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e-Adoption of Smart Learning in Higher Education

ABSTRACT

e-Adoption is essentially focused in 21st century around the globe as individuals and all sorts of organizations have adopted the world wide web and other web-based technologies for daily, learning and business activities. The evolution of web and online technologies, and swift emergence of smart devices have changed the learning environments. Smart learning has transpired as novel paradigm which have facilitated anytime, anywhere learning. The traditional features and environment of e-Learning have been unsuccessful to gauge the innovative features of recently emerged learning environments and resultantly, have ascertained the need of adoption of new patterns of smart learning so that educational needs of organizations and learning needs of technology-oriented learners may be fulfilled. For proposing an appropriate means of successful e-Adoption, this research study enlightens the characteristics of smart learning. This study also amasses the opinions and perceptions of university faculty members regarding

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acceptance of smart learning in their higher education institutions. Four components of smart learning, derived from distinctive features of e-Learning, mobile learning & ubiquitous learning, are mobility, interactivity, personalization, and collaboration. Technology Acceptance Model (TAM) is utilized for measuring the intentions of university faculty regarding e-Adoption of smart learning. These features of smart learning differently impact on, i) perceived usefulness (PU) and ii) perceived ease of use (PEOU) of smart technologies in higher education. Mobility, interactivity, and personalization have significant relationship with PU and PEOU. Data is analyzed using structural equation Modeling (SEM). The analysis presents effective direction and support for e-Adoption of smart learning in higher education.

Key Words: *e-Adoption, smart learning, ubiquitous learning, mobile learning, social learning, Technology acceptance model, higher education.*

Introduction

e-Adoption is essentially focused in 21st century around the globe as individuals and all sorts of organizations have adopted the world wide web and other web-based technologies for daily, learning and business activities. Educational organizations have adopted web-based technologies and tools for enhancing the effectiveness and efficiency and turnover of organization. Students are using e-Adoptions for equipping themselves through online active participation in variety of online learning activities. Since advanced technologies are used in education, educational environments are altogether changed with amplified impacts on learning and teaching.

Emergence of digital technologies and e-learning has significantly affected the educational scenario. In recent past years, e-Learning has gone through its latest generations as m-Learning became known being driven by evolution in mobile as well as wireless technologies. According to Sharples et al. (2009), the learning method which uses mobile technologies as well as wireless communication technologies is known as Mobile Learning (m-Learning).

Mobile learning is acknowledged by improvements in e-Learning in wake of flexibility of location, ease of use, device cost, and time flexibility. However, the key difference is about using wireless technologies and mobile devices in m-Learning. As technologies kept on improving, m-Learning has shifted to u-Learning i.e. Ubiquitous Learning. u-Learning environments enable the students to study anywhere, anytime through varied digital terminals. So, the u-Learning environments may be approached in diverse situations and contexts but here learning is self-directed and interactive. Immediacy and permanency of information are two significant features of u-Learning which trigger according to need and context of learners. Sensing technologies like GPS (Global Positioning System), RFID (Radio-Frequency Identification), and QRC (Quick Response codes) have extended abilities of learning systems for identifying real world contexts and locality of learners. This set-up has facilitated the promotion of context-aware u-learning environments, that are intelligent enough for students to spot their status of real-world settings and also their environmental contexts. Liu and Hwang (2010) rightly argue that there is a shift in Technology-enhanced learning from web-based learning (e-Learning) to m-Learning and then from m-Learning to context-aware u-Learning.

Smart Learning

In spite of these technological modifications in learning scenarios, researchers have specified the need of more aspects and features for designing and developing learning environments that enable the learners to learn in 'smart' ways in their real-world contexts.

According to Hwang (2008), many researches get on concentrating to the significance and need of authentic learning activities where learners learn through working with real world problems. To engage the students in authentic learning activities, it is vital to shape learning that blends real as well as virtual learning environments. Smart learning (s-Learning) corresponds to several aspects and features of m-Learning & u-Learning, which enables the learners to learn across place and time by transforming learning into individualized and social learning through smart devices (Chan et al. 2006).

