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A Personalized Mobile Learning System for Solving STEM Teachers' TPACK Problems

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Abstract: STEM education is an educational concept that encourages learners to learn and integrate the knowledge of science, technology, engineering, and mathematics. If we consider an in-service teacher as a learner, then we can apply the STEM concept using computer engineering techniques to build tools to promote the learning of scientific knowledge for them. This research proposed the design and development of an adaptive mobile learning through computer engineering processes. We designed algorithms to select learning media by analyzing data consisting of a learners' learning styles, learning problems, learning media attributes, mobile device capabilities and network quality to create a personalized learning environment. This study focused on the development of teaching knowledge regarding TPACK framework in a domain of digital science learning approaches, where 78 in-service secondary school science teachers participated in this study. The results of our study indicated that the algorithms can work effectively with more than 65% of user satisfaction in at least good level, and more than 90% user satisfaction in at least moderate level. The learners have significantly improved learning achievements in almost all kinds of knowledge based on the TPACK framework with 95% confidence level. The results show that our system is promising to provide learning tools to improve STEM teachers' proficiencies under the TPACK framework.

Keywords: Adaptive learning, personalized learning, mobile device, TPACK, STEM education

1. Introduction

At present, the conceptual learning in various scientific phenomena still have some limitations and difficulties, such as they cannot be observed by naked eyes, e.g. visualizing molecules, or lack of learning resources in classrooms. Moreover, other subjects other than Science in STEM: Science, Technology, Engineering, and Mathematics education also face the same problems since many concepts in these fields are abstract. Therefore, the technology has been applied to create tools to support these science and STEM learnings, such as using animation to demonstrate molecules, and using simulation to conduct virtual experiments in classrooms. Therefore, teachers must have knowledge about various technologies that help distribute STEM knowledge to students effectively. Teachers must improve their teaching strategy and also teaching quality, thus supporting STEM education, by bringing technology into the learning and teaching process (Srisawasdi, 2011). As a result, it is necessary that an in-service teacher must have good understanding of how to apply or create technological learning tools for science and STEM lessons, in addition to having the traditional pedagogical and content knowledge.

Having knowledge of how to apply technology in class effectively plays important role in teacher professional development and this kind of knowledge related to the three teaching-specific knowledge domain, that is the integration among content knowledge, pedagogical knowledge, and technological knowledge, as it called Technological Pedagogical and Content Knowledge (TPACK) (Mishra & Koehler, 2006; Srisawasdi, 2012a). TPACK can be applied to promote the quality and effectiveness of teaching and learning activities for both pre-service and in-service teachers in the 21st century education. In Thailand, the TPACK framework has been adopted for teacher professional development (e.g. Srisawasdi, Pondee, & Bunterm, 2017; Srisawasdi, 2014; Srisawasdi, 2012b, 2012c; Srisawasdi, 2011). However, there is still no convenient tool to diagnose TPACK cognitive problems for teachers. Moreover, there is a lack of experts capable of analyzing the problems for a wide-range of in-service teachers. These problems are very challenging since lacking the proper understanding of TPACK knowledge bases will directly affect the quality of teaching in Thailand.

Should a teacher lack on some knowledge bases of the TPACK framework, the teacher needs to "learn" to become proficient in the knowledge. Nevertheless, due to a heavy work load of in-service teachers, they might not have time and resources to improve their TPACK literacy. A mobile learning technology, which is known to promote personalized and ubiquitous learning, has a big potential to mitigate this problem. Moreover, using computer engineering techniques, we can craft the mobile learning system to suit teachers' varied device capabilities, such that the system can be widely adopted and make a large impact.

