Predicting User Acceptance of e-Learning Applications: Web Usage Mining Approach

Noraida Haji Ali[1], W.M. Amir Fazamin W. Hamzah[2], Hafiz Yusoff[3] and Md Yazid Saman[4]

[1]School of Informatics and Applied Mathematics,
Universiti Malaysia Terengganu,
Mengabang Telipot, 21030 K. Terengganu,
Terengganu, Malaysia
[1]aida@umt.edu.my
[2]amirfazamin@gmail.com
[3]hafiz.yusoff@umt.edu.my
[4]yazid@umt.edu.my

ABSTRACT

The successful implementation of e-learning applications is closely related to user acceptance. Previous studies show the use of log files data in the web usage mining to predict user acceptance. However, the log files data did not record the entire behaviour of users who use the e-learning applications that are embedded in a website.Therefore, this study has proposed the web usage mining using Tin Can API to gather user's data. The Tin Can API will be used to track and to record user behaviours in e-learning applications. The generated data have been mapped to the Unified Theory of Acceptance and Use of Technology (UTAUT) for predicting of user acceptance of e-learning applications. From regression analysis, the results showed the performance expectancy and effort expectancy were found directly and significantly related to the intention to use e-learning applications. Behavioural intention and facilitating conditions also were found directly and significantly related to the behaviour of use of e-learning applications. Thus, the approach of web usage mining using Tin Can API can be used to gather usage data for predicting user acceptance of e-learning applications.

Keywords*: E-learning, user acceptance, UTAUT model, web usage mining*

INTRODUCTION

The term of e-learning has been used to explain instructional content or learning experience delivered or enabled by electronic technologies (Downes, 2005). Another definition of e-learning is the use of telecommunication technology to deliver information for education and training (Sun et al., 2008). E-learning offers a more flexible way of learning without depending on the time and place for learning sessions to occur. The increased use of e-learning among learners and teacher has led to a change in the learning environment. The use of e-learning applications in website is one way to conduct online education by distributing materials, and learning process through the Internet. However, if e-learning applications are unattractive and did not meet user requirements, learners and teachers possibly will not use it (Bang et al., 2014; El-seoud et al., 2009; Maldonado et al., 2011; Priego, 2010). Therefore, one of the main goals of e-learning applications developer should have to ensure user acceptance. This is because, user acceptance is an important factor of successful e-learning applications. Prior to this, there are studies that use log files to predict user acceptance. Even so, when students access the e-learning applications that are embedded in a website, the log files did not record the entire data of user behaviour who use it. Therefore, the lack of data causes the difficulty to predict user acceptance.

In previous study, the use of Tin Can API for web usage mining in e-learning applications on the social network is discussed. The Tin Can API can be used to track the behaviour of students who use e-learning applications that are embedded in a website. However, the study of web usage mining using Tin Can API for predicting user acceptance of e-learning applications is not done clearly. The objective of this paper is to design and propose a model for predicting user acceptance of e-learning applications using web usage mining approach.

RELATED WORK

E-learning

The use of technology to deliver learning programme and training is a field that is closely related to e-learning. Typically used to describe media

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such as CD/DVD-ROM, internet/intranet, audio/video and mobile learning. The computer and network-enabled transfer of skills and knowledge are the examples of e-learning. According to Hrastinski (2008), e-learning should be defined basically as learning and teaching facilitated online through technologies of the network. Learner motivation is also related to the actual use of tools and contributing to the interaction in learning situations (Giesbers et al., 2013). According to El-seoud et al. (2009), the increase of learner motivation is also based on a factor as interactive features of e-learning applications. E-learning applications can be a small program such as micro-learning, mobile learning or embedded program in the website.

