

Educational data mining acceptance among undergraduate students

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Abstract The acceptance of Educational Data Mining (EDM) technology is on the rise due to, its ability to extract new knowledge from large amounts of students' data. This knowledge is important for educational stakeholders, such as policy makers, educators, and students themselves to enhance efficiency and achievements. However, previous studies on EDM have focused more on technical aspects, such as evaluating methods and techniques, while ignoring the end-users' acceptance of the technology. Realising its importance, this study has analysed the determinants that could influence the acceptance of EDM technology, particularly among undergraduate students since they are the most affected by the technology. For this reason, 11 hypotheses have been formulated based on determinants of technology readiness index (TRI) and technology acceptance model 3 (TAM3), which could render an in-depth insight regarding EDM acceptance. A survey was conducted on 211 undergraduate students from six public universities in Malaysia for a period of 6 months (May to October 2014) using questionnaires as the instrument to collect data to test the hypothesised relationships. The partial least squares structural equation modeling (PLS-SEM) approach was used to analyse the proposed acceptance model, which was run using SmartPLS, version 3 software. The findings have revealed that 'relevance for analysing', 'self-efficacy', 'facilitating conditions', 'perceived usefulness', 'perceived ease of use', 'optimism' and 'discomfort' have influenced the acceptance of EDM technology among undergraduate students.

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1 Introduction

Data mining technology (DMT) has been applied in many research areas, particularly by those attempting to exploit extensive datasets. The application of DMT in education is known as Educational Data Mining (EDM), which has become new paradigms in Institutions of Higher Learning (IHLs) for enhancing the learning process and guide the students' learning (Chamizo-Gonzalez et al. 2015). The technology is capable of exploring the unique types of data in IHLs to improve the quality educational data analysis on large scale for proactive and knowledge-driven decision-making (Bousbia and Belamri 2014; Romero and Ventura 2013; Siemens and Baker 2012). EDM is seen critical for IHLs to remain competitive and be at least one-step ahead of their competitors (Nemati and Barko 2010).

Despite EDM being able to shape an advanced educational data, the technology is complex and beyond the scope of what users may want to use (García et al. 2011; Romero and Ventura 2010). Little effort has been paid to analyse the acceptance of users towards EDM (Gašević et al. 2015) which hinders users from appreciating its capabilities. Similar to other technologies, EDM needs to obtain the users' acknowledgement; to avoid them from abandoning the technology despite its prevalent benefits (Jan and Contreras 2011). Thus, it is vital to understand users' acceptance, as this could help minimise underutilisation of the technology.

2 Educational data mining

Educational data mining (EDM) refers to the application of data mining techniques in analysing specific types of datasets in the educational setting (Baker 2010; Romero and Ventura 2013). It is a promising computer-based educational system (CBES), capable of analysing large-scale educational data to better understand the learning process. This system could also be used to address distinct educational problems. EDM focusses on all levels of users in the educational context, such as students, teachers, administrators and institutions (Romero et al. 2011; Romero and Ventura 2010, 2013). This application is oriented to mining raw data; extracted from conventional education (face-to-face contact between educators and students, organised in a classroom), or web-based education systems (e-learning, learning management systems (LMS), web-based adaptive systems and intelligent tutoring systems (ITS)). It is oriented to support the specific needs of each previously mentioned user.

There are also other techniques commonly used to analyse educational data, which are academic analytics (AA) and learning analytics (LA). While AA is a data driven process that focuses on users at an institutional level (Barneveld et al. 2012), LA limits its focus to only students and educators in understanding and optimizing their learning environment (Daniel 2014; Papamitsiou and Economides 2014; Romero-Zaldivar et al. 2012). Is there any distinct difference between EDM, AA and LA? It is argued that the differences between these applications are vague and overlapping (Ferguson 2012)

since each application has its own target user, with different goals in terms of emphasis and orientation (Ocumpaugh et al. 2014). Furthermore, AA and LA must be supported by EDM to increase their educational efficiency and attainment (Romero-Zaldivar et al. 2012). Thus, EDM is central and with the foundation for implementing AA and LA.

Recently, several IHLs have begun to develop and implement EDM with the hope that this technology would offer greater flexibility in education. For instance, EDM has been used to enhance the existing learning management system (LMS) with PDCA (Plan, Do, Check, Act) method at the University of Kragujevac, Serbia (Blagojević and Micić 2013). By incorporating EDM technology, the proposed system was able to predict behaviour patterns, thus leading to increased efficiency for the target users (students and educators). In another study, (Arnold and Pistilli 2012) developed ‘Course Signals’ (CS) at Purdue University, in the U.S.A., a well-known students’ success system that allows the faculty to provide meaningful feedback to each student based on data mining predictive models. Since its emergence, nearly 24,000 students have been impacted by the technology, and more than 145 educators have used CS in at least one of their courses (Arnold and Pistilli 2012).

With growing interest towards EDM capabilities, some institutions have become actively involved in EDM research, such as (i) Worcester Polytechnic Institute, Carnegie Mellon University, University of North Carolina, University of Memphis, and Vanderbilt University in the United States; (ii) Cordoba University, Spain; and (iii) University of Sydney, Australia (Peña-Ayala 2014).

While IHLs continuously invest in developing various EDM applications to support management, teaching and learning processes, limited studies have evaluated the acceptance of such technology among end-users (Gašević et al. 2015). Previous studies have identified the acceptance of university administrators (Arnold et al. 2010; Ranjan et al. 2013) and educators (Liaqat et al. 2013) towards the technology. However, the acceptance of such technology from a single top level perspective (university administrators and educators) to undertake the EDM technology may lead to a less than successful endeavour (Arnold et al. 2014). Therefore, it is imperative to understand students’ acceptance, to help policy makers and software developers identify the wide range of students’ preferences towards the technology. For this reason, the underlying relevant technology acceptance theories must be identified, which are discussed in the subsequent section.