In order to have a personalized, ubiquitous, and device-suitable mobile learning system, we proposed algorithms to select appropriate learning media that is relevant to a learner's situation, meets a learner's needs, suits a learner's learning style, and supports the capabilities of a device and the quality of the network. The algorithms analyze data from a learner's TPACK problem(s), a learners' learning style, the learning media attributes, the device capabilities and the quality of the Internet connection. In addition, we proposed the design and development of an adaptive mobile system that utilizes the proposed algorithms to create a personalized learning environment. In this paper, we aimed to find answers to the following questions:

1) What are the efficiencies of algorithms designed to select appropriate learning media by analyzing data from multiple dimensions, in the context of learning problems, meeting the needs of learners, appropriate learning styles, appropriate mobile device capabilities, and the quality of the user's Internet connection?

2) what are the effects of the proposed adaptive mobile learning system to motivate and encourage learners to acquire knowledge based on the TPACK framework?

The paper is divided in to six sections. Section 2 discusses related work. We discuss the system and algorithm designs in details in section 3. Section 4 describes research methodology, while section 5 discusses results. We conclude our paper in section 6.

2. Relevant work

2.1 Mobile Learning and Teacher Professional Development

Mobile learning (Korucu & Alkan, 2011) is a system that integrates mobile technology into e-learning (Pal et al., 2013). It takes advantages of the portability and wireless networking technology to deliver learning media to learners anywhere, anytime to provide more learning opportunity (Pal et al., 2013). However, mobile learning technology still has limitations due to device variations and limitations (Hashemi et al., 2011), such as small screen sizes and different screen ratio, storage capacity, processing efficiency, quality of connections (Korucu & Alkan, 2011). Our work tried to mitigate these limitations by designing a system that can support various types of mobile devices and qualities of networks.

Mobile devices have become attractive learning devices for education, and teachers' adoption of mobile technologies have been recognized as a potential way for transforming traditional teaching into student-centered approach (Srisawasdi, Pondee, & Bunterm, 2017). In context of teacher education and professional development, mobile learning has been recognized as a strategy to foster teachers' teaching competencies and enhance their professional knowledge of modern teaching with the support of mobile technology. In term of teacher development, there are two methods for integrating mobile learning into teacher education contexts; (a) teacher training about mobile learning, where teachers learn how to integrate mobile tools into their classrooms, and (b) teacher training with mobile learning, where teachers interact to learn with mobile technology (Baran, 2014). This study emphasized on how teachers learn how to teach science with the support of digital technology with mobile learning delivery.

2.2 Adaptive Mobile Learning System

An adaptive learning is a learning environment that fits in well with the different learning goals and learning capabilities of different learners. An adaptive mobile learning is a concept of creating a personalized learning environment on mobile devices. It allows a learner to learn by him/herself through a learning environment that is adapted for the learner's specific needs, on his/her mobile device anywhere, anytime. The Intelligent Tutoring System (ITS) (Phobun & Vicheanpanya, 2010) was introduced to encourage self-learning through such system. ITS has four main components: 1) the Expert Model that assesses the learner's level of comprehension and ability by processing a learner's behavioral data, 2) the Learner Model that identifies individual learner's basic knowledge and thinking skills, 3) the Instruction Model that decides on a teaching technique that is relevant to each learner, and 4) the Interface Model that interacts with a learner as a learning environment.

However, the variety of mobile devices and network connections used by different learners is an important factor that should be considered when designing an adaptive mobile learning system that can fully support users. Therefore, our work incorporates mobile device and network connection parameters with adaptive learning (Park & Lee, 2004) and ITS to create an adaptive mobile learning system that supports personalized learning environment that can work adaptively in different mobile devices and network connection qualities.

2.3 Technological Pedagogical Content Knowledge (TPACK)

TPACK (Koehler & Mishra, 2008) is the framework of a combination of three main areas of teaching knowledge including 1) Content Knowledge (CK), a knowledge of theories, principles, facts of the lesson and the ability to gather knowledge to create content that facilitates the learning of learners, 2) Pedagogical Knowledge (PK), a knowledge about teaching processes and the ability to use technical skills and teaching strategies for effective teaching and learning, and 3) Technological Knowledge (TK), a knowledge of applying technology or creating tools using technology. This framework promotes the quality of instructions for the 21st century education personnel.