User Acceptance

Previously, user technology acceptance on e-learning has been examined widely. There have been various theories that have been published by researchers from the social-psychology that may help to describe the use of information and communication technologies. These theories include the Theory of Reasoned Action (TRA) by Ajzen et al. (1980), the Technology Acceptance Model (TAM) by Davis (1985) and the Theory of Planned Behaviour (TPB) by Ajzen (1991)1985, 1987. Research by these authors generated various adoption metrics or instruments that can be used to predict user acceptance.

Investigation of various research approaches for measuring user acceptance in e-learning was perceived that the majority of them have used questionnaire technique for collecting data. There have been few studies into user acceptance using web usage mining. Dasgupta et al. (2002), in the study of user acceptance of e-collaboration technology has been using data log file, such as: performance of users of the system, the total usage of the system, and usage of file exchange capabilities within the system. The study was conducted on a Courseware Management Tool. Meanwhile, Ma and Yuen (2011) have been used log files data based on eight different activities in Interactive Learning Network to predict user acceptance. Among those activities were viewing community announcement, enrolling in the course module, uploading assignment, modifying my profile/my folder, entering the discussion forum, scheduler/calendar, and total log. However, the study did not examine user acceptance of e-learning applications that are embedded in a website.

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UTAUT Model

A unified model, called the Unified Theory of Acceptance and Use of Technology (UTAUT), has been designed specifically to unite together all the different models previously. This model can describe individual technology acceptance decisions across a wide range of information technologies and user populations (Venkatesh et al., 2003). It is formulated as a unified model that integrates the element through eight models in the literature that included the Theory of Rational Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model (MM), the Theory of Planned Behaviour (TPB), the theory combined with TPB and TAM (C-TAM-TPB), the Model of PC Utilization (MPCU), an Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT). The UTAUT was formulated with four core factors of intention and usage: performance expectations, effort expectations, social influences, and facilitating conditions. There are four moderators of key relationships: age, gender, computer experience and voluntariness. The UTAUT model was strong in predicting intention and use behaviour. It also contains relevant factors to explain intention and use behaviour. However, most of the studies adopted the Unified Theory of Acceptance and Use of Technology (UTAUT) on user acceptance of e-learning are based on quantitative research.

Web Usage Mining

Web usage mining is a type of web mining. It is the process of applying data mining techniques to the discovery of significant patterns from data generated from interaction of client-server on the web. The information about users' behaviours and their usage patterns are made known through web usage mining (Han et al., 2012). Mining information from web usage data also enables the prediction of user acceptance in e-learning is done. The process of web usage mining can be separated into four different phases: data preparation, pre-processing, pattern discovering, and pattern analysis (Han et al., 2012; Singh & Singh, 2010). There are three main sources for log file in web usage mining: web servers, proxy servers, and web clients (Hu et al., 2002). One method to get the data is to use the Tin Can API. This method enables the tracking of user behaviour in e-learning applications that inside the website is done.

Tin Can API

Tin Can API or experience API (xAPI) is an e-learning software specification developed by Advanced Distributed Learning (ADL) and Rustici Software (Del Blanco et al., 2013). Tin Can API can track and record all types of experience in e-learning applications. The students' behaviour is recorded in the Tin Can statement as learning data. The Tin Can statement will be stored in the Learning Store Store (LRS), which exist in the Learning Management System (LMS), or by itself. The in-depth reporting and analysis on learning activities can be done through the LRS.