3 The relevant technology acceptance theories

Technology acceptance has been defined as the willingness of a user to use technology for the tasks it is designed to support (Teo 2011). This study is grounded in two kinds of theoretical models that could measure students’ acceptance of EDM technology: (i) the technology acceptance model 3 (TAM3) (Venkatesh and Bala 2008); and (ii) the technology readiness index (TRI) (Parasuraman 2000). Although the original technology acceptance model (TAM) and other extended models (TAM2, UTAUT, UTAUT2) are parsimonious and might be good predictors of technology acceptance, the integration of TAM3 and TRI would contribute to a more comprehensive explanation for individual users’ acceptance to use a specific technology. Descriptions of each model are as follows.

3.1 Technology acceptance model 3 (TAM3)

Prior to understanding TAM3, it is essential to be familiarised with its theoretical grounding, which include TAM, TAM2 and the determinants of PEOU. TAM was originally developed by Davis (1989), to predict and explain the acceptance of users towards basic computer applications (word processing, email and graphic tools). It consists of cognitive responses, namely perceived usefulness (PU) and perceived ease of use (PEOU), as important determinants that can analyse what would lead users to accept or reject a technology (Davis 1989; Venkatesh and Davis 2000). PU refers to an individual's belief that using a particular technology could enhance job performance, while PEOU refers to the degree of an individual's belief that a given technology would be free of effort (Davis 1989). Apart from PU and PEOU, TAM has other essential determinants: external variables, attitude (ATT), behavioural intention to use (BIU), and actual use (AU). TAM has served as the analytical foundation for user acceptance of diverse information technology (IT) applications. It offers several advantages, such as instrument reliability, validity, parsimony and social psychology (Huang et al. 2012).

Venkatesh and Davis (2000) later introduced TAM2 to explain the impact of social influence processes (subjective norm, image, experience and voluntariness) and cognitive instrumental processes (job relevance, output quality, result demonstrability and perceived ease of use) on PU and BIU. Since TAM2 focuses more on the determinants of PU, Venkatesh (2000) has proposed the determinants of PEOU to further understand how the perception of users forms and changes over time with increasing experience. These determinants encompass three different components (i.e., control, intrinsic motivation, and emotion) as general anchors; with increasing experience, these anchors will change into adjustments (perceived enjoyment and objective usability).

Venkatesh and Bala (2008) then proposed TAM3 to explain individual user's acceptance more deeply, and to enhance the robustness of TAM. In TAM3, the determinants of PU (Venkatesh and Davis 2000) and PEOU (Venkatesh 2000) were integrated to influence BIU. However, the determinants of PU could not influence PEOU and vice versa. The separation is due to the effects of social influences (subjective norm, image, experience, and voluntariness) and cognitive instrumental processes (job relevance, output quality and result demonstrability) that are closely related to PU. In contrast, the determinants of PEOU are primarily based on individual differences and general beliefs that relate to anchors (control beliefs, intrinsic motivation and emotion) and adjustment-based model (perceived enjoyment and objective usability).

Huang et al. (2012) have asserted that DMT is a type of decision tool suitable for individual users. Therefore, TAM3 was used and extended to understand DMT acceptance among the business intelligence community. Their findings have shown that cognitive instrumental processes (job relevance, output quality and result demonstrability) and control beliefs (computer self-efficacy and external control) are the most important determinants of DMT acceptance. Similarly, Khaled and Mohammed-Issa (2015) have found that TAM3 is significant in the identification of individual user's acceptance of mobile commerce. Other scholars have also successfully used and extended TAM3 to predict and explain students' acceptance towards the potential and actual use of an e-learning system (Agudo-Peregrina et al. 2014), and cloud

computing (Behrend et al. 2011). While the aforementioned studies had focused more on an individual's cognitive instrumental processes (technology dimensions), an individual's personality dimensions also play vital roles in determining acceptance levels (Chiu et al. 2010; Godoe and Johansen 2012). Therefore, Parasuraman's (2000) technological readiness represents one such personality dimensions that could enhance the acceptance of individual user towards a new technology.

3.2 Technology readiness index (TRI)

Parasuraman (2000) has developed the TRI to determine an individual's predisposition towards new technologies. This model is composed of four personality dimensions: optimism, innovativeness, discomfort, and insecurity. Optimism relates to a positive view of technology and a belief that technology offers increased control, flexibility, learning opportunities and efficiency. Innovativeness refers to the tendency of an individual to be a technology pioneer and thought leader. Discomfort involves the feeling of lacking the control over technology and a sense of being overwhelmed. Insecurity is an inclination towards distrusting technology and doubting the capability of technology to work properly. Of these, optimism and innovativeness are contributors (positive feelings) to technology readiness, while discomfort and insecurity are inhibitors (negative feelings). Such positive and negative feelings may coexist and these personality dimensions can be measured from strongly positive to strongly negative (Roumeliotis and Maria 2014).

Liljander et al. (2006) and Summak et al. (2010) have argued that TRI plays a minor role in explaining the behaviours of individual users despite some studies have agreed that TRI is vital in identifying individual user's intention to use a new technology prior to its implementation (Caison et al. 2008). In addition, TRI also influences the speed of a user's acceptance of a new technology (Hung and Cheng 2013). It is evident that the integration of TRI and TAM can explain the complexity of a user's positive and negative feelings towards a new technology (Lin and Chang 2011). Walczuch et al. (2007) have investigated how each feeling related to the TRI could influence the main predictors of TAM. Their results have shown that most of the personality dimensions have significant impact on cognitive dimensions (PU and PEOU). Similarly, Kuo et al. (2013) have also confirmed that the personality dimensions are significant factors of PU and PEOU, while, Godoe and Johansen (2012) have found that the integration of TRI and TAM may contribute to a holistic view of technology acceptance. When adopting a new technology, a user's personality dimensions, in terms of technology, should be considered, especially if the technology has not been tested prior to adoption.

