaew, Chaturarat, & Khrutthaka, 2017). Findings show that personalized learning system can enhance students' learning motivation, learning attitudes (Wang & Liao, 2011). Also, several studies considered learning behavior during the learning process by adopting learning analytics (G.-J. Hwang, Kuo, Yin, & Chuang, 2010; G. J. Hwang et al., 2017).

3. Overview of Online Personalized Learning System

In this section, the overview of an online personalized learning system is presented hereinafter called OPLS. This system is designed to work with the proposed mechanism (to be presented in the next section) to analyze and adapt the ongoing learning experience for individual students based on their learning behavior and capability during the learning process. In other words, the system can monitor and adapt the treatment upon the ongoing results. Moreover, the system gives personalized guideline and learning feedback to students.

The overall structure of OPLS is shown in Figure 1. The student firstly received the pre-learning diagnostics and recommended learning chapters with Learning Diagnostics and Recommendation Module. After that, the student enters the learning chapters from Learning Module. Note that the solid square is recommended chapter, while the square with a regular line is open to learning. In each chapter, there are several learning units, as shown in circles, associated with learning objectives. The learning unit requires the student to think, relate the experience, and give responses via Prompt & Feedback. The student can select any unit to learn. Based on learning experience in the learned unit, the Learning Experience Adaptation (LEA) Module will analyze and present the appropriate learning experience for the units remained (the solid circle is recommended). For example, if the student learned U_j as a first unit after LEA analyzed, U_i and U_k may have a different learning experience, but still, keep learning smooth and connected with the previously learned units. To say, the ongoing learning experience has been personally adapted.

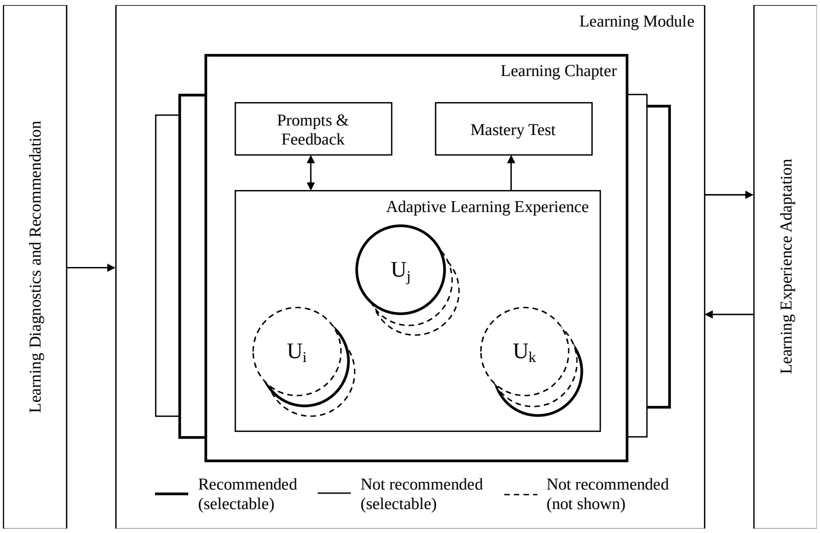

Figure 1. Overall system structure.

The topic implemented in this study is the secondary school's digital literacy, following the standard curriculum of the country. It emphasizes a variety of threats on computer and internet, how to protect and solve the problems that occurred. Also, media and information literacy are highlighted as they are related to different platforms, ranging from social media, game, web, and mobile application. In addition, cyberbullying is included. The students can learn these lessons interactively, while the materials and activities were designed with experiential learning storytelling, visual/motion graphic representations, in concerning mobile responsive UI and UX concepts. The highlights of this system are that the students not only get the recommendation and experience adapted for them but also have the freedom to learn, via mobile devices without any installation.

4. Ongoing Learning Experience Adaptation

In this section, a mechanism of LEA module in OPLS and its development following data mining process are discussed. The result of this mechanism development is a classification model for analyzing and adapting ongoing learning experience.

As illustrated in Figure 2, the LEA mechanism starts from considering ongoing learning experience of individual students, from interactive learning media and materials with storytelling, questions and prompts during the learning process, and constructive feedback. Such data generated during the learning process, including learning duration, learning capability, interaction with feedback, is stored as input data for the developed classification model (algorithm), while the output is the recommendation to adjust the ongoing learning experience of the following learning units.

