Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 14 (18): 2129-2138, 2014
ISSN 1812-5654 / DOI: 10.3923/jas.2014.2129.2138

Data Mining Technology Adoption in Institutions of Higher Learning: A Conceptual Framework Incorporating Technology Readiness Index Model and Technology Acceptance Model 3

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Abstract: The adoption of Data Mining Technology (DMT) is on the rise due to its ability to discover hidden knowledge amongst large amounts of data. This technology is particularly important to organisations for making well-informed decisions and formulating strategic plans. However, previous studies on DMT have focused more on evaluating methods and techniques-rather than focusing on end-user perspectives. Moreover, studies on the adoption of DMT have been successfully conducted in various fields except for education, in particular, regarding the utilisation of DMT at an individual-level. Motivated by these problems, this study seeks to integrate the Technology Readiness Index (TRI) and the Technology Acceptance Model 3 (TAM3) into a model that will investigate end-user (individual-level) determinants of DMT adoption, specifically in the context of Institutions of Higher Learning (IHLs) in Malaysia. Several determinants from past literature were adopted and adapted in proposing the newly integrated TRI and TAM3 model. Ultimately, this model could aid management personal, particularly decision makers, to predict the acceptance or rejection of DMT in IHLs.

Key words: Technology acceptance model 3, technology readiness index model, data mining technology, adoption, institutions of higher learning

INTRODUCTION

Data Mining Technology (DMT) is a robust technology that can help organisations to make optimal informed decisions-instead of guesswork decisions (Nemati and Barko, 2010), by extracting precious knowledge from huge amounts of data. This technology is comprised of various methods and techniques which have been extensively used in businesses, industries and corporate sectors. The techniques and methods used in these sectors could also be applicable to the education environment (Ranjan and Malik, 2007).

DMT is capable of exploring the unique types of data in educational databases (Romero and Ventura, 2013). This could help to improve the quality educational data analysis on a large-scale (Siemens and de Baker, 2012) for proactive and knowledge-driven decision-making (Bhullar and Kaur, 2012). Based on such benefits, Institutions of Higher Learning (IHLs) should embark on DMT projects as a new avenue for understanding and enhancing the teaching and learning process (Ghaffari *et al*., 2012). In fact, the technology is critical for IHLs to remain competitive and be at least one-step ahead of their competitors (Nemati and Barko, 2010).

Although, some IHLs have made large investments in DMT, they have always focused either on the technical aspect or the development of DMT application algorithms-without considering users' perception of the technology (Romero and Ventura, 2010; Garcia *et al*., 2011; Johnson, 2013). Little effort has been used to analyse how users utilise the technology (Baepler and Murdoch, 2010) which hinders users from appreciating DMT's capabilities. Similar to other technologies, DMT needs to obtain the users' acknowledgement; otherwise, the users might abandon it (Jan and Contreras, 2011) despite the prevalent benefit. It is important to identify the users' behaviour prior to adopting the technology, as this could help minimising underutilisation or eventual abandonment.

Technology Acceptance Model (TAM) and its extended models are related to the user's behaviour towards technology. Since the main purpose of this study is to investigate the influence of an individual's readiness

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to accept DMT in IHLs, the Technology Readiness Index (TRI) (Parasuraman, 2000) model will be integrated with TAM3 (Venkatesh and Bala, 2008). Integrating these two models would enrich the understanding of individual usage behaviour towards DMT, hence contributing to the corpus of knowledge related to innovative adoption studies.

DATA MINING TECHNOLOGY IN EDUCATION

The application of DMT in education is known as Educational Data Mining (EDM). EDM refers to "the area of scientific inquiry centred around the development of methods for making discoveries within the unique kinds of data that come from educational settings" (De Baker, 2010). It is also defined as the application of DM techniques to specific types of datasets in an educational environment (Romero and Ventura, 2007, 2010, 2013). There are a wide variety of methods (e.g., prediction, clustering and relationship mining) and techniques (e.g., decision trees, neural network, rough set and k-means) that could be used to mine educational data. The most commonly used are decision trees, neural networks and Bayesian networks (Romero and Ventura, 2010).