Although TRI was initially used to understand the readiness of users towards technology-based services, some studies have used this model to explore users' readiness towards DMT in the contexts of banking (Noornina et al. 2002a), telecommunication (Noornina et al. 2002b) and insurance (Ramayah et al. 2007). However, as far as this study is concerned, no empirical study has ever used TRI as personality dimensions for understanding individual students' acceptance of EDM technology. Therefore, this study aims to elucidate the personality dimensions (TRI) with an integration of individual user's acceptance (TAM3) to better understand students' acceptance of the EDM technology.

4 Research model and hypotheses

The research model for this study is depicted in Fig. 1 with the determinants and relationships between TRI and TAM3 were revised to reflect the new conditions of the EDM environment. The determinants selected are:

4.1 Relevance for analysing and perceived usefulness

Venkatesh and Davis (2000) have introduced the concept of job relevance to explain the applicability of technology to support an individual's job. Agudo-Peregrina et al. (2014) have deemed this concept to have 'relevance for learning', specifically in identifying the applicability of an e-learning system for students' learning-related tasks. Following Agudo-Peregrina et al. (2014), this study replaces the term 'job relevance' with 'relevance for analysing' (RA), since the main characteristic of EDM is to analyse students' data. Venkatesh and Davis (2000) have postulated that job relevance is a cognitive judgement that has a direct effect on the PU of technology. Job relevance (Hart et al. 2007; Huang et al. 2012; Venkatesh and Bala 2008; Venkatesh and Davis 2000) and relevance for learning (Agudo-Peregrina

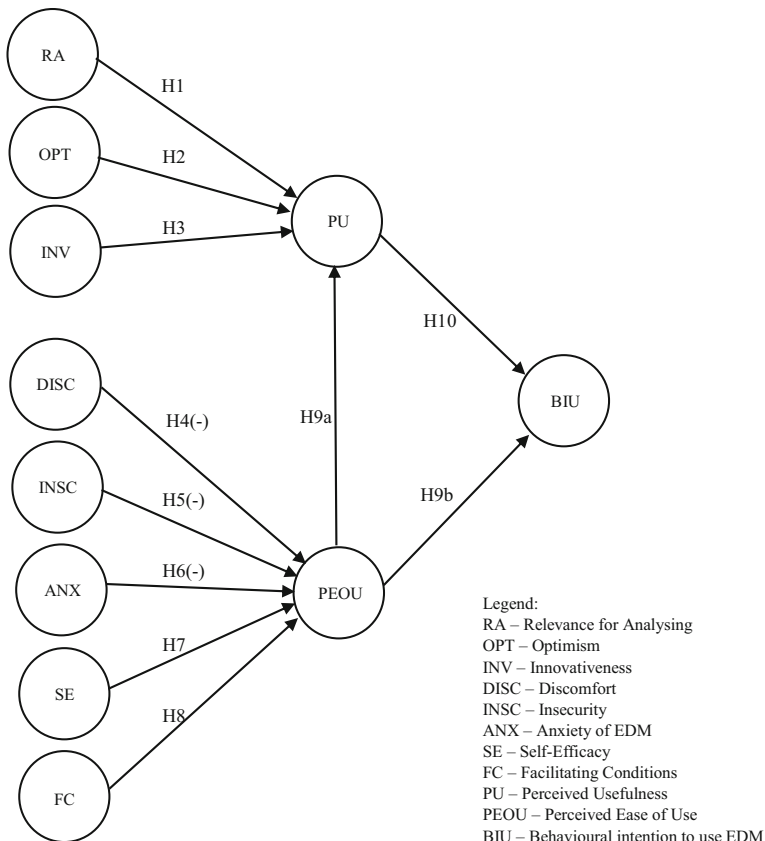


Fig. 1 The proposed research model and hypotheses

et al. 2014) have been proven to be significant positive impacts on PU. Therefore, the following is hypothesised:

H1: There is a positive relationship between relevance for analysing and perceived usefulness of EDM technology.

4.2 Optimism and perceived usefulness

Optimism (OPT) is a general dimension that captures specific feelings, which assume that “technology as a good thing” (Tsikriktsis 2004). Optimistic individuals are more likely to adopt rather than avoid technology, and they are less worried about possible negative outcomes from technology (Hung and Cheng 2013; Walczuch et al. 2007). Prior studies have reported that OPT plays a significant role in PU for diverse fields, such as Facebook (Jin 2013), knowledge sharing in virtual communities (Hung and Cheng 2013), mobile electronic medical record systems (Kuo et al. 2013), electronic health records (Godoe and Johansen 2012), electronic human resource management (Erdoğan and Esen 2011), and software applications (Walczuch et al. 2007). In this study, the OPT construct has been proposed to be the extent to which a student believes that the application of EDM technology would offer better academic performance and greater benefits. Therefore, the following is hypothesised:

H2: There is a positive relationship between optimism and perceived usefulness of EDM technology.

4.3 Innovativeness and perceived usefulness

Innovativeness (INV) refers to the extent to which an individual believes that he or she is at the forefront of using new technologies and is considered by others as a thought leader for technology-related issues (Tsikriktsis 2004). This type of individuals may also feel regretful if they lose the opportunity to explore new things or fail to try a new technology (Hung and Cheng 2013). Jin (2013), and Erdoğan and Esen (2011), among others, have confirmed that INV is a significant determinant of PU. In this study, the INV construct is proposed to be the extent to which students believe that they are willing to be the first users of a new EDM technology and become thought leaders. Therefore, the following is hypothesised:

H3: There is a positive relationship between innovativeness and perceived usefulness of EDM technology.