Proposed Model for Predicting User Acceptance of E-Learning Applications

The proposed model for predicting user acceptance of e-learning applications is shown in Figure 1 below. The model and construct definition was based on UTAUT (Venkatesh et al., 2003).
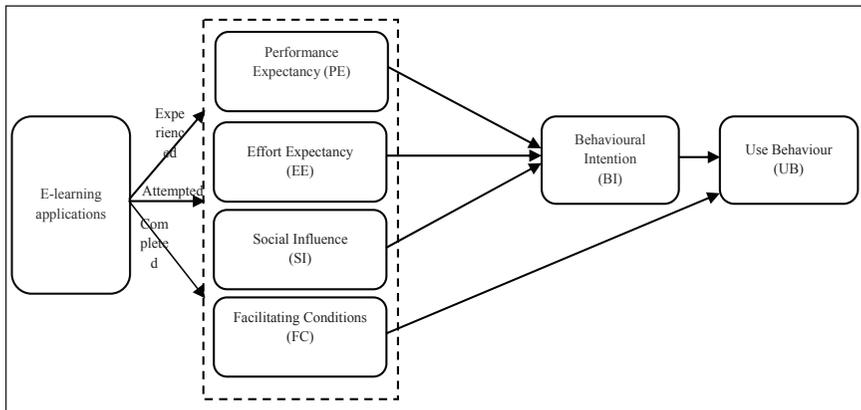
Figure 1: Proposed Model

Referring to this model, learning data such as: "experienced", "attempted", and "completed" from the use of e-learning applications will be achieved. Subsequently, learning data were mapped on four core determinants of *behavioural intention*, and *use behaviour*, namely: *performance expectancy, effort expectancy, social influence,* and *facilitating conditions*. Originally, there were four moderators that can affect constructs in UTAUT model: *gender, age, experience,* and *voluntariness of use*.

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However, all moderators were removed in this study. This is because researchers assume it does not affect the construct because the development of e-learning applications was specifically for learners who will be tested. Previous studies have shown almost all the moderators not much affect the constructs (Jairak et al., 2009; Sundaravej, 2003; Wang et al., 2006). The definitions of construct in the proposed model are explained as below:

Performance expectancy is defined as the degree to which an individual believes that using the e-learning applications will help him or her to attain gains in reaching learning goals. *Performance expectancy* would influence the *behavioural intention* of the individual to use e-learning applications. It is reasonable to predict that the higher the level of the individual believes that the application of e-learning is useful for learning, an individual will intend to use e-learning applications.

Effort expectancy is defined as the degree of ease associated with the use of e-learning applications. *Effort expectancy* would influence the *behavioural intention* of the individual to use e-learning applications. It is logical to predict that the higher the degree of ease of using e-learning applications, an individual will intend to use e-learning applications.

Social influence is defined as the degree to which an individual perceives that important others believe he or she should use the new systems. *Social influence* would influence the *behavioural intention* of the individual to use e-learning applications. It is reasonable to predict that, if an individual perceives that important others believe he or she should use e-learning applications; he or she will intend to use e-learning applications.

Facilitating conditions is defined as the degree to which an individual believes that an organizational and technical infrastructure exist to support for the use of e-learning applications. This construct is direct determinant of use behaviour. *Facilitating conditions* would not influence the *behavioural intention* of the individual to use e-learning applications. However, it is logical to predict that the existence of an organizational and technical infrastructure that support e-learning applications influenced an individual to use it.

Behavioural intention is defined as the degree to which an individual has expressed conscience plans to perform or not perform some specified

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future behaviour. In this study, *use behaviour* will be influenced by *behavioural intention*. It is reasonable to predict that individuals who intend to use e-learning applications in the future will use it after the first attempt.

METHOD

Background

The participants were 24 students from Form Six in a secondary school. They were chosen without taking into account factors like sex and computer experience. They learnt the subjects of *Pengajian Am STPM*. This subject is compulsory pass for each student. In addition of classroom learning, they also used e-learning applications that are embedded in the subject website of *Pengajian Am*. Therefore, the development of better e-learning applications was essential to increase the understanding and performance of students. The research on the user acceptance was important for e-learning applications. In this study, e-learning applications for the *Pengajian Am* subject were developed to measure user acceptance. The period of data gathering for the use of e-learning applications was about one month.

Data gathering, preparation and pre-processing

Advantages of today's technology allow learners' interaction that can be detected through the use of e-learning applications integrated with the Tin Can API. The use of the Tin Can API enables tracking of learning experiences, including conventional learning data, such as scores, or completion of the task. In this study, the Tin Can API was used to gather the learning data for web usage mining. It can record learners' interaction such as content navigation, reading notes, or answering quiz questions. The statements of experience will be delivered to and stored in a Learning Record Store (LRS).

