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A Hybrid Diagnostics-based Learning System for Promoting College Students' Digital Security: A Challenge to Digital STEM in College

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Abstract: Numerous of traditional online system are not response to learner's preference. Learners can have a lack of encouragement and a learning achievement rate is getting low. This research aims to develop an adaptive learning system using Hybrid Learning Diagnostic Approach (HLDA) in order to diagnose and detect learners' learning styles according to the criteria in the Index of Learning Style (ILS) into 3 dimensions (1) active-reflective, (2) visual-verbal, and (3) sequential-global. A Learning EcoSystem (LES) was purposed and implemented as a web-based learning system consists of four main learning modules engaging with a story-based learning content regarding cyber threat. The experiment with students at Mae Fah Luang University show that the posttest results higher than the pretest, indicating that students from Learning Eco System had a significant improvement of learning outcome. Besides, this study also presents the challenges of STEM-based education in digital environment by integrating with many areas of learning disciplines.

Keywords: adaptive learning system, learning style, social learning analytics

1. Introduction

The fundamental purpose of an adaptive learning system (ALS) is to enhance the learning processes of its learners through personalization and adaptability of the learning content (Santos et al., 2003). In order to achieve this for each individual learner, formulating an adequate diagnosis is one of the essential procedures. Diagnosis in an adaptive learning system refers to the processes and methods used in identifying the nature of a learner's learning style. During the past few decades, numerous research studies and application on the mechanism of learning indicate that different individuals are influenced by different styles and techniques of learning (Al-Dujaily, 2008). This is why obtaining a sturdily fine diagnostic process is very much crucial for 21st century learners. As an endeavor to provide systematic distinctions among different learning styles, various models for learning diagnosis have been constructed and published. Some of the most widely recognized learning style models used in learning diagnosis are Felder-Silverman (1988), Kolb's learning styles (1984), Honey and Mumford model (1986) etc. Learning diagnosis plays an important role not only in providing more meaningful and personalized learning experiences but also in enlarging the learner's motivation and attitude (Hwang et al., 2008).

Despite the rising acceptance and popularity of adaptive learning systems, the lack of consideration for utilization of learners' data from outside resources still draws back their sophistication. In practice, the diagnostic models utilized in most ALSs mainly analyze learners based on their actions and knowledge gathered throughout the course of learning (Santos et al., 2003). For instance, data regarding learners' current knowledge on a subject is collected only through questionnaires, quizzes, and other onsite interactions as a learning process. However, these are not as sufficient since external factors that most contribute to learners' motivation and attitude such as learners' preference and learning styles (Hung, Chang, & Lin, 2016; Graf & Kinshuk, 2007;) are being disregarded. Without regard to these learning attributes, diagnosing and building an adaptive model solely from learners' interactions with a given system becomes a potential problem when the data gathered don't reflect the real intentions of the learners (Yoon et al., 2008). For example, when a learner interacts with a diagnostic system that is inconsistent with his interest, the data produced from such interaction become less meaningful for the diagnosis outcome (Yoon et al., 2008). Thus, minimizing these problems could help maximize the sophistication of adaptive learning systems for 21st century education.

Alongside the rise of social networking among the population in the present days, conducting the analysis on patterns and behaviors of users occurred on those social platforms has benefited many areas, including education. In fact, social learning analytics (SLA) is a term used to describe the utilization of activities and behaviors of learners conducted from such platforms to learning environments (Shum & Ferguson, 2012). The data accumulated from these sources can reveal a great deal about learners, ranging from simple profile data to social interaction and preferences. Utilizing these prime data to learning diagnosis opens up more possibilities to help identify a more precise learning trait and characteristic about a learner (Baker & Inventado, 2014; Siemens & Baker, 2012). With the incorporation of SLA as part of the diagnosis process, the outcome for learning style and preferences of a learner could genuinely reflect those that naturally occur on his social platforms.