4.4 Discomfort and perceived ease of use

Discomfort (DISC) represents the extent to which an individual believes that he or she tends to be exclusionary rather than inclusive of technology (Tsikriktsis 2004). An individual who scores highly on this construct may feel a lack of control or extremely

controlled by technology (Hung and Cheng 2013; Walczuch et al. 2007). Nemati and Barko (2003) have demonstrated that the level of technological expertise is leveraged to the success of a data mining project. Nonetheless, it is useless if the users feel some level of DISC with the technology because it may cause them to reject the technology. In this study, the DISC construct has been considered to be the extent to which students feel a lack of control over the use of EDM technology along with a lack of confidence in using it properly. Walczuch et al. (2007) have demonstrated that individuals with minor DISC of technology have contributed to a high PEOU of the technology. Therefore, the following is hypothesised:

H4: There is a negative relationship between the discomfort of EDM and perceived ease of use of the technology.

4.5 Insecurity and perceived ease of use

Tsikriktsis (2004) has argued that insecurity (INSC) is somewhat related to DISC. However, INSC focuses on specific aspects of technology-based transactions (e.g., electronic self-services, electronic commerce, financial services and telecommunications). This study has revised this construct to fit the role of EDM in undergraduate education, particularly for academic data and activities. Thus, INSC in this study refers to the extent to which students believe that they distrust EDM technology for security and privacy reasons. Previous scholars have concluded that INSC imposes a significant negative impact on PEOU on Facebook (Jin 2013), mobile electronic medical record systems (Kuo et al. 2013), and software applications (Walczuch et al. 2007). Therefore, the following is hypothesised:

H5: There is a negative relationship between insecurity of EDM and perceived ease of use of the technology.

4.6 Anxiety of EDM and perceived ease of use

Venkatesh (2000) has defined computer anxiety as an individual's uneasiness when using a computer. The generalizability of prior studies on this concept is problematic since computer technologies represent various technology-specific features. Hence, further study is required to examine the individual emotions that could be linked to the specific features of a new technology rather than on computer technology in general. For instance, Huang et al. (2012) have examined the adoption of data mining among online business communities in Taiwan. Results have shown the insignificant impact of computer anxiety on the PEOU of technology. This is because the examination of a user's emotions was related to computers in general and not on data mining specifically. Therefore, to suit the individual's emotional reaction towards a specific technology, this study has decided to replace the term 'computer anxiety' with 'anxiety of EDM' (ANX). Based on related studies on computer anxiety, ANX is expected to have a negative relationship with the PEOU of this technology (Agudo-Peregrina et al. 2014; Hart et al. 2007; Huang et al. 2012; Venkatesh 2000; Venkatesh and Bala 2008).

In other words, the decreasing level of a student's ANX will lead to an increasing level of PEOU towards the technology. Therefore, the following is hypothesised:

H6: There is a negative relationship between anxiety of EDM and perceived ease of use of the technology.

4.7 Self-efficacy and perceived ease of use

Self-efficacy (SE) relates to internal control, having been defined as the belief that an individual has the ability to execute a certain behaviour (Lai 2008). In this case, computer self-efficacy means that a judgment is made regarding an individual's capability to use a computer for what can be done in the present or future, but not for what he or she has done in the past (Compeau and Higgins 1995). Similar to computer anxiety studies, most previous studies (e.g., Agudo-Peregrina et al. 2014; Huang et al. 2012; Venkatesh and Bala 2008; Terzis and Economides 2011) have extensively examined the SE construct in terms of computer applications. Yet, there is a lack of research that exams it with regards to a specific feature of technology. Therefore, this study has conceptualised the SE construct as a student's belief that he or she could use the EDM technology for analysing high amounts of academic data at present or in the future. Previous studies have revealed that computer self-efficacy has a significant positive impact on PEOU (Huang et al. 2012; Terzis and Economides 2011; Venkatesh and Bala 2008). Therefore, the following is hypothesised:

H7: There is a positive relationship between self-efficacy and perceived ease of use of EDM technology.

4.8 Facilitating conditions and perceived ease of use

Facilitating conditions (FC) are viewed as external controls rather than internal controls, such as the SE construct. In particular, FC is a construct that influences an individual's judgement to perform a task (Terzis and Economides 2011). Venkatesh and Bala (2008) have asserted that this construct is related to the availability of organisational resources and support facilities. This construct is also associated with the organisational and technical infrastructure that exists to support users in their use of technology (Venkatesh et al. 2003). Huang et al. (2012) have acknowledged that data mining is a complex technology, which is difficult to use if the support of technical infrastructure is unavailable. In this study, the FC construct is proposed to be the extent to which a student believes that data resources and technical infrastructures are provided by public universities in order to facilitate the use of EDM technology. Prior studies have confirmed that a positive relationship exists between FC and PEOU (Agudo-Peregrina et al. 2014; Huang et al. 2012; Terzis and Economides 2011). Therefore, the following is hypothesised:

H8: There is a positive relationship between facilitating conditions and perceived ease of use of EDM technology.