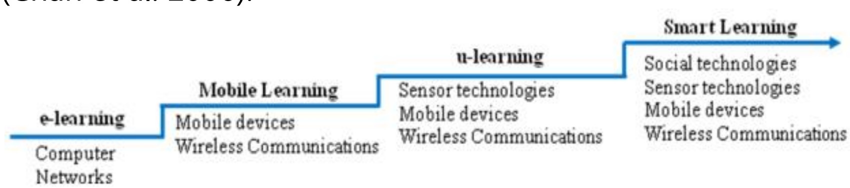

Figure 1: e-Learning to Smart Learning

Smart Learning (s-Learning) is a novel style which endows with personalized and adaptive learning practices in social learning environment influencing the potential features and affordances of smart devices e.g. iPads, smart phones and tablets. However, there is no obvious and cohesive definition of s-Learning but this concept is widely discussed in educational scenarios. Different researchers discuss different features of s-Learning. Hwang and Li (2014) believes that smart learning basically is context-aware ubiquitous learning. Kim et al. (2013) confers to Smart Learning is not limited to only using smart devices but it should be defined taking in account multiple perspectives of u-Learning and m-Learning. Noh et al. (2011) explicated the concept of smart leaning combining the beneficial features of ubiquitous learning and social learning which occurs in collaborative and student-centered learning environments, primarily rooted by services and interactive digital content. Learner-centric features and benefits of smart learning are also specified by Middleton, 2015; Merrill, 2013. Enhanced learning engagement and more open individualized learning are two leading features of smart and personalized technologies in affluent contexts.

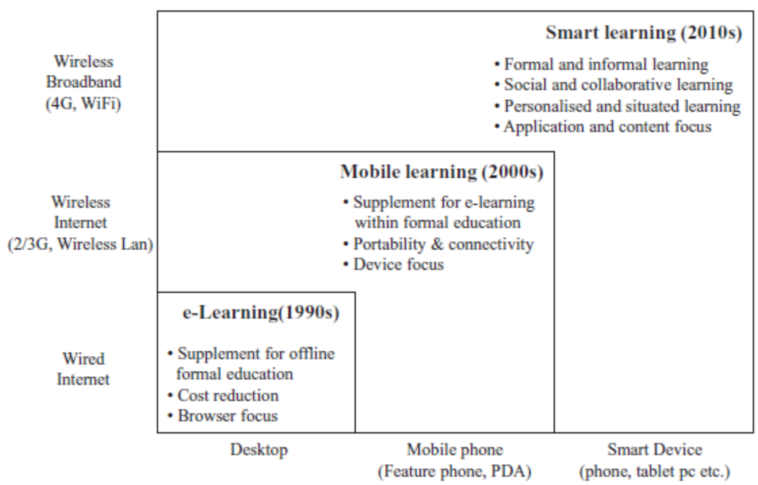

Figure 2: Evolution of Smart Learning

Smart learning was introduced by the Korean government, who delineated smart learning as educational environment comprised of smart devices presenting the features of personalization, self-motivation and self-learning (Kim, Cho & Lee, 2013). The concept of s-Learning was suggested at 'Smart Learning Korean Forum' by Gwak (2010) as:

i) it is more concerned about learners and content rather than smart devices,

ii) smart learning is supported by advanced technological infrastructure making it intelligent and effective mode of learning.