Due to the current COVID-19 epidemic situation, communication between teachers and learners must be changed. Social Distancing is a necessary thing between learners and teachers. Online learning has therefore played a huge role in learning method on this day, but online learning has its limitations, with the teacher unable to observe the learners' behavior during study. According to a study by the Zhenghao et al. (2015) study of Coursera learners, only 4% of those enrolled completed one course. Statistics show that online learning has a very low number of students complete the course. The research team hypothesized that the learning characteristics of each learner are different. The research team wanted to design a system with a learning environment suitable for each learner. To provide learners with complete knowledge from learning in online classes. Learning system takes into the learning characteristics of the learners divided by the Index of Learning Style (ILS) (1) active-reflective, (2) visual-verbal, and (3) sequential-global. From the Index of Learning, it can be used to separate the learning behavior of each learner. This learning system will be a model of a learning system that can be adaptable base on learning behaviors and style of learners. In this paper, there will be a system development section describing The Overall Structure of the Adaptive Learning EcoSystem and Content of Learning EcoSystem (LES) and describes about the experiment and result.

In addition, this study looks further to the challenges of promoting this system to digital STEM in college with a variety of applications integrating with different learning disciplines, e.g. Language learning, Social studies, Computer, etc. These challenges focus on making STEM on digital platforms by utilizing the benefits on the proposed system.

2. Related Literature

2.1 Learning Preference Analysis

Many researches and studies on pedagogy have validated that learners best achieve from learning through a teaching pattern that matches their own learning style the most (Bajraktarevic, Hall & Fullick, 2003). Learning style refers to the preferences and attributes of a learner that facilitate his learning process and understanding on a subject. Oftentimes, the term "learning style" and "learning preferences" are interchangeable (Phung et al., 2018).

Among various models and frameworks that aim to determine learners' types of learning based on various descriptions and classifications, the Index of Learning Styles (ILS) is a set of questions specifically designed to identify types of learners based on the four dimensions classified in the Felder-Silverman model (Felder & Soloman, 2001). ILS consists of 44 questions that target to point out learners' affections between two contrasts in the four dimensions which are (1) active-reflective, (2) sensing-intuitive, (3) visual-verbal, and (4) sequential-global (Phung et al., 2018). (1) Active learners enjoy actively trying things out while reflective learners like to think and reflect on materials, (2) sensing learners prefer concrete facts and procedures while intuitive learners learn through abstractions such as theories and ideas, (3) learners with visual preference learn best through pictures, charts and diagrams while those with verbal preference prefer written or spoken textual representations, (4) sequential learners understand things through small incremental steps while global learners comprehend in holistic views or big pictures (Graf et al., 2006).

There are a number of researches conducted to verify the reliability and validity of ILS. The results from the studies of Zywno (2003), Livesay et al. (2002) and Felder et al. (2005) suggested that ILS is in fact reliable and suitable for assessing learning styles (Felder & Spurlin, 2005). The recent utilization of ILS can also be found in many contemporary approaches and strategies for e-learning. For example, with an integration of J48 data mining algorithm, Nongkhai et al. (2015) presented a framework for e-learning recommendation by analyzing learners based on ILS. (Nongkhai & Kaewkiriya, 2015) The stated framework aimed to determine the best learning styles of learners.

The implementation of ILS by identifying learners' behaviors according to each contrast end in four dimensions can help promote the process of determining a more precise learning style in an adaptive learning system.

2.2 Social Learning Analytics

The internet revolution has built up a complex network of vast interconnections among people of all ages, especially younger generations. The interactions among these people on social networks such as Facebook generate a tremendous amount of useful data on a daily basis. Some of this data initially comes from friending, liking, posting, sharing, etc. which are further mined and analyzed into valuable statistics, patterns and insights that can be applied in many fields of specializations.

With the focus on analyzing and utilizing such data in the field of learning, Social Learning Analytics (SLA) can benefit the learning processes through five possible approaches. (1) Social network analytics: analyzing the relationship among people to determine the society, (2) Discourse analytics: analyzing language, communication, and knowledge formation, (3) Content analytics: analyzing the content that users generated, (4) Disposition analytics: finding learning motivation that characterize online social media, and (5) context analytics: mobile processing that can access and understand the context of users. (Shum & Ferguson, 2012)

The applications of social learning analytics (SLAs) can be found across a variety of works and research topics by many contemporary researchers. Li et al. (2015) applied social learning analytics by examining social relations and different behaviors among users to increase the efficiency of the recommendation system for online learning communities. Zhou et al. (2016) deployed social learning analytics (SLA) to design and propose an Open Learning Platform in which the stakeholders, i.e. learners and instructors are provided more individualized support and services.