4.9 Perceived ease of use, perceived usefulness and behavioural intention to use EDM

Davis (1989) has defined PEOU as the extent to which an individual considers the use of technology as free of effort. Venkatesh and Davis (2000) have demonstrated that PEOU has significant positive effects on PU. This relationship has been criticized as inapplicable when an individual has a high level of experience in using the technology (Venkatesh and Bala 2008). However, such criticism does not hinder this study from evaluating this relationship, since our respondents (undergraduate students) are considered to be moderately experienced with EDM technology. Meanwhile, Godoe and Johansen (2012) have asserted that the relationship between PEOU and PU is vital for providing precious knowledge in designing and implementing a new technology. For instance, Hart et al. (2007) and Huang et al. (2012) have confirmed that such relationships are significant for the implementation of new data mining applications in their environments. In this study, the PEOU construct is proposed to be the extent to which a student believes that the use of EDM is free of effort. If EDM is relatively easy to use, the student will be more willing to use it, since this technology could improve his or her learning and academic performance. Hence, the following association is hypothesised:

H9a: There is a positive relationship between perceived ease of use and perceived usefulness of EDM technology.

Huang et al. (2012) have found that PEOU is the most significant factor of BIU of data mining among online business communities in Taiwan. Hence, an increasing level of a student's PEOU of EDM is expected to increase the BIU of the technology as well. Therefore, the following is hypothesised:

H9b: There is a positive relationship between perceived ease of use and behavioural intention to use EDM technology.

4.10 Perceived usefulness and behavioural intention to use EDM

Venkatesh and Bala (2008) have defined PU as the extent to which a user perceives the use of IT could improve his or her work performance. Several studies have confirmed that PU plays an important role as a determinant of BIU in various kinds of educational technology acceptances (Agudo-Peregrina et al. 2014; Merhi 2015; Park and Kim 2014). Despite some studies arguing that actual use is a better predictor of technology acceptance, BIU may still predict future technology acceptance, particularly if the technology is in the pre-implementation stage (Agudo-Peregrina et al. 2014). Since the application of EDM technology in the education environment remains in its infancy, the dependent variables used in this study were restricted to BIU. Thus, students may believe that technology could improve their learning and academic performances, which consequently, may develop future growth in their intention to use EDM. Therefore, the following is hypothesised:

H10: There is a positive relationship between perceived usefulness and behavioural intention to use EDM technology.

5 Research method

Previous studies related to the acceptance of data mining have revealed that a survey via questionnaires is an appropriate method to gather data (Huang et al. 2012; Noormina et al. 2002a, b; Ramayah et al. 2007). In keeping with previous studies, this study has employed the questionnaire method to explore the hypothesised relationships on the acceptance of EDM among undergraduate students, particularly in the context of public universities in Malaysia.

5.1 Development of instruments

The instruments were derived from prior studies (i.e., Huang et al. 2012; Parasuraman 2000; Venkatesh and Bala 2008) and have been slightly adjusted to suit the purposes of this study. A total of 60 indicators were adapted to measure 11 constructs in the research model. Among these, seven constructs contained four indicators, whereas the other constructs were made up of eight indicators. All indicators have been measured using a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

5.2 Pre-test and pilot test

The pre-test was performed to ensure the validity of the questions. Validity is essential for ensuring that the concept is well-defined by the measure (Hair et al. 2010). Two undergraduate students, two experts in data mining and two experts in statistics were involved in the pre-test. The questionnaire was then altered according to their feedbacks; the adjustments were mainly on the length of the questions, the format of the scales, and the validity of the constructs. After the pre-test, a pilot test was conducted on 23 undergraduate students to determine the reliability of the questions. Reliability refers to the consistency in the intended measurements (Hair et al. 2010). The reliability of the questions in this study can be calculated by using Cronbach's alpha, which indicates that the value of all constructs must be greater than the recommended value of 0.7 (Hair et al. 2006; Nunally 1978). A statistical tool, SPSS v20 was used to run the Cronbach's alpha. The results have shown that the value of all constructs have ranged between 0.74 and 0.94. This range of values indicates that the questions were reliable and were properly tailored to measure the research model in this study.

5.3 Sample and data collection

The target sample for this study was undergraduate students who had attended a Data Mining course in their respective universities (six public universities in the Klang Valley area). A cross-sectional process was conducted to collect data that ran from May until the end of October of 2014. Copies of the questionnaire were initially distributed to 360 students and only 229 (63.6 %) copies were returned. According to Babbie (1990), a return rate of greater than 60 % is good and more than 70 % is considered as very good. Thus, the 63.6 % return rate has been considered to be adequate to generalise the population of this study.

The data was first assessed for completeness and correctness prior to analysis using the PLS-SEM approach. The data should be removed if it has more than 25 % missing data (Sekaran 2005). Data should also be removed if it has straight lining (respondent marks the same values) (Hair et al. 2014a). Consequently, 18 data points were removed, leaving a total of 211 out of 229 for analysis.

6 Analysis and results

This section will discuss the analysis and results based on the PLS-SEM approach, which has examined the hypothesised relationships in the proposed research model. The PLS-SEM approach was selected due to the following reasons:

- i. the study focuses on predicting and explaining the variance in key target constructs;
- ii. the study aims to analyse new relationships among constructs, which is believed to be in the early stage of theory development, thus creating the opportunity where a new phenomenon requires exploration; and
- iii. the study accepts the advantage of PLS-SEM in terms of minimum restrictions in measurement scale, sample sizes, and data distributions since this method enables researchers to create and estimate the proposed research model without imposing other limiting constraints.

The SmartPLS 3.0 software has been used to run the analysis. Examination of the analysis began with the assessment of the measurement model, followed by the structural model.