EDM is concerned with how to analyse large-scale educational data for better understanding about learning and how to provide information regarding the learning process (Romero *et al.*, 2011). Figure 1 illustrates the process of EDM which acts like a 'heart' that transforms large amounts of data into precious knowledge.

DMT is used to access educational data either from traditional education or web-based education systems (Romero and Ventura, 2013). Traditional education is based on face-to-face contact between educators and students organised in a classroom environment (Romero and Ventura, 2007) and can also use computer-based educational systems as a complementary tool (Romero and Ventura, 2013).

In the traditional education settings, DMT is used as a stand alone system to assist educators to predict future trends and behaviours of students (i.e., performance and curriculum) during the course session. For instance, Antunes (2011) used DMT (i.e., CAR-based ASAP classifiers) for predicting students' failure in the "Foundation of Programming" course at Instituto Superior Tecnico, Portugal. The results revealed that the proposed classifier is an optimal classifier compared to the others in predicting students' failure. Pal (2012) also used DMT (i.e., Naïve Bayes classifier) for engineering students' dropout management system in India. The results showed that the method is able to predict the number of students who were inclined to dropout from their studies.

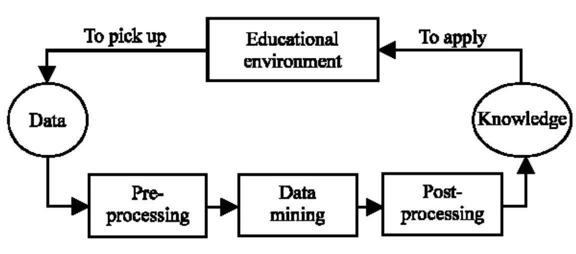

Fig. 1: Educational data mining process (Garcia *et al.*, 2011)

Recently, DMT has been increasingly used within web-based education systems (e.g., e-learning, Learning Management System (LMS), Intelligent Tutoring System (ITS) and Adaptive Educational Hypermedia System (AEHS) to better understand students' online learning behaviour (Romero and Ventura, 2013). For example, Zafra and Ventura (2012) applied DMT (i.e., multi-instance grammar guided genetic programming technique) for predicting student performance in the University of Cordoba.

The prediction is based on students' activities (e.g., content viewed, assignments submitted, time spent and quiz results) extracted from logged data in a web-based education system. The results reveal that the technique could be used for early identification of students who are at risk, particularly in large classes and allowed educators to determine more effective activities that could improve students' learning (Zafra and Ventura, 2012). Therefore, this technology is vital in enhancing web-based education environments for both educators and students to better evaluate the learning process and to help students in their learning endeavours (Zaiane, 2001).

Specific tools are required for mining educational data, such as Clementine, WEKA, XLMiner, IlliMine and SAS Miner, among others. However, most of these tools are scarcely used in the academic context (Ranjan and Malik, 2007). Table 1 shows several DM tools specifically developed for solving a wide range of educational problems.

Despite the fact that DM tools are potentially able to shape modern advanced educational systems, they are complex and beyond the scope of what educators may want to use (Romero and Ventura, 2010; Garcia *et al.*, 2011), as the tools are always used for comparing various methods, techniques and algorithms of DMT. Moreover, the design of the tools are argued to be simple rather than sophisticated and flexible (Romero and Ventura, 2013). Therefore, prior to employing the DM tool in IHLs, the user's acceptance of the DMT will have to be made known (Romero and Ventura, 2010) since not all users understand the technology (Johnson, 2013).