In addition, the integrations of the 3 knowledge areas create four other skills, including Technological Content Knowledge (TCK), Pedagogical Content Knowledge (PCK), Technological Pedagogical Knowledge (TPK), and Technological Pedagogical Content Knowledge (TPACK) which is a knowledge of integrating TK, CK and PK to apply technology to support learning activities, apply technology and theory or basic knowledge to create learning media, create tools to help make the work more convenient, and encourage learners to learn effectively.

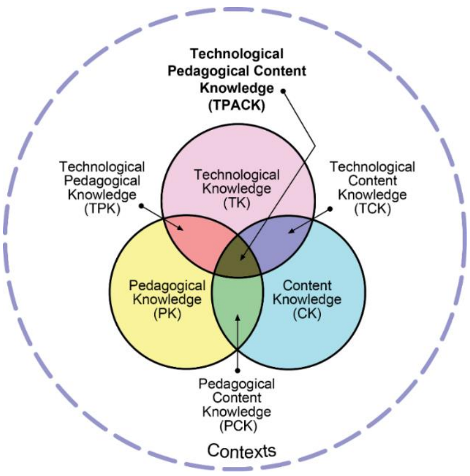

Figure 1. TPACK framework (Koehler & Mishra, 2008)

3. System Design

3.1 System Overview

This research has designed an adaptive mobile learning system that creates learning environment based on learner's difference and difference of equipment and network quality. A user interacts with the system via an Android mobile application, while most data processing happens at the server. In the mobile application, a user takes the learning style test, takes TPACK diagnostic tests for various topics, and selectively learns TPACK knowledge based on the test performance. The server evaluates the test results and suggests TPACK knowledge lesson(s) on which the user needs to improve. It selects and sorts different types of learning media by the user’s learning style and the device’s capabilities. This is to ensure the personalized and uninterrupted ubiquitous learning. In addition, a user can view his/her learning styles and view the progress in TPACK knowledge tests for each topic in the mobile application.

3.2 System Architecture

The system consists of two main parts: the mobile learning application (client) and the server. In general, the mobile learning application collects data such as questionnaire and test answers, and sends the data to be processed at the server. The server sends results back to the mobile application for a user as shown in Figure 2.

The Index of Learning Style (ILS) Test module on the application side is a module for collecting answers of an index of learning style questionnaire. It sends the data to the Learner Model on the server to analyze learning patterns. TPACK Test module is a module on the application side for collecting answers of the TPACK knowledge assessment. It sends the data to the Expert model on the server to assess learners' knowledge. The learner-specific information in the Learner Personalized Data, coupled with the attributes from the Device Information Reader on a mobile device, will be analyzed by the Instructional Model. It provides an adaptive learning environment for the learner by selecting and sorting suitable learning media items for the learner. Finally, the Content Presenter downloads media from Content File Storages according to the adaptive learning environment, and show to the learner.