Figure 2 shows how the gathering of learning data. Learners access the e-learning applications that are embedded in a website. Then, learner experiences using learning applications recorded in Tin Can statements. These statements were delivered and stored in the learning record store (LRS).

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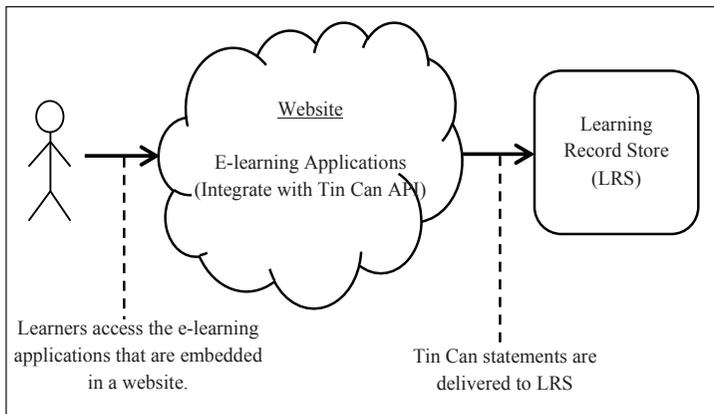
Figure 2: The Flow of Data Gathering

Tin Can statements format was based on activity types, and activity streams (Actor, Verb, and Object). The examples of activity types were module, course, cmi.interaction, and objective. Meanwhile, for the activity streams, the actor was the agent the statement was about, learner, instructor, teacher, or group. The verbs describe the action of the statement, such as attempted, experience, answered, completed, passed, or failed. The object was what the Actor interacted with, a note, a quiz, or a class. The Tin Can statements from this study are shown in Figure 3.

Figure 3: Tin Can Statements

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In the preparation phase, the gathered data will be cleaned, and filtered. Data that was not relevant and not required such as overlapping data will be removed. The information required will be identified. Then, the data will be extracted to the information of usage, content and the structure of the information contained in various existing data sources into the data format required for pattern discovery (Srivastava et al., 2000). In this pre-processing phase, it was necessary to ensure data of user behaviour, and activity in the LRS was readable, and achieved.

Pattern Discovery

Statistical technique was the use of method in pattern discovery to extract the user data of e-learning applications. The statistical analysis is based on the frequency of user behaviour and activities in order to predict the user acceptance of e-learning applications. Data will be extracted using queries and filters in the LRS. The extracted data will be divided into the following categories: "attempted", "experienced", and "completed". Based on these data, the behaviour of users who use e-learning applications can be explored.

Pattern Analysis

Data generated through the use of e-learning applications were the type of text. There were more than 22,000 statements of data. Analysis of quasi-statistics (Horowitz & Becker, 1971) was performed because the qualitative data was big. This method also called an enumeration, the process of quantifying data. In this method, data will be checked and calculated on the frequency of user behaviour. The usage data of "experienced," "attempted," and "completed" have been mapped as constructs in the proposed model. Table 1 shows the constructs, usage of e-learning applications, and descriptions.

Table 1: Constructs, Usage of e-learning Applications and Descriptions

UTAUT Constructs	Usage of e-learning applications	Descriptions
Performance expectancy (PE)	The frequency of attempted e-learning applications at different times.	The individuals who attempted e-learning applications at the different range of times (after 40 minutes of each session).
Effort expectancy (EE)	The frequency of attempted e-learning applications with completed.	The individuals who attempted e-learning applications with completed.
Social influence (SI)	The frequency of experienced "like" and "share" in e-learning applications.	The individuals who clicked "like" and "share" in e-learning applications.
Facilitating conditions (FC)	The frequency of attempted e-learning applications at different places.	The individuals who attempted e-learning applications at the different range of IP address.
Behavioural Intention (BI)	The total frequency of attempted and experienced e-learning applications after the first attempt.	The individuals who intend to use e-learning applications in the future will use it after the first attempt.
Use Behaviour (UB)	The total frequency of attempted and experienced e-learning applications.	The individuals who use e-learning applications with repeatedly.