Table 1: Educational data mining tools (Romero and Ventura, 2013)

EDM tools	Goal
EPRules	To discover prediction rules to provide feedback for courseware authors
GISMO	To visualise what is happening in distance learning classes
TADA-ED	To help teachers to identify relevant patterns in students' online exercises
O3R	To retrieve and interpret sequential navigation patterns
Synergo/CoIAT	To analyse and produce interpretative views of learning activities
LISTEN mining tool	To explore large student-tutor interaction logs
MINEL	To analyse navigational behaviour and the performance of the learner
LOCO-analyst	To provide teachers with feedback on the learning process
Measuring tool	To measure the motivation of online learners
Datashop	To store and analyse click-stream data, fine-grained longitudinal data generated by educational systems
Decisional tool	To discover factors contributing to students' success and failure rates
CIECoF	To make recommendations to courseware authors about how to improve courses
SAMOS	To browse student activity using overview spreadsheets
PDinamet	To support teachers in collaborative student modelling
AHA! Mining tool	To recommend the best links for a student to visit next
EDM visualisation tool	To visualise the process in which students solve procedural problems in logic
Meerkat-ED	To analyse participation of students in discussion forums using social network analysis techniques
MMT tool	To facilitate the execution of all the steps in the data mining process of model data for newcomers
SNAPP	To visualise the evolution of participant relationships within discussions forums
AAT	To access and analyse students' behaviour data in learning systems
DRAL	To discover relevant e-activities for learners
E-learning web miner	To discover student's behaviour profiles and models in virtual courses

Understanding the determinants that could influence users in accepting or adopting DMT is challenging-since everyone has their own predicament regarding perspectives. Table 2 displays several previous studies on DMT adoption. While studies related to DMT adoption have been extensively conducted in banking (Dahlan *et al*., 2002a), finance (Chang *et al*., 2003), accounting (Rahman, 2008), telecommunications (Dahlan *et al*., 2002b), insurance (Ramayah *et al*., 2007), business (Huang *et al*., 2012; Wah and Bakar, 2003), multiple industries (Nemati and Barko, 2003) and small and medium enterprises (Huang and Chou, 2004), as far as this study is concerned, no study has been carried out in the educational context.

Table 2 also shows that all studies on DMT adoption emphasis on organisational-level except a study by Huang *et al*. (2012). This has eventually called for a study on user adoption of DMT focusing at the individual-level.

TECHNOLOGY ACCEPTANCE MODEL (TAM) AND EXTENDED MODELS

The debate on the most relevant determinants which can predict and explain user adoption, acceptance and the use of either general or specific types of IT, continues to persist. The Theory of Reasoned Action (TRA) which explains users' attitude towards technology (Fishbein and Ajzen, 1975), has been used to be the basis for developing TAM (Davis, 1986). TAM is then used for predicting and explaining individual technology acceptance based on the internal psychological beliefs of the individual user.

TAM is comprised of Perceived Usefulness (PU) and Perceived Ease Of Use (PEOU) as fundamental determinants of the user's behavioural intention to use new technology (Al-Qeisi, 2009; Venkatesh and Davis, 2000; Davis, 1989). Behavioural intention refers to the measure of strength, requests and efforts of an individual's intention to perform a specified behaviour (Fishbein and Ajzen, 1975; Erdogmus and Esen, 2011). PU is defined as a person's belief that using a particular technology could enhance job performance and PEOU refers to the degree to which a person believes that a given technology would reduce job intensity (Davis, 1989).

Although, TAM has been widely cited, replicated and extended empirically by various studies (Lin *et al*., 2007), it typically explains approximately 40% of user adoption (Venkatesh and Davis, 2000). The number of researchers concerned with the imperfection of this model is, however, increasing particularly with reference to the exclusion of significant variables (Huang *et al*., 2012).

TAM was later extended to TAM2, Unified Theory of Acceptance and Use of Technology (UTAUT) and TAM3 for improving the classification of user determinants regarding the use of new technology. TAM2 was introduced to explain PU and usage intentions based on social influence (subjective norm, voluntaries and image), cognitive instrumental processes (job relevance, output quality and result demonstrability) and experience. This model was able to explain 60% variance of user adoption (Venkatesh and Davis, 2000) and fit to address the technology adoption in mandatory settings only (Yoo *et al*., 2012).