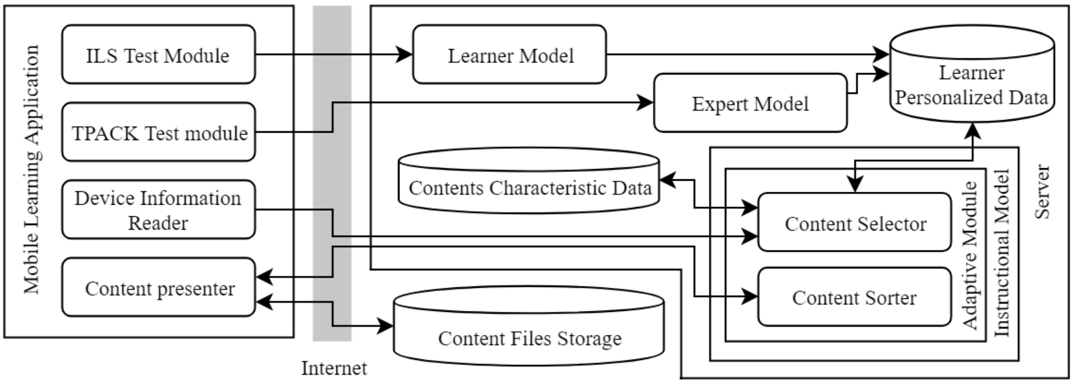

Figure 2. System architecture

3.3 Attributes for a Learning Environment

To create a personalized learning environment, the system collected key data attributes from a learner: learning style, TPACK test analysis, and user device data. Although, we adopted the Felder-Silverman Learning Style model (Felder & Silverman, 1988) which has 8 learning styles, in this study, we only analyzed a learner based on two learning styles: visual and verbal styles. This was due to the limitations of resources to properly produce online learning materials. For the TPACK knowledge test, we used a TPACK assessment test that was designed by educational experts. We used the same set of questions for pre-test and post-test to access and analyze the learner’s improvements after using our system. For the results, we classified leaners into 5 proficiency levels: excellent, good, moderate, low and deficient. If a learner scored under the moderate level in any TPACK knowledge, they must learn the materials until they can pass the test.

The special feature of our system is that we also used the user device capabilities to aid the user’s mobile learning: a device's available storage, Internet connection type, wireless signal strength, and data download speed, which differ by devices and situations. For example, in a location with poor connection quality, learning from streaming video will be often interrupted. Moreover, it will not be preferable if the media file occupies much space on a device that does not have much available storage.

3.4 Media Selection and Sorting Algorithms

The goal of our system is to select suitable media files for an individual learner according to their learning style, TPACK problems and device properties. Therefore, we needed to label each media files upfront such that we could match appropriate media files with these three personal attributes. A learning media have difference relevancy to learning styles value (C_{LS}) ranging from 0 (not relevant) to 1 (most relevant), indicating how well each type of learner can learn from the media. For example, a text-and-picture media has the C_{LS} of 0.5 for a visual learner and 1 for a verbal learner. The learning media file types used in this work include video (streaming), video (downloaded), pdf, ppt and html, having different resource consumption (C_{FT}). The C_{FT} value ranges from 5 (requiring heavy resource such as video streaming) to 1 (requiring low resource such as an html file).

An effective personal learning environment must be able to reduce the learning load of learners. There should not be unnecessary components, thus confusing or overwhelming learners. Therefore, we proposed an algorithm for selecting necessary learning media for a specific learner. The algorithm identifies the TPACK knowledge problems of a learner, and searches for corresponding learning media as follows. First, if there is only one media item for the given topic, pick that item. Second, the file size must be less than that of the available storage size on a learner’s device. Third, if the learning media is a streaming video, the learner's network quality must support the minimum effective access. Lastly, The learning media must be corresponding to the learner’s the learning style.

If there are more than one suitable learning media screened from the media selector, the system sorts the media with the “lowest cost” for the learner. We proposed an algorithm to calculate the media file cost for each file. Our algorithm utilized all of collected personal data and media information: learning style, media file resource consumption and file size, wireless signal strength, device’s storage space, and download speed, as shown in equation 1. The cost of learning media (content cost) is calculated as follows:

$$Content_{Cost} = (1 - C_{LS}) + \frac{C_{FT}}{D_{NSS}} \times \left(\left(\frac{C_{FS}}{D_{FSS}} \right) + \left(\frac{8 \times C_{FS}}{D_{DS}} \right) \right) \quad (1)$$

We denote:

C_{LS}	as the relevancy of the media to the learning style	D_{FSS}	as the device free storage
C_{FT}	as the resource consumption of the media file	C_{FS}	as the media file size
D_{NSS}	as the internet signal strength level	D_{DS}	as the download speed

From equation 1, each media file is calculated a content cost by the following concept. The content cost will be small if 1) the relevancy to the learner’s style (C_{LS}) is high, 2) if the media file requires high resource consumption (C_{FT}), but the network signal (D_{NSS}) can support the file transfer, 3) if there is a plenty of available storage (D_{FSS}) compared to the file size (C_{FS}), and 4) if the file size (C_{FS}) is small or the download speed is fast (D_{DS}). We can see that the cost of the media depends heavily on the available resources of the user’s mobile device, in addition to learning style. If there is a low resource, media that requires low resources will be given to a learner. This algorithm allows users with various range of mobile device to use our system efficiently, anytime, anywhere.