RESULTS AND DISCUSSION

Web usage mining approach with the Tin Can API enables usage data of the e-learning applications that are embedded in a website successfully achieved. The usage data was filtered based on pattern analysis in Section 4.4. Multiple linear regression procedures with "enter" method was used in analysing the usage data for predicting user acceptance of e-learning applications. The analyses were divided into two parts: regression analysis on behavioural intention, and use behaviour.

Regression analysis on behavioural intention (BI)

BI was treated as the dependent variable, and are predicted by independent variables such as PE, EE, and SI. Analysis is shown in Table 2.

Performance expectancy and effort expectancy were found directly and significantly related to intention to use the e-learning applications. The beta coefficients for the constructs were 0.398 ($p<0.05$), and 0.399

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(p<0.05). The prediction of performance expectancy influencing behavioural intention based on "Frequency of attempts the e-learning applications at different time" can be accepted. Similarly, the prediction of effort expectancy influencing behavioural intention based on "Frequency of attempts the e-learning applications with completion" can be accepted. Social influence was found not to be significantly related to intention to use the e-learning applications. The beta coefficient was 0.277 (p>0.05). The prediction of social influence influencing behavioural intention based on the "Frequency of experienced "like" and "share" in the e-learning applications". This may be caused by lack of usage "like" and "share" in the e-learning applications. However, the coefficient of determination (R2) was high (R2 = 0.799, p<0.001).

Table 2: Regression Analysis on Behavioural Intention (BI)

Constructs	β	t-value
Performance expectancy (PE)	0.398	2.354*
Effort expectancy (EE)	0.399	2.839*
Social influence (SI)	0.227	1.665
R^2	0.799	
Adjusted R^2	0.769	

*p < .05

Regression analysis on use behaviour (UB)

UB was treated as the dependent variable, and were predicted by independent variables such as BI, and FC. Analysis is shown in Table 3.

Behavioural intention and facilitating conditions were found directly and significantly related behaviour of use the e-learning applications. The beta coefficients for the constructs were 0.839 (p<0.05), and 0.175 (p<0.05). The prediction of behavioural intention influencing use behaviour based on "Total frequency of attempts, and experienced the e-learning applications after first attempt" can be accepted. Meanwhile, the prediction of facilitating conditions influencing use behaviour based on "Total frequency of attempted, and experienced the e-learning applications" also can be accepted. The coefficient of determination (R2) was high (R2 = 0.955, p<0.001).

Table 3: Regression Analysis on Use Behaviour (UB)

Constructs	β	t-value
Behavioural intention (BI)	0.839	11.942*
Facilitating conditions (FC)	0.175	2.494*
R^2		0.955
Adjusted R^2		0.951

*p < .05

CONCLUSION

Predicting user acceptance based on the interaction with the e-learning applications that are embedded in a website is challenging because information about user interaction, and behaviour are difficult to be gathered. The ability to detect the learners' experience during the interaction with e-learning applications can bring many benefits to predict the user acceptance of e-learning applications. The use of web mining to identify the user acceptance in e-learning settings is practical. This can be achieved by using the Tin Can API that was integrated with e-learning applications to obtain learning data. The learning data is a text statement that describes the behaviour of students who use e-learning applications. Analyses of multiple linear regressions have been done based on the frequency of "experienced", "attempted", and "completed" of e-learning applications to predict user acceptance. With this method, the prediction of user acceptance using UTAUT model for e-learning applications can be implemented. From the analysis of results, only the social influence was found not to be significantly related to intention to use e-learning applications. The enhancement of e-learning applications can be made after the user requirement has been identified through the analysis.

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