In order to enhance the adoption of technology, the UTAUT model was formulated to comprise of four core determinants (performance expectancy, effort expectancy,

Table 2: Related studies on DMT adoption

	Areas								
	Banking	Telco*	Business	Industries	Finance	SME*	Insurance	Accounting	Business
Factors	Dahlan *et al.* (2002a)	Dahlan *et al.* (2002b)	Wah and Bakar (2003)	Nemati and Barko (2003)	Chang *et al.* (2003)	Huang and Chou (2004)	Ramayah *et al.* (2007)	Rahman (2008)	Huang *et al.* (2012)
Individual									
Optimism	√	√					√	√	
Innovativeness	√	√						√	
Discomfort	√						√		
Insecurity	√								
Behavioural intention to use								√	√
Perceived usefulness								√	√
Perceived ease of use								√	√
Users' skill and experience	√	√	√	√			√	√	√
Job relevance								√	√
Output quality									√
Result demonstrability									√
Response time									√
Format									√
Computer self-efficacy									√
Perceptions of external control									√
Computer anxiety									√
Computer playfulness									√
Education								√	
Age								√	
Gender								√	
Organisation									
Business strategy	√	√		√			√		
Data-driven culture	√	√			√		√		
Organisation culture/support			√		√				
IT infrastructure and expertise	√	√	√	√	√		√	√	
Project (time, cost, resources)			√	√					
IT-based industry			√			√			
Decision-making style					√				
Competitiveness					√	√			
Organisation size						√		√	
Organisation age						√			
Business complexity						√			
Internet strategy						√			
International strategy						√			
Website content strategy						√			
Technological benefits						√		√	
External factors								√	

*Telco: Telecommunication, SME: Small and medium enterprise social influence and facilitating conditions) of intention and usage as well as four moderators (gender, age, experience and voluntariness of use) of key relationships (Venkatesh *et al*., 2003). This model is comprehensive and has a parsimonious structure that can explain up to 70% of variance in usage intentions (Al-Qeisi, 2009). However, the highest score could not be reached without all of the four moderating variables (gender, age, experience and voluntariness). This makes the UTAUT model less parsimonious than the first two TAM models (Van Raaij and Schepers, 2008). Moreover, it is impractical to address all UTAUT's constructs in promoting the adoption of new technology among users (Yoo *et al*., 2012).

Venkatesh and Bala (2008) proposed an integrated model (nomological network), known as TAM3, for understanding individual-level Information Technology (IT) adoption and usage. This model integrats the determinants of PU (i.e., TAM2) (Venkatesh and Davis, 2000) and PEOU (Venkatesh, 2000) but both determinants did not cross-over which means that determinants of PU could not influence PEOU and vice versa. The idea of separation is due to the determinants of PU that are tied to social influence (subjective norm, voluntariness and image) and cognitive instrumental processes (job relevance, output quality and result demonstrability) (Venkatesh and Davis, 2000).

In contrast, the determinants of PEOU are primarily based on individual and situational variables that relate to anchoring (i.e., internal control (computer self-efficacy), external control (facilitating conditions), emotion (computer anxiety) and intrinsic motivation (computer playfulness)) and adjustments-based theoretical model (i.e., perceived enjoyment and objective usability) (Venkatesh, 2000). Experience would moderate the relationships between PEOU and PU, PEOU and behavioural intention, subjective norm and behavioural intention, subjective norm and PU, computer anxiety and PEOU, computer playfulness and PEOU, perceived enjoyment and PEOU as well as objective usability and PEOU.

TAM3 is more comprehensive than the previous models in the sense of understanding individual user reactions towards new IT in the workspace due to the omission of cross-over effects between determinants of PEOU and PU (Venkatesh and Bala, 2008). The TAM3 was applied for identifying how users perceived and adopted DMT in broadening practical knowledge for the business intelligence community in Taiwan. The results showed that the proposed model was able to explain 58% of variance (Huang *et al*., 2012). In relation to this, this study focuses on TAM3 which is seen to be able to give a new, in-depth insight for explaining the acceptance, adoption and use of the technology when integrated with the Technology Readiness Index (TRI) model.