3.5 User Interface Design

We implemented the system as an Android mobile application. As Figure 3 shows, there is a toggle menu bar that contains graphic icons with short menu names on the left side of a screen. All the tests in this application are multiple choices with a standard user interface style. In the learning style analysis page, we use a radar chart to represent the results as shown in Figure 3 a). This will clearly indicate the trend of the learner's learning styles and there is learning style explanation below the chart on the page.

a) b) c)

Figure 3. a) Learning style results b) TPACK test results c) Personalized learning material*s*

In the TPACK learning page as shown in Figure 3 b), the application shows another radar chart on a learner's progress of each knowledge category of TPACK. Pre-test and post-tests scores progresses are also shown in color tag bars. A tag bar displays a learner knowledge in 5 proficiency levels: green is excellent, yellow is good, orange is moderate, red is low and gray is deficient. Figure 3 c) shows the TPACK knowledge title(s) that a learner needs to learn, along with the media types selected and sorted by our algorithms. The media is shown in a corresponding standard file type icon which makes it easy for a user to understand.

4. Experiment Methodology

4.1 Data Collections

We tested our system with 78 in-service secondary school science teachers in the Northeastern region of Thailand, who participated in the Khon Kaen University Smart Learning Academy. We collected data twice on 31 October 2017 and 13 May 2018. During the experiment, participants used the system through their mobile devices. We first instructed them on the system usage. After that, we let them complete the learning style test, take TPACK pre-test on the topic of solution concentration, learn corresponding TPACK lessons, and take TPACK post-test. Finally, we asked them to evaluate the system. The whole session took 1 hour and 30 minutes.

4.2 Data Analysis

After getting data from in-service teachers, we cleaned the data by eliminating faulty or incomplete data. To analyze data, we used inferential statistics, with the 95% confidence level of the significance of the differences. We first used data from the satisfaction survey to analyze the performance of the algorithm to select learning media. The survey questionnaire was adapted from

TAM3 model (Venkatesh & Bala, 2008), measuring the users' acceptance of the software by asking the level of user agreement with the question statements. Then we presented the results of the learning achievement analysis from pre-test and post-test scores for each knowledge of the TPACK framework, to analyze the overall effectiveness of the system.

5. Results and Discussions

5.1 Analysis of the efficiency of the algorithm for selecting learning media

According to Table 1, we found that 67.50% of the sample population satisfactorily recognized that the application offered learning media that was corresponding to their problems. However, there were 28.75% of the population with the moderate level of satisfaction, which was not a small number. These results indicated that although the algorithm for selecting learning media was effective at an acceptable level, further research is needed to find out the reasons the media selections were not consistent with the some of the learner's problem.

As for the learning styles, we found that 66.25% of the participants indicated that the learning media selection algorithm was able to select the learning media that met their needs and was consistent with their learning style at least at a good level. Similar to the learning problem matching satisfaction, very few teachers were unsatisfied with the selection, while 28.75% of learners were moderately satisfied with the results. In this case, further study is also needed to improve the system.

To evaluate the effect of the appropriate mobile device capabilities and the quality of the user's Internet connection in selecting proper media for learners, we inferred from the last two questions in Table 1. There were 35% of users agreeing that the application did not recommend the kind of learning media that they wanted. This could be due to the capabilities of their devices and Internet connection. For example, a visual learner is better off learning from a video media. However, if his/her device did not support the delivering of such media, the program would not select the video for him/her, thus lower the level of satisfaction. To solve this problem, the system should show all learning media for users, but in the appropriated order organized by our algorithm. There were 80% of the users agreed with this solution, as seen from the last question in Table 1.