Smart Learning is the combination of existing scenarios of technological advancements in e-learning. This can be rightly said that smart learning is the latest generation of e-learning which encompasses all the characteristics and features of older cohort of e-Learning i.e. mobile learning (m-Learning) and ubiquitous learning (u-Learning) with additive features of social learning in this current age of learning. Smart learning can simply be expressed as:

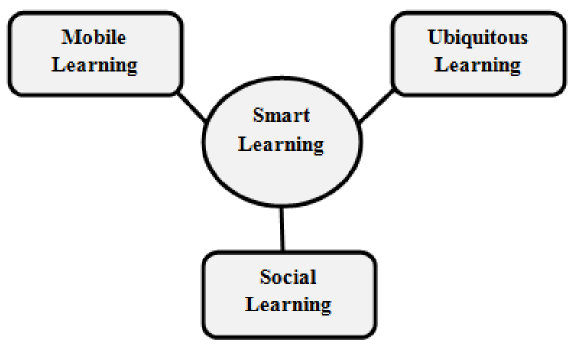

Figure 3: Constituents of Smart Learning

Hwang et al. (2008) discuss in detail about Smart Learning environments (SLE) from the aspect of context-aware ubiquitous learning. According to Micheal (2016), smart learning environment specific characteristics of knowledge; learner sensitivity, reflection, context sensitivity, task support and feedback. Spector (2014) believed that SLE provides the alternative innovative traits of efficiency, engagement, effectiveness, adaptivity, flexibility and reflectiveness to instructors and learners.

Important components of Smart Learning

As smart learning is combination of other technological formats of e-Learning, it comprises of a combination of components of e-Learning generations, i.e. social learning, u-Learning, and m-Learning. A pictorial illustration of components of smart learning environment containing all the possible features of m-Learning, u-Learning and social learning is given.

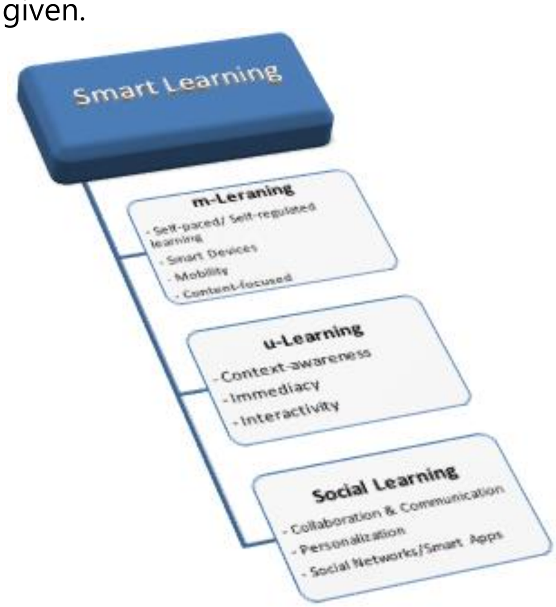

Figure 4: Components of Smart Learning

Mobile Learning Features: According to Zhang *et al*. 2010; Looi *et al*. 2010, 2011; Frohberg *et al*. 2009; Martin & Ertzberger, 2013, mobile technology supports learning within diverse contexts and locations. The important features of mobile learning are:

1) *Mobility:* supported by (Sharples et al. 2005, 2007; Trentin & Repetto, 2013; R. Martin, MacGill, & Sudweeks, 2013)
2) *Self-regulated and self-paced learning*: supported by (Hwang & Chang, 2011; Sheppard, 2011; Zimmerman 2001; Kitsantas & Dabbagh, 2010, 2011; Dabbagh & Kitsantas, 2012; Nicol, 2009)
3) Smart devices : Supported by (Gosper, Malfroy & McKenzie, 2013)
4) Content-focused learning : supported by (Rueckert et al., 2012)

Ubiquitous Learning Features: The new paradigm of u-Learning have shifted the learning from teacher-centered to self-directed learning embedding the features of e-Learning and m-Learning (Song, Kim & Jung, 2009). The essential features of u-Learning are:

1. Context-awareness: supported by (Kakihara & Sorensen, 2002; Pica & Allen, 2004; Sherry & Salvador, 2004; Chiu et al. 2008)
2. Immediacy: supported by (Yahya, 2010)
3. Interactivity: supported by (Wang, 2006)