TECHNOLOGY READINESS INDEX (TRI) MODEL

Parasuraman (2000) developed TRI in order to identify people's tendency to accept and use new technologies. The TRI model consists of four constructs (optimism, innovativeness, discomfort and insecurity) which are able to measure an individual's general belief (i.e., readiness) towards new technology. Optimism refers to a positive perception of technology and a belief that technology can increase control, flexibility and efficiency. Innovativeness involves the tendency to be a technology pioneer and thought leader. Discomfort relates to a feeling of lack of control of technology and a sense of being overwhelmed. Insecurity consists of perceptions of distrusting technology due to self-insecurity and doubting its ability to work properly.

The readiness for using new technologies is contributed by positive and negative feelings. The positive feelings are optimism and innovativeness while the negative feelings are discomfort and insecurity. These feelings serve as constructs that are relatively independent of each other (Elliott *et al*., 2008) and each individual might possess any combination of them (Massey *et al*., 2005). Furthermore, users with high optimism and innovativeness score high on the TRI since they do feel comfortable (only call for minimal proof of its performance) in using new technology while users with lower TRI scores tend to be more critical (always asking for help and feel uncomfortable) with new technology (Walczuch *et al*., 2007).

The TRI model was initially used to understand the readiness of customers toward technology-based services (e.g., financial services, online services, electronic commerce and telecommunications). The results revealed that the model is significant in predicting individual usage behaviour (Parasuraman, 2000). The concept was then applied widely to other specific technologies such as mobile data services (Massey *et al*., 2005), airline check-in services (Van Riel *et al*., 2006), self-service technologies (Elliott *et al*., 2008), electronic healthcare records (Caison *et al*., 2008), ICT in education (Summak *et al*., 2010) and social networking sites (Borrero *et al*., 2014), among others.

Some studies report TRI to play a minor role in explaining customer behaviour (Van Riel *et al*., 2006) and teachers' readiness (Summak *et al*., 2010) towards technology while other studies discovered that TRI is vital in identifying the expected users that intend to use the technology prior to implementation (Caison *et al.*, 2008) and the degree of user satisfaction from the technology (Massey *et al.*, 2005). This model also significantly moderates the social and psychological factors of a user's technology readiness (Borrero *et al.*, 2014). Thus, TRI is important in accessing technology readiness among users in order to make the right decision in terms of designing, implementing and managing the relationship between the user and technology (Parasuraman, 2000).

While the leading focal point on TRI has been the technology-based services, there have been some studies focusing on DMT readiness in the contexts of telecommunication (Dahlan *et al.*, 2002a), banking (Dahlan *et al.*, 2002b) and insurance (Ramayah *et al.*, 2007). However, none of these studies have empirically validated the DMT readiness in the educational context. Furthermore, previous studies might also not be applicable for an educational setting due to different objectives (Romero and Ventura, 2010). Van Riel *et al.* (2006) call for rigorous study to explore the ability of TRI in predicting users' acceptance of technology. This would be more relevant if TAM3 is integrated with TRI to investigate the acceptance of user towards new technology.

The integration between TRI and any TAM has been the main concern of some researchers, as shown in Table 3. Based on the table, most studies confirmed that the TRI's constructs (independent variables) are related to user acceptance behaviour. Furthermore, the integration of TRI and TAM can give a new, in-depth insight in explaining the complexity of the user's positive and negative feelings about technology (Lin and Chang, 2011).

Understanding the feelings of users is essential when a new technology is introduced. Users need a general belief about the technology (i.e., individual-specific) that can be identified through TRI constructs. In this regard, TAM plays a critical role in explaining the general view of a particular technology (i.e., technology specific) (Lin *et al.*, 2007; Godoe and Johansen, 2012; Guhr *et al.*, 2013). Little attention has been given to exploring the effects of integrating TRI and TAM3, particularly for DMT. Studies are required to elucidate the expected integration that could enhance the individual's adoption of DMT in the IHL context.