6.1 Measurement model assessment

The measurement model, which is the first step in the PLS-SEM approach, has mainly been used to validate the outer model (relationships between the constructs and their indicators). Without proper measurements, the proposed model may not be fully developed with adequate measures and procedures (Davcik 2014). Generally, there are two different relationships between the construct and its indicators, namely reflective measurement and formative measurement. Reflective measurement refers to indicators that are affected by the same underlying construct (their covariance) (Sarstedt et al. 2014), while the direction of causality is derived from the construct to the indicators (Jarvis et al. 2003). On the contrary, formative measurement assumes that the indicators have an impact on the underlying construct and the direction of causality flows from indicators to construct (Jarvis et al. 2003). For constructs using reflective measures, ‘loadings’ have been used to represent the bivariate correlation between the indicators and the construct scores (Gefen et al. 2000; Hair et al. 2014b). Conversely, formative measures use ‘weight’ to provide information regarding the importance of each indicator in forming the construct. These indicators are assumed to be uncorrelated to each other (Chin 1998a). Henseler et al. (2009) have suggested that to avoid the misspecification of the measurement model, determination of causality flow is primarily dependent on previous studies. Thus, based on knowledge acquired during literature review, all constructs in this study were modelled as reflective measurements.

The standard metrics for measurement model assessment include the indicator reliability, internal consistency reliability, convergent validity and discriminant validity (Hair et al. 2014a). A popular rule of thumb for accessing indicator reliability (reflective measurement) is the acceptance of indicators with loadings above 0.708 (Hair et al. 2014a). However, a loading of 0.60 is still considered as acceptable for new applications or situations when other indicators that measure the same construct have high reliability scores (Chin 1998b; Zhang et al. 2006). For the internal consistency, composite reliability should exceed 0.70 (Hair et al. 2013). Meanwhile, the convergent validity is assessed by examining the average variance extracted (AVE), thus providing the amount of variance that a construct obtains from its indicators (Fornell and Larcker 1981). The AVE value should be above 0.50 (Fornell and Larcker 1981; Hair et al. 2013). Table 1 provides an overview of the final set of indicators used. It shows that all loadings were above 0.6, with the elimination of nine indicators from the original 60 indicators. The composite reliability values had ranged from 0.824 to 0.951, exceeding the minimum requirement of 0.7. These values indicate the internal consistency of all constructs. Furthermore, all AVE values were above 0.5, indicating a convergent validity at the construct level.

Once reliability and convergent validity of reflective measurements have been successfully established, discriminant validity was examined. Discriminant validity is concerned with the measures of different constructs that are truly distinct from one another or not to measure something else (Urbach and Ahlemann 2010). Two approaches are common for measuring discriminant validity, namely the Fornell-Larcker's criterion and cross loadings. Following Fornell and Larcker's (1981) criterion, the square root of AVE should be greater than the correlations between each construct and with other constructs. Table 2 demonstrates that all AVE values on the diagonal were higher than the squared interconnected correlations, therefore confirming the discriminant validity for this analysis. Similarly, the value of cross loading provides further evidence for discriminant validity.

6.2 Structural model assessment

Once the constructs were confirmed to be both reliable and valid, the structural model was assessed to identify the relationships between constructs as hypothesised in the research model. The goodness of the research model was examined in terms of the R^2 values (coefficient of determination) of the endogenous constructs and the significance of path coefficients estimation (Chin 2010). Both R^2 and path coefficients are crucial to indicate how well the analysed data support the hypothesised model (Chin 1998b). This study has examined the significance of path coefficients, first by running the bootstrapping procedure. Bootstrapping is a nonparametric method used to assess the significance level of partial least square estimates (Chin 1998a). This generates a certain number of subsamples by randomly choosing a case from the original data set. In this study, the bootstrapping procedure was run using 5000 subsamples, as recommended by Hair et al. (2014a). Table 3 shows the results of the structural model.

In this study, a one-tailed t -value was used, since all the hypotheses were directional. These hypotheses will be supported if the t -value is greater than 1.645 and the p -value is less than the significance level ($\alpha = 0.05$). Accordingly, a hypothesis is not supported if the sign of path coefficient is in a contraindication to the theoretically-assumed

Table 1 Loadings, composite reliability and AVE

Constructs	Indicators	Loadings	Composite Reliability	AVE
Relevance for analysing (RA)	RA1	0.857	0.910	0.716
	RA2	0.828		
	RA3	0.883		
	RA4	0.815		
Anxiety of EDM (ANX)	ANX1	0.946	0.951	0.867
	ANX2	0.920		
	ANX4	0.926		
Self-efficacy (SE)	SE1	0.843	0.918	0.737
	SE2	0.838		
	SE3	0.881		
	SE4	0.870		
Facilitating conditions (FC)	FC1	0.823	0.900	0.692
	FC2	0.850		
	FC3	0.803		
	FC4	0.851		
Perceived ease of use (PEOU)	PEOU1	0.929	0.952	0.833
	PEOU2	0.913		
	PEOU3	0.893		
	PEOU4	0.916		
Perceived usefulness (PU)	PU1	0.888	0.947	0.816
	PU2	0.928		
	PU3	0.917		
	PU4	0.880		
Behavioural intention to use EDM (BIU)	BIU1	0.876	0.940	0.798
	BIU2	0.933		
	BIU3	0.905		
	BIU4	0.857		
Optimism (OPT)	OPT1	0.836	0.920	0.697
	OPT4	0.849		
	OPT5	0.854		
	OPT6	0.849		
	OPT7	0.786		
	INV1	0.770		
INV2	0.802			
INV3	0.796			
INV4	0.809			
INV5	0.781			
INV6	0.853			
INV7	0.809			
INV8	0.694			
Discomfort (DISC)	DISC1	0.768	0.888	0.534
	DISC2	0.773		

Table 1 (continued)

Constructs	Indicators	Loadings	Composite Reliability	AVE
Insecurity (INSC)	DISC3	0.843	0.824	0.541
	DISC4	0.723		
	DISC6	0.648		
	DISC7	0.659		
	DISC8	0.679		
	INSC1	0.793		
	INSC3	0.786		
	INSC5	0.698		
	INSC7	0.656		

relationship (Urbach and Ahlemann 2010). Based on Table 3, an analysis of *t*-value and *p*-value has shown that eight hypotheses were supported. All the eight path coefficients have also shown that these paths did not contradict the research model, therefore confirming the hypothesised relationships. The results have also shown that INV had no significant effect on PU, while INSC and ANX had no significant effect on PEOU. Thus, H3, H5, and H6 were rejected.