The differences between individual learners needed to enhance adaptive learning systems can be better determined with an inspection into the aspects of their social networking platforms.

2.3 Personalized Learning for 21st Century Learners

In this age of information, it is rational to argue that the classical "one-size-fits-all" model of education is no longer relevant for learners in the 21st century (McFarland, 2018). Owing to vast digitalization, providing a more personalized learning experience for each individual learner is within reach. Personalized learning eases the learning processes of learners by lessening their learning hassles and taking advantage of their cognitive traits, personalities and learning preferences.

In fact, "personalized learning (PL)" is an umbrella term used by many academic scholars and researchers to broadly refer to concepts and approaches that involve the use of learners' personal attributes to enhance the learning processes. (Groff, 2017) Some of the most common technologies and methodologies related to PL include (1) Adaptive Learning Environments: response to learner' inputs and interactions, (2) Cognitive Analytics: uses machine learning on existing data to build a self-learning feedback loop, (3) Learning Analytics: analyze data of learners in order to understand and optimize the learning environments, (4) Intelligent Tutoring Systems: simulate computer-aided tutoring instructions, (5) Educational Data Mining: data mining for educational purpose, etc. (Groff, 2017)

As personalized learning becomes a more thrilling alternative for learning in the 21st century, a large number of researches and proposals that aim to represent such learning have emerged. For instance, Herath & Jayaratne (2018) presented the use of web mining techniques, i.e. analysis on learners' usages and behaviors on web navigation and web contents to exclusively provide a more personalized learning experience compared to traditional e-learning which provides the same content for all of its learners. The personalized recommendations intend to motivate learners by offering them courses that match their needs and expectations. Similarly, Muruganandam & Srinivasan (2014) proposed a method to provide adaptive personalized learning contents for learners based on the learning analytics of their profiles combined with sequential pattern data mining techniques.

Ultimately, the primary goal of personalized learning is to establish a learning structure that accounts for the adaptability and adjustments for each individual learner in the 21st century.