PROPOSED CONCEPTUAL FRAMEWORK

The framework for this study is derived from the in-depth study on TAM, TAM2, UTAUT, TAM3 and TRI. Despite the fact that various studies have examined a range of determinants on intention to use and actual use behaviour, this study has considered the determinants that empirically give significant impact towards DMT adoption. The non-significant impacts have been eliminated to ensure the high validity and reliability of each construct.

The three dimensions identified as major determinants contributing to DMT adoption are cognitive

Table 3: Studies on the integration of TRI and TAM

Technology	Variables: Independent	Variables: Dependent	References
Software application that they use most (not specific technology)	Optimism, innovativeness, discomfort, insecurity	Perceived usefulness, perceived ease of use	Walczuch *et al.* (2007)
e-service systems (online stock trading systems)	Optimism, innovativeness, discomfort, insecurity	Perceived usefulness, perceived ease of use, behavioural intention to use	Lin *et al.* (2007)
Self-Service Technologies (SSTs)	Optimism, innovativeness, discomfort, insecurity	SST-behavioural intention to use SST-satisfaction	Lin and Hsieh (2007)
Internet	Optimism, innovativeness, discomfort, insecurity	Adoption time, personel use	Lam *et al.* (2008)
Self-Service Technologies (SSTs)	Technology readiness, perceived usefulness, perceived ease of use.	Behavioural intention, attitude	Lin and Chang (2011)
e-HRM systems	Optimism, innovativeness, discomfort, insecurity	Perceived usefulness, perceived ease of use, behavioural intention to use	Erdogmus and Esen (2011)
Self-Service Technologies (SSTs)	Optimism, innovativeness, discomfort, insecurity	Attitude, perceived usefulness perceived ease of use, perceived reliability, perceived fun	Elliott *et al.* (2008)
Electronic Health Record (EHR) and Instant Messaging (IM) system	Optimism, innovativeness, discomfort, insecurity	Perceived usefulness, perceived ease of use, actual use	Godoe and Johansen (2012)
Mobile payment (m-payment) services	Perceived usefulness, perceived ease of use, optimism, innovativeness, discomfort, insecurity	Behavioural intention to use	Guhr *et al.* (2013)
Information and Communication Technology (ICT)	TRI, optimism, innovativeness, discomfort, insecurity	ICT acceptance	Gombachika and Khangamna (2013)

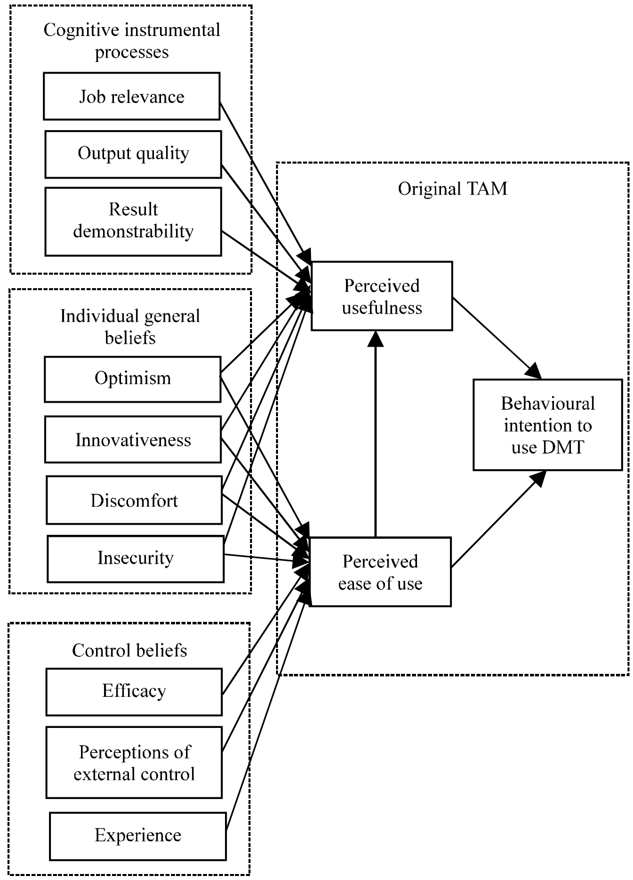

Fig. 2: Proposed conceptual framework

instrumental processes, control beliefs and individual general belief (i.e., readiness). The cognitive instrumental processes and control beliefs are derived from TAM3 while the individual general beliefs are from Parasuraman's TRI. Figure 2 illustrates the proposed conceptual framework of this study.