Social Learning Features: Albert Bandura, in late 1970s, presented the eminent theory of 'Modern Social Learning' which suggested that people learn in their social context. An educational shift towards student-centered learning stimulates interest in the social learning rather than u-learning. Resultantly, educators have explored the educational potential of latest social technologies, which include web 2.0 SNS (social network services) & mobile web 2.0 etc. Researches show that these social technologies greatly support to social constructivism (Cochrane & Bateman, 2010). It is therefore argued that smart learning as new paradigm has emerged as convergence view of ubiquitous learning and social learning (Adu & Poo, 2014). Wilen-Daugenti (2011) further emphasized that the learning services which are delivered through the mobile devices of learners stick to obligation that learning ought to be tailored to the characteristics, situations and needs of the learners, thus making learning more effective (Blackmore, 2010; Buckingham & Ferguson, 2012). Some important components of smart social learning are:

1. Collaboration: supported by (Chen & Bryer, 2012; Mason and Renniet, 2008)
2. Personalization: supported by (Hsu & Ching, 2013; Valdivia and Nussbaum 2007)
3. Smart devices/smart apps: supported by (Adu & Poo, 2014)

e-Adoption of Smart Learning in Higher Education

The researchers have rightly enlightened the facts that learning no more can be perceived only as a delivery of instruction undertaken in traditional educational environments. But in recent trends of learning and technology, advent of smart learning environments, social networks and smart devices have changed the state of learning being smart. Smart approaches to learning are thus vital for investigating the adoption of teaching and learning approaches in new paradigms of smart learning. The existing researches and literature on the issue of technology adoption covers the acceptance of e-Learning, m-learning and to some extent u-Learning in online or virtual teaching and learning. However, studies have not been broadened to look into the issues of teaching and learning in smart learning environments and/or with smart devices.

Recently, students of higher education institutions exceedingly utilize smart devices, i.e. smart phones, tablets, or iPads in their routine life. Extensive availability of smart devices and wifi/internet connections have made it possible to them to use their smart phones or tablets for their learning purposes. The smart devices make it possible for learning to occur anytime and anywhere. Also communication and collaboration opportunities through smart devices turn the learning to be student-centered, where students get control on their learning. These characteristics confer the sense of m-Learning enabled by smart phones which facilitated the feature of mobility in learning by focusing on the content from phone screens. But, the additive features of context-awareness and social learning has engendered the gist of s-Learning.

There exist many research models and theories which can be utilized for the adoption of technology evolved over time. Some of them are:

Table 1: Theories and Models of Technology Acceptance

THEORY/MODEL	DEVELOPED BY
MAPS (Model of Acceptance with Peer Support)	Sykes et al. (2009)
UTAUT (Unified Theory of Acceptance and Use of Technology)	Venkatesh et al. (2003)
TAM (Technology Acceptance Model)	Davis (1989)
E-TAM (Extended Technology Acceptance Model)	Venkatesh & Davis (1992)
MPCU (Model of PC Utilization)	Thompson et al. (1991)
TPB (Theory of Planned Behavior)	Ajzen (1985)
TRA (Theory of Reasoned Action)	Ajzen and Fishbein (1975)

The above mentioned theories and models of technology adoption can be utilized in different situations depending on the nature of research. These models and theories spin around particular constructs such as attitudes, job fit, behavioral intentions, social factors, subjective norms, usefulness, performance expectancy, facilitating conditions, motivation etc. These factors may be brought into study while selecting particular theory or model for measuring adoption of technology in different states and circumstances.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) developed by Davis is a representation that how users accept technology and use it.

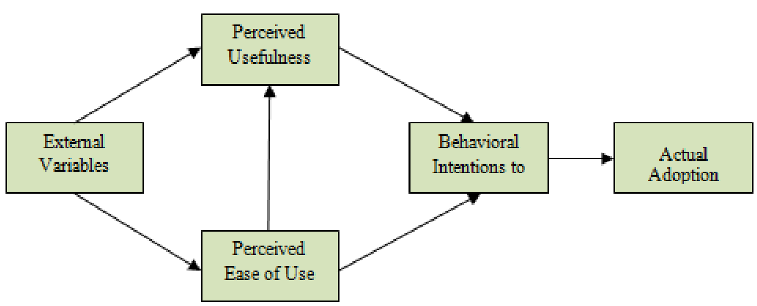

Figure 5: Technology Acceptance Model (TAM)