3. System Development

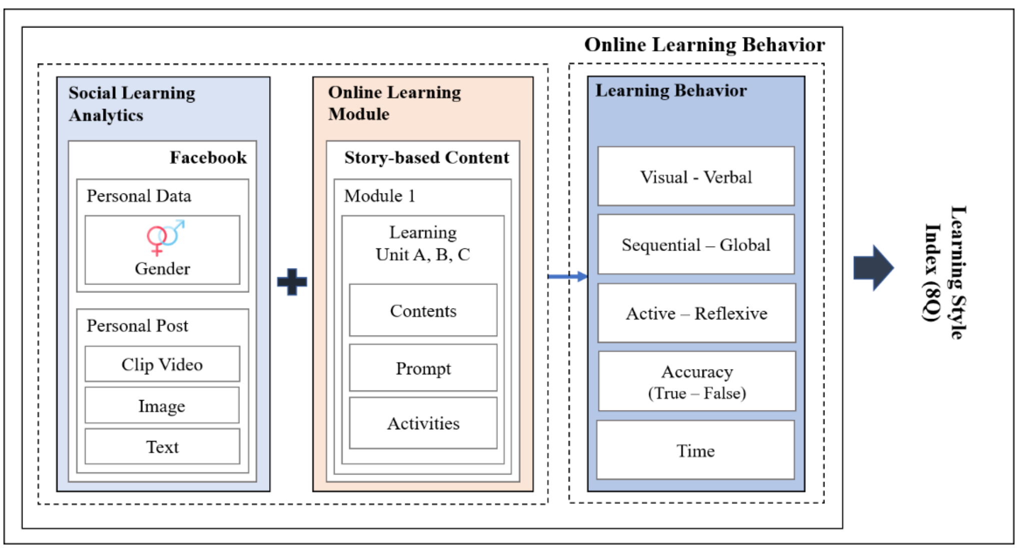

Figure 1. The Overall Structure of Adaptive Learning EcoSystem

Learning EcoSystem (LES) is an adaptive learning system regarding digital security that implements Hybrid Learning Diagnostic Approach (HLDA) as its diagnostic process. HLDA is deployed in the initial learning module of LES in order to diagnose and detect learners' learning styles. In the initial learning module, learners' profile data such as gender and data representing their five most recent Facebook posts are collected with learners' permission. Learners are then continued to be diagnosed by engaging with a story-based learning content regarding cyber threat which consists of various user interactions such as characters, situations, communications, etc. The data collected from these two diagnoses are then analyzed according to the criteria in the Index of Learning Style (ILS) into 3 dimensions (1) active-reflective, (2) visual-verbal, and (3) sequential-global. One indication from each dimension can be combined into 8 different sets of classification where each set indicates one unique learning style. The learning styles detected with HLDA then act as a determiner for the conveyance style of subsequent learning modules of which the learners will receive.

The main objective of the Learning EcoSystem (LES) is to deliver learners, primarily freshman students at Mae Fah Luang University, the information regarding "Digital Security." LES consists of four main learning modules. The first learning module introduces the awareness and danger of cyber threat, the second module covers its precaution and prevention, the third suggests the laws and penalty regarding cybercrime, and lastly the fourth learning module presents the issues regarding of cyberbullying and game addiction.

LES is a web-based learning system that is structured according to the client-server model. This means learners interact with the learning system through web browsers such as Google Chrome, Safari, Internet Explorer, etc. on the "client" side of the application. These interactions on the client side trigger requests for services provided by the "server", for example, services to retrieve or update data resources

Table 1. *Contents of LES*

Learning Modules	Learning Objectives	Story-based Content	Resource
Module 1	This module offers the definition, statistics, and types of cyber threat that commonly occur e.g. 9 types of computer malwares	Starting with an introduction from a character, this module is further divided into 3 units. The transition between each unit is carried out by a conversation from the characters while learners are given minor activities such as prompt questions to solve.	The first unit offers the definition of cyber threat, the second one presents its categories, and the third gives a concrete case study. In addition to verbal descriptions, each unit explains the materials with relevant infographics, images and videos.
Module 2	This module presents methods and procedures an individual can follow to keep oneself and the public safe from the risk of cyber threat e.g. 10 ways of cyber threat prevention	This module begins with an introduction of the cyber threat by a character. The module is divided into 3 smaller units in order to suggest 3 different groups of cyber prevention. Learners are continuously engaged with a prompt question about the prevention methods at the end of each unit.	Dividing into 3 units, the first provides 10 general ways to prevent cyber threat, the second presents 12 protection methods for organizations, and lastly the third offers 6 ways of cyber prevention for the general public. All sets of prevention approaches are listed and explained through infographics.
Module 3	This module provides knowledge regarding computer related laws to prevent individuals from unknowingly violating computer crimes e.g. the computer crime act (CCA) of Thailand	This module starts with an introduction of computer laws by a character. Dividing into 3 units, this module aims to provide firstly why computer related laws are needed, secondly what they are, and	The first unit of this module provides the definition and purpose of the computer crime act, the second unit offers a glimpse into the laws and penalty, and the third one presents a case study example. The

		lastly an example case of a computer crime. A prompt question regarding the content in each unit is brought out by a character alongside some conversations.	materials are explained through the use of images, infographics and videos.
Module 4	This module informs learners the potential dangers of cyberbullying and game addictions including methods and approaches to prevent them from happening e.g. 6 main types of cyberbullying and how to prevent them	This module starts with an introduction of cyberbullying and game addiction by a character. Learners are asked whether they have encountered cyberbullying and game addiction in their life.	Dividing into 4 different units, the first one describes the definition of cyberbullying, the second unit presents 7 ways to prevent cyberbullying, the third explains game addiction and the fourth unit offers 4 ways to prevent game addiction. The explanations are assisted by icons and images while the prevention approaches are presented through infographics.

that are stored in the database. The client side of LES is built using basic web technology such as HTML, CSS and Javascript. The server side, on the other hand, is built on Node.js with Express framework to read and write data in a MongoDB database and it is deployed as a container using Docker. The client sends and retrieves data from the server using AJAX (Asynchronous Javascript And XML) techniques.