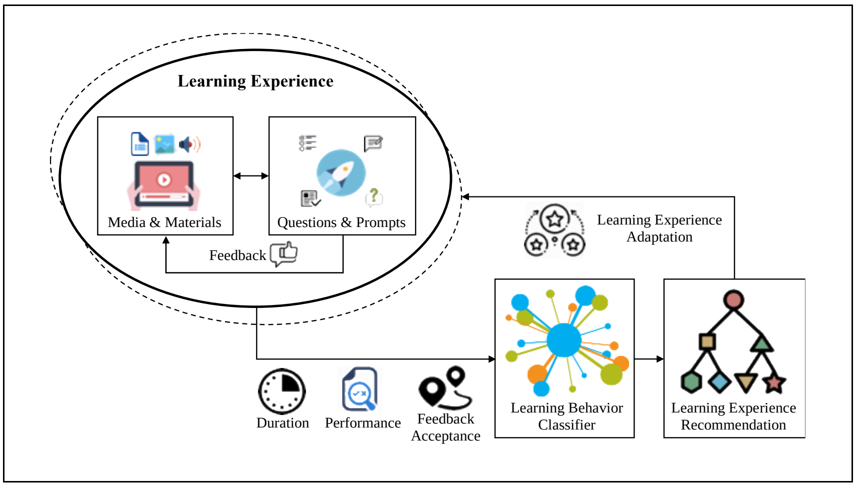

Figure 2. Overview of learning experience adaptation.

In the following topics, the classification model (algorithm) used in LEA will be developed following the data mining process.

4.1 Problem Definition and Data Acquisition

In this very first step, it needs to define the purpose/problem for the mining; moreover, it needs to determine what and how data can be acquired. The reasons to conduct this process are that there are many variables (attributes) that affect the analysis of learning experience, e.g., the duration used in each learning page, the responses given to the prompts, and the interactions with the presented feedback. Such data is different and significant in amount, which makes it challenging to analyze.

In addition to that, the data used in this mining is from the learning logs of students during three weeks from the OPLS prototype version. The total 253 data records are stored in JSON via real-time NoSQL database, as shown in Figure 3, while the students' profiles are variety in gender, age, mobile experience, and digital literacy, as summarized in Table 1. The target data consists of 25 attributes from one learning unit and one attribute from the literacy test.

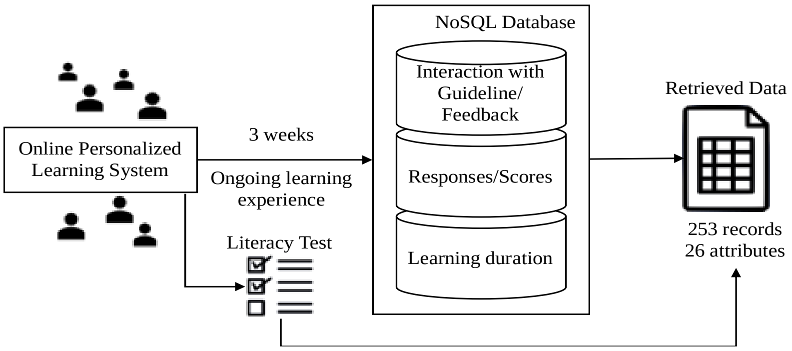

Figure 3. Data acquisition process.

Table 1

Statistical Data of Students' Profile

Variables	Male (N = 119)				Female (N = 134)			
	Min	Max	Mean	SD	Min	Max	Mean	SD
Age (years)	10.42	15.59	12.79	0.77	10.19	15.10	12.32	1.35
Mobile experience (years)	1.00	7.12	4.35	1.45	0.70	6.96	3.74	0.71
Literacy test (score = 10)	2.00	10.00	3.98	1.76	0.00	8.00	3.16	1.45

4.2 Data Preparation and Transformation

Once data was acquired, the next two steps are essential in preparing data, including data preprocessing and data transformation. This was operated on Jupyter Notebook in Anaconda Navigator environment with Python language and Pandas, Seaborn and Scikit-learn libraries.

This first step is to improve quality of data with data cleansing. Some data records were found duplicated, e.g. records from the same student. Hence, they were deleted. Some data values were missing, e.g., no responses from some prompts. Mean replacement was then used. Some attributes were categorical data, e.g., true-false questions, yes-no feedback acceptance. Therefore, such data was encoded to be numerical with One-HOT Encoding technique.