TAM implies that when a new technology is presented to the users, their decisions about using that technology are mainly influenced by two factors. These factors are:

(PU) Perceived usefulness: Fred David defined PU as "the extent to which an individual believes/accepts that using a specific technology would increase his/her job performance".
(PEOU) Perceived Ease-of-Use: Davis defined PEOU as "the extent to which a person believes /accepts that employing a particular technology would be free from effort"

Most of educational researches on e-learning, m-Learning or latest technologies utilize TAM (Technology Acceptance Model) to measure the acceptance of technology in educational institutions by different working groups such as teachers, students, Managers, administrators, principals, curriculum planners etc. (Schoonenboom, 2014; Alharbi & Drew, 2014; Padillla-Melendez et al. 2013; Edmunds, Thorpe & Conole, 2012; Park, Nam & Cha, 2012; Shroff et al., 2011; Moran, Hawkes & El Gayar, 2010; Sanchez-Franko, 2010; Park, 2009; Porter & Donthu, 2006; Saade & Bahli, 2005; Elwood, Changchit & Custshall, 2006; Landry, Griffeth & Hartman, 2006). The strong suit of TAM reclines into its straightforwardness and simplicity because it comprises only two constructs, i.e. "perceived usefulness & Perceived ease of use" for predicting the degree of adoption of innovative technologies at individual level. Additionally, TAM can be utilized when researchers aim to explore the acceptance of any specific technologies by particular individuals.

Focusing on e-Adoption of smart learning in higher education, it is necessary to incorporate the opinions of faculty members of HEIs who are key people to decide the use of smart learning in particular educational plans and programs of universities and HEIs, and also its adoption by students and teachers for teaching and learning in different educational organizations. (as argued by Nystroma et al. 2002). So, the research into the adoption of smart learning by university faculty will uncover meaningful educational implications on teaching and learning.

Research Framework

This research builds up a framework supported by TAM, as TAM is the most commonly used model for adoption and acceptance of technological innovations (Alharbi & Drew, 2014). This research framework uses perceived usefulness (PU) and perceived ease of use (PEOU) as precursors for the e-adoption of smart learning. The variables which affect these primary factors were inferred from existing literature. As smart learning is comprised of several components of e-learning, u-Learning, m-Learning and social learning. The most important factors which effect smart learning, according to literature are, mobility; personalization; interactivity, and collaboration. By choosing these variables, present study analyzes the effects of these factors and their relationships on adoption of smart learning. From university faculty perspective, this research discovers that how smart learning attributes improve the learning at higher education level, by encouraging learners capabilities and employing an efficient smart learning environments.

Hypotheses

Based on the theoretical components of the TAM, This research proposes following hypotheses, supported by theoretical components of Technology Acceptance Model (TAM), regarding E-Adoption of smart learning in higher education.

Table 2 : Research Hypotheses

H1	Perceived usefulness positively influences the intentions to adopt smart learning in Higher education.
H2	Perceived ease of use positively influence the intentions to adopt smart learning in higher education.
H3	Perceived ease of use positively influences the perceived usefulness of smart learning in higher education.
H4	Mobility positively effects the perceived usefulness of smart learning in higher education.
H5	Mobility positively effects the perceived ease of use of smart learning in higher education.
H6	Interactivity positively effects the perceived usefulness of smart learning in higher education.
H7	Interactivity positively effects the perceived ease of use of smart learning in higher education.
H8	Personalization positively effects the perceived usefulness of smart learning in higher education.
H9	Personalization positively effects the perceived ease of use of smart learning in higher education.
H10	Collaboration positively effects the perceived usefulness of smart learning in higher education.
H11	Collaboration positively effects the perceived ease of use of smart learning in higher education.

The following figure illustrates the research framework used in this study.