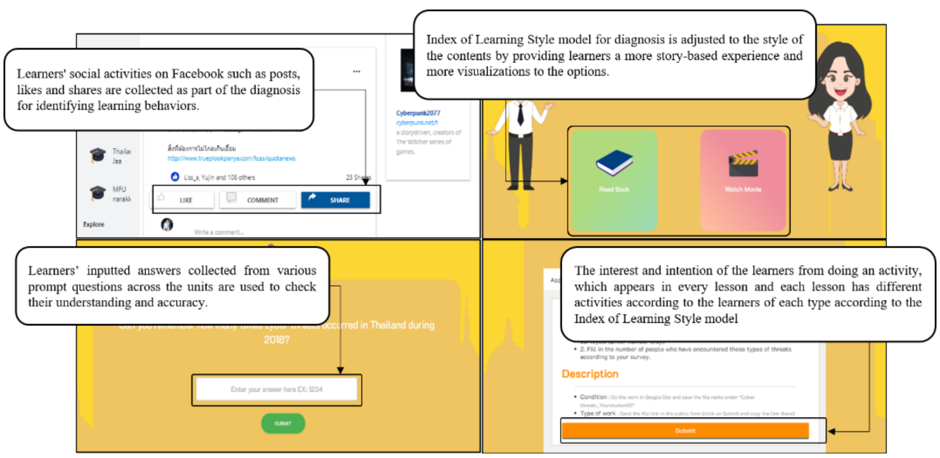

Figure 2. The Overall Structure of Adaptive Learning EcoSystem

Figure 2 describes the diagnosis processes implemented in the LES system. The first screen capture above shows how the most recent Facebook posts which learners share on their Facebook profile are collected as an initial diagnostic process. Afterwards, they are continued to be diagnosed with ILS which is presented through a story-based interaction. For example, as described in the figure, learners are asked by the two characters whether they mostly prefer reading books or watching movies with the aid of relevant visualization. Moreover, as a prompt question to test learners' engagement and understanding, the third screen capture shows how learners can interact and respond to the question. Lastly, the fourth image displays what kind of assessment activity learners will receive at the end of each learning module.

Figure 3 briefly describes how the contents in LES are presented to learners with story-telling as well as adaptive techniques. The first screen capture shows how a short introduction regarding cyber threats is directly addressed to learners in second-person sentences. After introduction, the learning materials are presented to each learner according to his or her learning style detected in the diagnosis in module one. For example, as shown in the second image, learners may receive video or infographic explanations depending on their learning style. Moreover, the third image describes an assignment task and submission form learners will receive after finishing the learning materials. Finally, the fourth screen capture shows how learners are greeted by characters and given implications regarding the next learning module.