Here comes to the second step, after the data has been preprocessed. Data values in each attribute have different scales, which affect the weight for developing classifier; therefore, it is necessary to rescale into the same range (0-1) with normalization method. This transformed data is formatted as CSV, which can be used later.

4.3 Data Modelling and Evaluation

In this project, a classification model was developed with Rapid Miner Educational Edition by splitting 253 data records for 70% training data and 30% testing data with the stratified sampling method. At this point, all attributes were labeled features (total = 25 features), and one attribute (digital literacy level) was labeled as a class. This class was categorized from the score as follows: 0.00-5.59: low (3), 6.00-7.99: med (2), 8.00-10.00: high (1). The classification models developed in this paper consists of Naïve Bayes, Decision Tree, Deep Learning, Random Forest, while the performance of each model is evaluated and presented in the next section.

Based on the developed models (algorithms), the evaluation results are concluded in Table 2. It was found that Deep Learning algorithm has the best Precision, F Measure, and Accuracy, while Decision Tree gains the highest Recall.

Table 2

Result of Classification Models

Models	Precision	Recall	F Measure	Accuracy
Naïve Bayes	87.4	41.7	55.4	65.2
Deep Learning	91.5	69.8	81.4	83.6
Decision Tree	62.5	82.1	68.8	62.4
Random Forest	83.5	68.2	76.5	17.4

The selected algorithm, Deep Learning, from this study can be deployed in the proposed ongoing learning experience adaptation for analyzing the ongoing learning data generated by individual students, including duration, learning capability, and interaction. The mechanism can eventually adapt the individual students' ongoing learning experience.

5. Discussion and Conclusion

This research study aims at proposing the mechanism for analyzing a large amount of learning data generated while learning process from individual students on the online personalized learning system, and adapting the ongoing learning experience accordingly. The classification model developed for the proposed mechanism was performed following the data mining process. The result shows that Deep Learning algorithm gives the best result in terms of accuracy and precision. It was optimal to be deployed in the system later. Besides that, this paper presented an overall structure of the online personalized learning system that works with the proposed mechanism.

Furthermore, the methodology used in this study was in the positive agreement with educational data mining process as it can help enhance the possibility and performance of online learning (Dutt et al., 2017). Moreover, it can find insights from the big data and develop a model to making decision or prediction for the benefits of learning. In the meantime, the performance of Deep Learning algorithm was the best among other models, which was also aligned with many studies owing to the fact that Decision Tree has a limitation in dealing with irrelevant features, Naïve Bayes is suitable for handling multiple classes, whereas Random Forest spends more runtime (Ahmad, Farman, & Jan, 2019; Tan, Steinbach, & Kumar, 2006).

However, this research study remains several limitations. The validation process of the fixed data of training data and testing data should be avoided, where the k-fold cross-validation technique can be used to address this point (Wong, 2015). The performance of the system environment should be examined when the model has been deployed, including speed/time/performance. Moreover, the algorithm developed in this project cannot be used with other learning lessons since it was trained and tested with the data acquired from that lesson. Different lessons can give different learning experience to the students. This project needs more works and investigations to be done in the future. It is interested in extending the capability of the developed model by considering more valid/possible features. More algorithms are needed for other different lessons. The model should be implemented into the learning system, where making API service can be considered for other subjects/platforms. Also, more investigations on the effects of learning motivation, attitudes, and learning performance are necessary.

In addition to that, the proposed system can be applied in STEM-related courses (Özyurt & Özyurt, 2015; Srisawasdi & Panjaburee, 2015). For example, the system can support learning sciences to provide more meaningful activities in a wide range of topics, e.g., chemical reaction, human anatomy, force, and gravity (Srisawasdi & Panjaburee, 2019). The applications of this system can cover those in computer and technology topics, such as basic programming, digital literacy and game development, by automatically tracking the learning and provide relevant learning experience (Wongwatkit et al., 2017). Moreover, this system can be more beneficial when applied with the topics in engineering and mathematics through the active learning process, inquiry-based learning, or experiential learning (Panjaburee & Srisawasdi, 2016; Srisawasdi & Panjaburee, 2014). Having the students learn by experiment and improve upon, the proposed system can facilitate the corresponding adaptive experience.

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