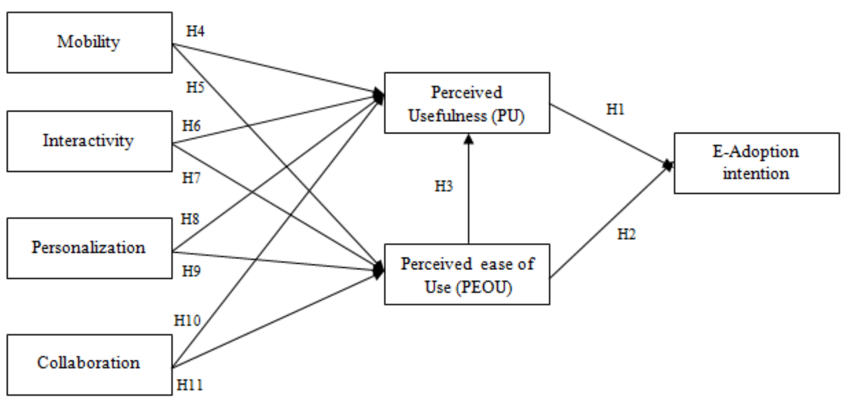

Figure 6: Research Hypotheses Framework with TAM

Data Collection

This study focuses on the e-adoption behavior of university faculty regarding smart learning, as university faculty plays a vital role in decision making for students of HEIs to use particular technologies and technological environments for teaching and learning. 54 respondents of this survey were faculty members of 5 private universities of Lahore which were having prior experiences in use of e-Learning in their institutions. The universities were selected on the basis of existing e-learning infrastructure and technological advancements in teaching and learning practices. A questionnaire was developed based on the proposed framework of e-adoption of smart learning in higher education. A larger number of items in questionnaire were selected using existing validated measures. Some items were tailored purposefully aligned with this study. Each item was measured on 5-point likert scale, where 1 was indicating 'Strongly disagree' while 5 was indicating 'Strongly agree'.

Table 3 : Survey Questionnaire for TAM & Smart Learning

Constructs	*Variables*	*Items*
Mobility (Mob)	Mob1	Smart learning possess excellent benefits in mobility.
	Mob2	Easy accessibility of smart learning is possible anytime and anywhere.
Interactivity (Int)	Int1	Smart leaning provides a variety of tools for learning and teaching purposes.
	Int2	Smart learning systems are very responsive to requests of learners.
Personalization (Per)	Per1	Personalized learning opportunities are provided to learners through smart learning applications.
	Per2	Suitable content for learners can be selected and combined by them in smart learning environments.
Collaboration (Col)	Col1	Learners are able to create content together and share among them.
	Col2	Learners can discuss content with each other, can have shared classes and group learning, through social networking services.
Perceived Usefulness (PU)	PU1	Smart learning system increase the effectiveness of learning of higher education students in my university.
	PU2	Use of smart learning enhances the learning performance of my university.
	PU3	Use of smart learning system increases the efficiency of my university.
Perceived Ease of Use (PEOU)	PEOU1	It is easy to use smart learning in higher education learning.
	PEOU2	Use of smart learning does not require much attention and care for students of higher education.
E-Adoption Intention (eAI)	eAI1	Our university expects to use smart learning system if provided opportunity.
	eAI2	Our university anticipates to utilize smart learning system at earliest.

Data Analysis

The proposed model was investigated by applying Structure Equation Modeling (SEM) which is used to analyze the causal relationships among manifold variables. PLS (Partial Least Square) was used which is component-based SEM technique which explains the compound relationships for small and medium sample sizes of latent constructs. The estimates of latent variables were determined derived from outer and inner relationships. Approximation procedures were performed and coefficient values of relationships were computed. The PLS method was preferred as complex relationships between the latent constructs are measured in this research entailing relatively small sample.