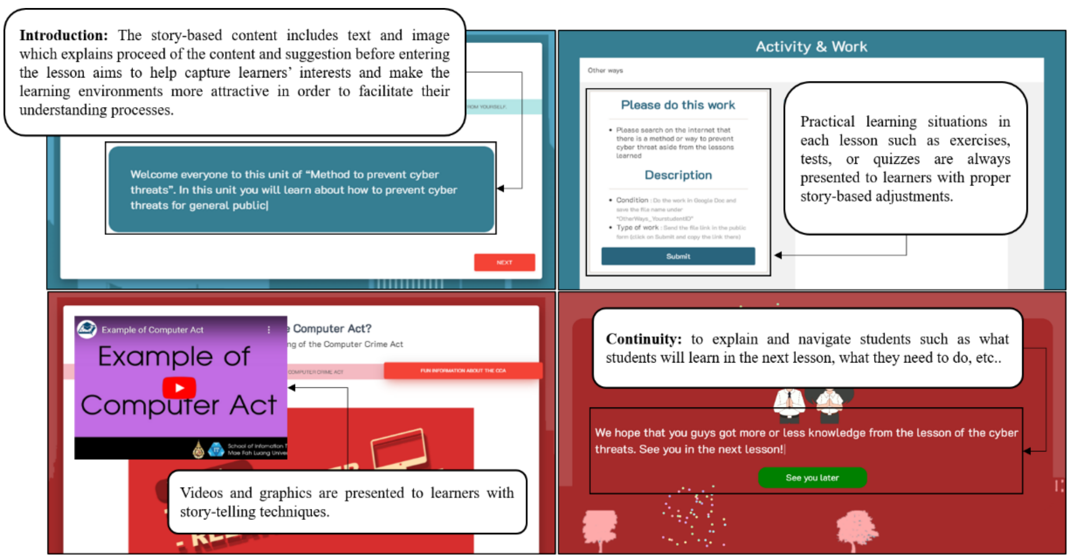

Figure 3. The Overall Structure of Adaptive Learning EcoSystem

In addition to the learning system which provides the learning materials concerning "Digital Security", LES also has its own analysis system for the teachers who maintain and monitor the resulting data of learners. This system provides data visualization representing learners' gender ratio, average time spent, average progress, scores (average, max, min, medium), and number of learners in each dimension of ILS, and in each learning style (Q). For example, the total number of learners alongside a donut chart representing its male-female ratio are shown in the first screen capture. To its right side are data showing the average time spent of all learners for each learning module, the average progress, as well as average, maximum, medium and minimum scores respectively. The total number of learners in each dimension of ILS are displayed numerically while that of the learning styles (Q) are displayed in a bar chart as shown in Figure 4.

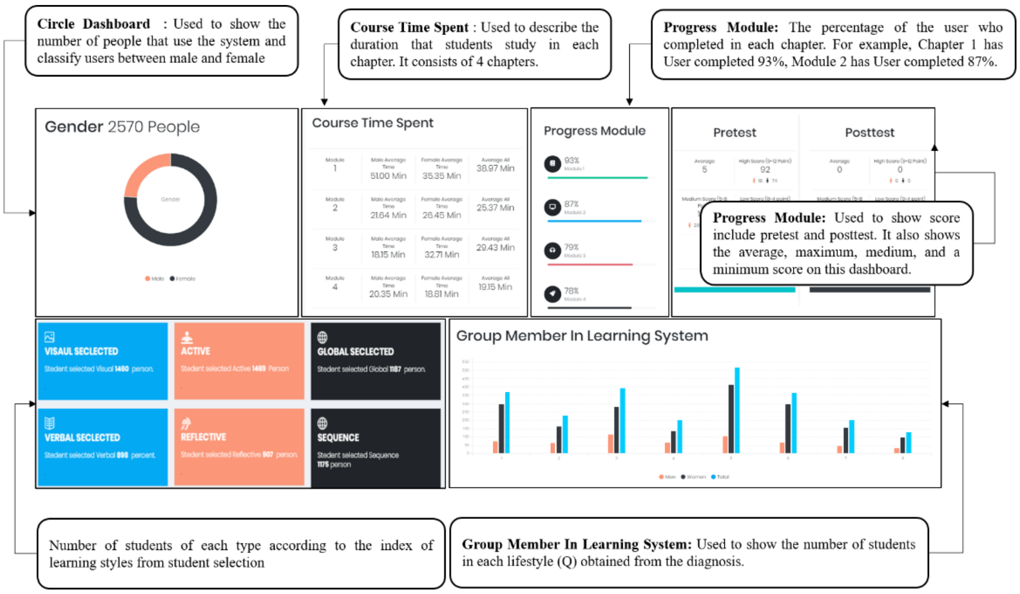

Figure 4. The Overall Structure of Adaptive Learning EcoSystem

4. Experiment and Results

4.1 Experimental Design

This experiment aims to study effectiveness of LES to learning preference by collecting learning assessment, feedbacks, and satisfactions from learners. Primarily freshman students at Mae Fah Luang University were participated in the experiment. Number of 1,487 students enrolled in an introduction to information technology and data science course. The participants were divided into 2 groups by purposive sampling. (1) An experimental group included 786 students which are 330 males and 456 females. (2) A control group included 701 students which are 273 males and 428 females.

Research instruments in this experiment are (1) Pretest and Posttest. (2) Learning attitude & satisfaction evaluation. The parallel tests in this learning evaluation includes 10 questions from learning modules using multiple-choice questions with good discrimination power and medium difficulty. The attitude & satisfaction evaluation consists of 20 questions with Likert Scale and open-ended questions.