The original TAM and its extended models, particularly TAM2 and TAM3, are comprised of PU and PEOU situated in the middle and behavioral intention to use situated before the end of the actual use construct. Several studies have demonstrated that the actual usage is the main determinant of technology adoption (Raman, 2011; Pynoo *et al.*, 2012; De Smet *et al.*, 2012; Tarhini *et al.*, 2013). However, other studies (Chau and Hu, 2002; Ramayah *et al.*, 2002; Al-Qeisi, 2009; Zacharis, 2012) confirm that when the technology is a new phenomenon to the user, the user's decision to accept or adopt the technology is a conscious act that is sufficiently explained by the behavioural intention to use.

Since, the application of DMT is still in its infancy for handling large amounts of educational data, the dependent variable used in this study restricted the 'behavioural intention to use'. The behavioural intention to use for this study is defined as the stage where the DMT is selected for use by users (e.g., students, educators or administrators) for assisting them in analysing large-scale educational data in IHLs.

As mentioned earlier, TAM3 is comprised of the determinants of PU and PEOU separately. The PU's determinants are social influence processes (subjective norm, voluntaries and image) and cognitive instrumental processes (job relevance, output quality and result demonstrability). The determinants of PEOU encompasses anchoring (computer self-efficacy, perceptions of external control, computer anxiety and computer playfulness) and adjustments perpectives (perceived enjoyment and objective usability) (Venkatesh and Bala, 2008).

For this study, the cognitive instrumental processes, such as job relevance, output quality and result demonstrability, are chosen as determinants for PU. This is due to DMT's capabilities (i.e., decision-making support) involving more cognitive instrumental processes rather than social influence processes (Huang *et al*., 2012). In addition, the effects of cognitive instrumental processes have often remained significant (Venkatesh and Davis, 2000).

Meanwhile, Huang *et al.* (2012) discovered that computer self-efficacy and perceptions of external control have direct effect on the PEOU of a DMT. As the determinants are significant for adopting DMT, this study will employed both determinants. However, the computer self-efficacy element is simplified as efficacy in DMT.

Despite the role of experience, it is significant to provide the moderator effects on behavioural intention to use of IT (Venkatesh and Bala, 2008). Although, Huang *et al.* (2012) argued that moderating effect of experience is not significant for the DMT adoption, there are other determinants that can positively determine DMT usage, such as skill and experience (Dahlan *et al*., 2002a). Due to these inconsistencies, this study decided to adopt experience as a direct determinant of PEOU. Thus, the efficacy, perceptions of external control and experience formed the control beliefs, as depicted in the proposed conceptual framework (Fig. 2).

The TRI is comprised of four constructs, whereby optimism and innovativeness are contributors of technology readiness while discomfort and insecurity are inhibitors. These constructs are used both as independent (Lin and Hsieh, 2007; Lam *et al*., 2008; Lin and Chang, 2011 and Guhr *et al*., 2013) and dependent variables (Dahlan *et al*., 2002a, b; Ramayah *et al*., 2007) which significantly determined the technology adoption. However, there is no study that has used these constructs as direct determinants (independent variables) for understanding the individual's general belief of DMT. Due to this fact, this study employs TRI's four constructs for investigating DMT adoption in IHLs since eliminating any one would make the readiness domain incomplete (Lam *et al*., 2008).

CONCLUSION

It is acknowledged that DMT is a type of decision-making support tool for users. Understanding the determinants of DMT adoption gains its importance, particularly from an individual-level perspective. Understanding the individual's perspective towards DMT can be done by means of integrating the TRI and TAM3 which may contribute to a comprehensive explanation of technology adoption.

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