Meanwhile, the coefficient of determination or R^2 value indicates the amount of variance in endogenous constructs that can be explained by the exogenous constructs. The values of the coefficient of determination are as such that $0 < R^2 < 1$, with higher levels indicating higher levels of predictive accuracy (Hair et al. 2014a). However, the acceptable R^2 value depends both on the model's complexity and research discipline (Hair et al. 2014a, b). Figure 2 shows that the predictive accuracy of the endogenous constructs PU (48 %), PEOU (44.2 %) and BIU (40.5 %) were satisfactory as all R^2 values were above 10 % (Escobar-Rodriguez and Monge-Lozano 2012; Falk and Miller 1992). Overall, this model can explain moderate variances in the endogenous

Table 2 Fornell-Larcker test of discriminant validity

	ANX	BIU	DISC	FC	INSC	INV	OPT	PEOU	PU	RA	SE
ANX	0.931										
BIU	−0.071	0.893									
DISC	0.379	0.071	0.731								
FC	−0.065	0.384	0.039	0.832							
INSC	0.354	0.259	0.465	0.217	0.736						
INV	0.064	0.473	0.077	0.348	0.108	0.790					
OPT	−0.001	0.458	0.115	0.470	0.280	0.377	0.835				
PEOU	−0.176	0.462	−0.131	0.521	0.109	0.492	0.419	0.913			
PU	0.000	0.614	0.132	0.400	0.246	0.426	0.592	0.523	0.904		
RA	−0.021	0.520	0.100	0.430	0.261	0.407	0.739	0.429	0.593	0.846	
SE	−0.116	0.261	0.018	0.433	0.069	0.378	0.191	0.556	0.214	0.235	0.858

Diagonal bold represents the square root of Average Variance Extracted (AVE)

Table 3 Results of the structural model based on PLS-SEM approach

Hypotheses	Constructs	Path coefficient (β)	Standard error	<i>t</i> -value	<i>p</i> -value	Results
H1	RA → PU	0.248	0.078	3.159	0.001	Supported
H2	OPT → PU	0.263	0.083	3.159	0.001	Supported
H3	INV → PU	0.100	0.075	1.323	0.093	Not Supported
H4	DISC → PEOU	-0.175	0.102	1.716	0.043	Supported
H5	INSC → PEOU	0.124	0.093	1.334	0.091	Not Supported
H6	ANX → PEOU	-0.086	0.078	1.099	0.136	Not Supported
H7	SE → PEOU	0.401	0.061	6.615	0.000	Supported
H8	FC → PEOU	0.321	0.062	5.223	0.000	Supported
H9a	PEOU → PU	0.257	0.108	2.394	0.008	Supported
H9b	PEOU → BIU	0.194	0.090	2.170	0.015	Supported
H10	PU → BIU	0.513	0.093	5.487	0.000	Supported

Critical values: $t > 1.645$; $p < 0.05$

constructs, since the R^2 values of 0.67, 0.33, and 0.19 were substantial, moderate, and weak, respectively, as suggested by Chin (1998a).

7 Discussions

The aim of this study is to develop a new acceptance model of EDM in the undergraduate education environment based on the integration of TRI and TAM3. This model was then analysed via the PLS-SEM approach. The results have shown that RA has a significant positive effect on PU of EDM. This is similar to the results obtained by Agudo-Peregrina et al. (2014); Hart et al. (2007); Huang et al. (2012); Venkatesh and Bala (2008), and Venkatesh and Davis (2000), which examined the effect of job relevance and the relevance for learning on PU. The positive effect of RA means that the students believed that using EDM technology could improve their learning and academic performances. In other words, by using EDM, students with higher performance expectations could try to make data-driven decisions rather than guesswork-driven decisions. Meanwhile, OPT had significantly predicted the PU of EDM technology. These results could expand more ideas related to individuals' general belief, as revealed by Erdoğan and Esen (2011); Godoe and Johansen (2012); Hung and Cheng (2013); Jin (2013); Kuo et al. (2013) and Walczuch et al. (2007). Specifically, students who are optimistic seemed to be more open and positive towards the application of EDM, since they believed that using this technology would offer great benefits and convenience to their academic learning.

In contrast to Erdoğan and Esen (2011) and Jin (2013), this study has failed to confirm the effect of INV on PU. One possible reason may be that the students felt that they could not be the first users of the new EDM, coupled with the feeling that they could not act as thought leaders due to their lack of awareness regarding important and newest features of the technology. Likewise, INSC did not significantly influence PEOU of EDM, probably because the technology was applied in different fields. For instance, in the marketing and business fields, customers may feel INSC, particularly