The experimental steps are purposive sampling, pretesting, learning, post testing, collecting data and evaluation. First, all participants had taken 30 minutes of pretest before they studied the first learning module. Second, the experimental group studied on LES while the control group studied on a traditional learning system. Then all participants took 30 minutes of posttest after they had finished the four learning modules. Finally, the participant evaluated the learning attitude and satisfaction in 4 domains which are (1) Learning analytics (2) Learning media and activity (3) System usability and performance (4) System acceptance.

4.2 Results

4.2.1 Pretest & Posttest Result

The result of pretest and posttest from both sampling group found that the experimental group (M = 8.26, SD = 2.52) had higher score than the control group (M = 6.04, SD = 1.87) with a statistical significantly (t = 19.10, p = 0.001) as shown in table 2. After investigation more on the experimental group, indicating that the posttest result (M = 8.26, SD = 2.52) higher than pretest (M = 3.14, SD =

2.81) with a statistical significantly (t = 38.03, p = 0.001) as shown in table 3. Results indicated that LES had improvement of learning outcome.

Table 2. *A Comparative Result of Posttest between LES and Traditional Learning System*

Group	Participants	*M*	*SD*	*t*	*p*
Experimental group (LES)	786	8.26	2.52	19.10	0.001***
Control group (Traditional)	701	6.04	1.84		

**** $p < 0.001$*

Table 3. *A Comparative Result of LES Between Pretest and Posttest*

Result	Participants	*M*	*SD*	*t*	*p*
Pretest	786	3.14	2.81	38.03	0.001***
Posttest	786	8.26	2.52		

**** $p < 0.001$*

4.2.2 Learning Attitude & Satisfaction

The evaluation of learning attitude and satisfaction from both sampling groups are shown in Table 4. Results show that the experimental group had higher score than the control group with a statistical significantly in 3 domains which are Learning Analytic, System Usability and Performance, and System Acceptance. The adjacent domain is Learning Media and Activity. The control group evaluated overall range 3.84 to 4.69 while the experimental group had higher score in overall range 4.37 to 4.73, indicating that the LES had better experienced to learners.

Table 4. *A Comparative Result of Learning System*

Domain	Experimental group		Control group		*t*	*p*
	M ± *SD*	Meaning	*M* ± *SD*	Meaning		
Learning analytic	4.68 ± 1.86	Highest	4.12 ± 2.77	High	4.61	0.001***
Learning media and activity	4.73 ± 1.22	Highest	4.69 ± 1.38	Highest	0.59	0.553
System usability and performance	4.61 ± 2.82	Highest	4.32 ± 2.57	High	2.06	0.03*
System acceptance	4.37 ± 2.49	High	3.84 ± 2.67	Medium	3.95	0.001***
Overall	4.60 ± 1.63	Highest	4.24 ± 1.80	High	4.04	0.001***

** $p < 0.05$, *** $p < 0.001$*

5. Conclusion and Challenges of Digital STEM

As the significant score of the posttest, indicating that the adaptive learning system improves learning outcome. A learning analytic is one of the highest evaluation scores which brings attention of learning preferences to learners. The system dashboard of the learning analytic shows that most learners' analytic results are visual, active, and sequence from the index of learning style.

This confirms that learners realize about personalized learning. The learners were excited about the learning style, even if they did not notice on when and how the analytic had worked. Therefore, a social media data can be blended to a learning analytic without an interruption of the learning process. One limitation of this research is the diagnosing of learning styles is not adaptability. Once the index of learning style is identified. learners could not change the preference. Thus, it is justifiable to feel bored.

A web-based learning system can be reached anytime and anywhere, thus the system can be utilized under the situation of COVID 19. Moreover, the learning media and activities are recommended for the high school students. Regardless of learning media and activity had highest score, the LES did not differ from the traditional. The percentage of completed on learning from 1 to 4 are descending. It is possible that the designed may not be variety. Further studies are therefore necessary to design the effective learning media and activity.

In the near future, this proposed system can be applied in various learning situations. More specifically, this system is set to integrate with STEM learning activities on different learning fields of studies by taking the advantage of digital environment. The challenges to this integration would be as follows: 1) the design of learning activities that would require the API among digital platforms and 2) the implementation of digital STEM on different contexts of learners located in different places and times. Digital STEM is not only a new engaging way of STEM education, but also promoting the equality of education to all learners who cannot access to the STEM-based learning situations physically.

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