Table 1

Satisfaction ratings score on topics related to algorithm performance.

Questions	Percentage of user agreement (%)				
	5	4	3	2	1
The application recommends learning media that corresponds to my problem	16.25	51.25	28.75	2.50	0.00
The application recommends learning media that corresponds to my learning style or needs	17.50	48.75	28.75	3.75	0.00
I feel that the application does not recommend the kind of learning media that I want	7.50	27.50	31.25	28.70	3.75
I agree if the application would show all learning media in ordered according to the learning style and consistent with my problem.	27.50	52.50	16.25	2.50	0.00

5.2 Analysis of the effectiveness of the mobile learning system

Table 2

Comparison of pre-test and post-test scores by knowledge based on TPACK.

Knowledge	N	$\bar{x}$		S.D		p-value
		Pre	Post	Pre	Post	
TK	71	1.1831	1.6338	0.9803	1.8640	0.0226
PK	56	0.8929	1.1786	1.0065	1.7130	0.1457

CK	56	1.0714	1.7857	0.6130	1.0805	0.0000
TCK	49	0.0000	1.7959	0.0000	4.0408	0.0000
PCK	47	0.0000	1.7872	0.0000	4.0407	0.0000
TPK	66	0.0000	0.9091	0.0000	2.8531	0.0000
TPACK	66	0.0000	0.2424	0.0000	0.9249	0.0446

We have analyzed the learning improvement after users used our system by examining the TPACK pre-test and post-test scores in each knowledge in the TPACK framework (TK, PK, CK, TCK, PCK, TPK, and TPACK). Table 2 shows that learners have significantly improved their learning in almost all knowledge categories with 95% confidence. The improvement for PK scores were not significant with the p-value of 0.1457. In the future, it may be necessary to improve the learning media used in the system or to increase the concentration of the pedagogical knowledge (PK) process.

Note that in each knowledge category in Table 4, the numbers of user (N) were not the same. This is because users who had passed the pre-test would not be taking the post-test, thus having no data to be compared. Examining the Ns, we can see that out of 78 in-service teachers, 71 teachers did not pass the TK pre-test, and 66 teachers did not pass the TPK and TPACK pre-tests. This emphasizes the importance to educating all teachers about how to apply technologies in teaching and learning science. Yet this study shows that our system has a good potential to help them learn to incorporate technologies into their classrooms.

However, because our experiment process took only 1 hour and 30 minutes, there might not be enough time for teachers to learn the TPACK concepts in time, thus affecting post-test scores. In the future, to gain more insightful results of the effectiveness of our system, we will need to let teachers to learn materials in their convenient time, also taking advantages of our anytime and anywhere learning system.

6. Conclusions

This research integrated education and computer engineering fields to design algorithms for selecting personalized learning media, and to design an adaptive mobile learning system to solving the lack of knowledge in the TPACK framework. Although we aimed for science in-service teachers, this system can be viewed as a platform for teachers in other subjects, including STEM in which science is a part.

Our system utilized a user's different learning styles, different TPACK problems, and different capabilities of mobile devices to create a personalized mobile learning environment for an individual learner. The results showed that the algorithms presented by this research could select the appropriate learning media efficiently. The mobile learning system proposed by this research significantly improved learners' outcomes in almost all knowledge in TPACK framework. Therefore, with further improvements, this system is a promising tool for teachers to be ready for the 21st century learning.

In the future, there should be an increase in learning time, which may result in learners' learning more effectively. We also have to assess the reliably and validity of the TPACK tests. Moreover, we need to design additional experiments with a control group and an experimental group to identify important parameters that affect learner's performance. We will analyze correlations between the variables that could affect learners' learning. Finally, in addition to the selection of current device variables such as memory and the amount of data downloaded, researchers should provide technical analysis to point out the differences and significance of the hardware and software variables that could affect learning achievement.

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