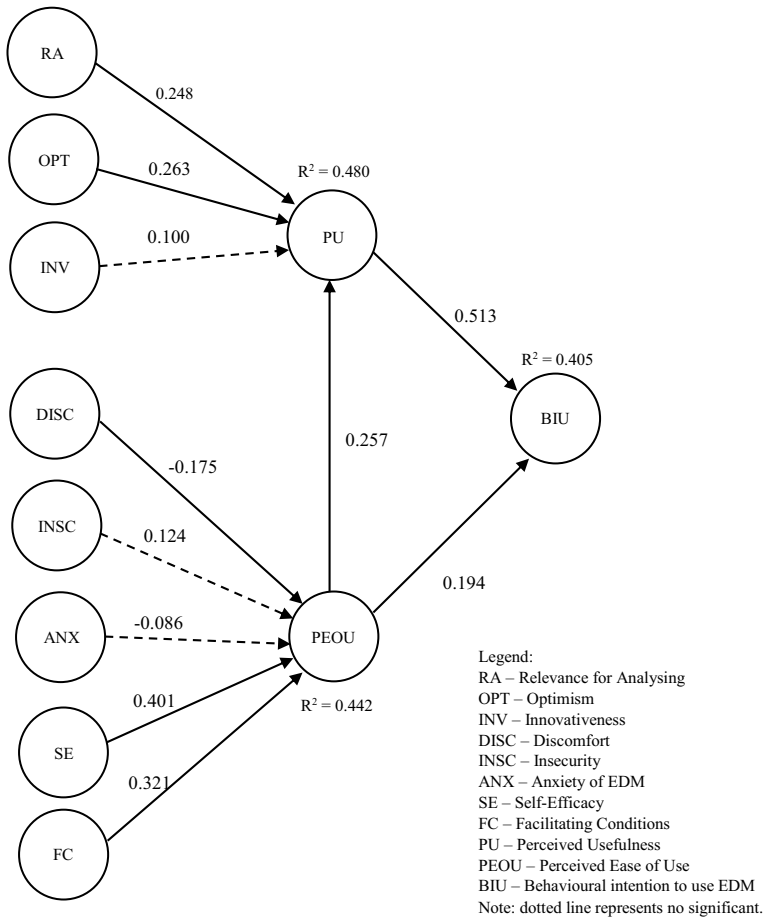


Fig. 2 The structural model

when they are forced to fill required data/information in an online transaction. This data and/or information may then be manipulated by data mining, which is favourable for traders to gain profit. Conversely, in an educational environment, EDM is used to access and manipulate academic data for enhancing students’ learning and academic performances. Hence, these students would have felt less concerned with security issues. This study has also failed to confirm the effect of ANX on PEOU of the technology. However, these results may enable the developers and practitioners to better understand that these students have not been affected by this emotional dimension (anxiety), although it has been hard for them to use this complex technology, since they have assumed the availability of technical supports to help them solve problems.

Meanwhile, the DISC construct has shown a significantly low negative impact on PEOU of EDM technology. This is an interesting result, which shows how students who scored low on this construct have led to high PEOU for the technology. This indicates that the students had more control over the technology, thus influencing them to continue to use EDM technology in the near future. The negative relationship between DISC and PEOU was also reported by previous studies (Jin 2013; Walczuch

et al. 2007). As hypothesised, SE has shown a significant positive impact on the PEOU of EDM technology, similar to those found in prior studies (Huang et al. 2012; Terzis and Economides 2011; Venkatesh and Bala 2008); thus, it is noteworthy that these students are likely to be independent and highly competent in using any new educational technology. Furthermore, FC has a significant positive impact on PEOU of EDM technology. It is worth mentioning that appropriate technical support infrastructure and available resources in an education institution could help students to perform their tasks smoothly by using EDM technology. Thus, these results are in agreement with the findings of Huang et al. (2012) and Venkatesh and Bala (2008).

As expected, PEOU has significantly predicted the PU of EDM technology. However, the score of this relationship was not as high as those found by Hung and Cheng (2013) and Kuo et al. (2013). This may be due to users in these studies lacking hands-on experience before adopting the technology. Thus, a user-friendly technology appears to be imperative. Conversely, the sample students in this study have had some experience with data mining. Therefore, they might have overcome their concerns about ease of use, and then, focused their attentions on the usefulness of the technology for an academic learning environment. Lastly, PU had a stronger effect on the BIU of EDM compared to PEOU. This is in accordance with the results of previous studies (Erdoğan and Esen 2011; Godoe and Johansen 2012; Hung and Cheng 2013; Jin 2013). Findings of the present study have indicated that the nature of students' overall assessments of the EDM utilisation have relied on perceptions of what is received than what is given (Zeithaml 1988). In other words, there is more emphasis on the 'get' component value, while less emphasis is given to the 'give' component value (Lin et al. 2007).

8 Conclusions

The present study has integrated the constructs of TRI and TAM3 into one refined research model. This integrated model expands prior models, while emphasising on individual and technology-specific features. The model was analysed using a PLS-SEM approach that can predict and explain the variances of the target constructs. In this study, BIU of EDM is the target construct, predicted and explained by different explanatory constructs of TRI and TAM3. The empirical results have shown that RA, OPT and PEOU have positively affected the PU of EDM technology. Furthermore, SE and FC have significant impacts on PEOU of EDM technology. Meanwhile, the insignificance of, (i) INV on PU; and (ii) INSC and ANX on PEOU did not hinder the students' intention to use the technology in an undergraduate educational environment. Interestingly, the low degree of DISC has led to a high students' perception towards PEOU of EDM technology. Overall, students were more concerned over what they could get or receive (i.e., perceived usefulness) from EDM, than what they could give (i.e., perceived ease of use) in terms of technology.

9 Recommendations

This study focuses on the acceptance of EDM technology among undergraduate students, which is assumed as a new technology in CBES, particularly in the

Malaysian context. Despite the proposed research model being replicable or revisable for other novel technologies in other organisational contexts, adopting this model for well-established technologies may be problematic, as TRIs' dimensions are less applicable to such technologies (Godoe and Johansen 2012). Therefore, researchers are encouraged to carefully choose appropriate theoretical models and constructs, along with prospective technology and context.

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