Measurement Model

Reliability and validity are two conditions which makes a measurement model acceptable. For ensuring the adequacy, it was required to assess the validity and reliability of this measurement model. SEM facilitates to test i) Composite Reliability (C.R.), ii) Convergent validity, and iii) Discriminant validity. Reliability of the measures is examined by (C.R.) Composite Reliability. The value recommended for C.R. is 0.7. The measure is regarded as reliable if C.R.>0.7. For this measurement model, the C.R. value of each construct was found between 0.731 and 0.928. Discriminant and convergent validity of the model were also tested. The convergent validity refers if every indicator of a construct adequately expresses the construct. For this there are two conditions, i) Factor loading > 0.5, and ii) cutoff value of AVE (Average Variance Extracted) > 0.5. Confirmatory Factor

Analysis (CFA) was performed and all factor loadings were found more than 0.5 and AVE was ranged from 0.658 to 0.871. C.R. and convergent validity are shown in table 4. The Discriminant validity refers that "specified indicators of a construct are considerably unlike of indicators of other unrelated constructs". This is calculated by doing a comparison of square root of AVE for other given constructs with other correlations. The desired value of discriminant validity must be greater than the value of correlations between that construct and other constructs. The correlation matrix with square root values of AVE is shown in table 5.

Table: 4 Reliability and Convergent Validity

Constructs	*Items*	*Factor Loadings*	*C.R.*	*AVE*
Mobility (Mob)	Mob1	0.759	0.831	0.749
	Mob2	0.863		
Interactivity (Int)	Int1	0.795	0.869	0.762
	Int2	0.855		
Personalization (Per)	Prs1	0.821	0.782	0.662
	Prs2	0.799		
Collaboration (Col)	Col1	0.861	0.923	0.852
	Col2	0.832		
Perceived Usefulness (PU)	PU1	0.782	0.815	0.743
	PU2	0.809		
	PU3	0.852		
Perceived Ease of Use (PEOU)	PEOU1	0.893	0.884	0.792
	PEOU2	0.731		
E-Adoption Intention (eAI)	EaI1	0.928	0.875	0.769
	EaI2	0.819		

Table 5: Correlation Matrix

University Faculty

	1	2	3	4	5	6	7
Mob	0.849						
Int	0.062	0.887					
Per	0.634	0.462	0.793				
Col	0.742	0.095	0.126	0.956			
PU	0.081	0.352	0.426	0.362	0.862		
PEOU	0.602	0.413	0.393	0.562	0.452	0.906	
eAI	0.321	0.061	0.062	0.052	0.378	0.701	0.894

Discriminant validity of constructs was assured as values of AVE square roots were greater than correlations as shown in table 5.

Structural Model

Structural models are developed to assess the statistical significance of proposed set of hypotheses. Bootstrap re-sampling method which of SEM which extracts supplementary samples from original but small sample data, was used for this purpose which is immensely applied to statistical methods and researches (Bras et al. 2008). This methods uses three important statistics, which are i) GOF (Goodness of Fit), ii) Geometric mean of AVE, and iii) Average R^2 (Tenenhaus et al. 2005). For this research study, 1000 bootstrap samples were used in bootstrap re-sampling method was used which the most is recommended sub-sample size for satisfying research requirements. GOF is calculated by using the statistical values of R^2 and G.M. of AVE. Cutoff values for Goodness of Fit (GOF) are:

Table 6 : Cutoff values of GOF

GOF_{small}	0.31
GOF_{medium}	0.41
GOF_{large}	0.58

The GOF is calculated using mathematical equation $GOF = \sqrt{AVE \times R^2}$. In this research study, GOF for the model of faculty members was calculated as 0.672. The results depicted that proposed model had an explanatory power greater than medium.

As hypotheses were tested, results explained that PU (Perceived Usefulness) and PEOU (Perceived Ease of Use), both were statistically significant for e-Adoption of smart learning for this model. PU and PEOU were strongly influenced by mobility (Mob), so it was also considered imperative for e-Adoption of smart learning by universities. Personalization was significant sign for PU. While, interactivity, collaboration and personalization were differently influencing to PU and PEOU.

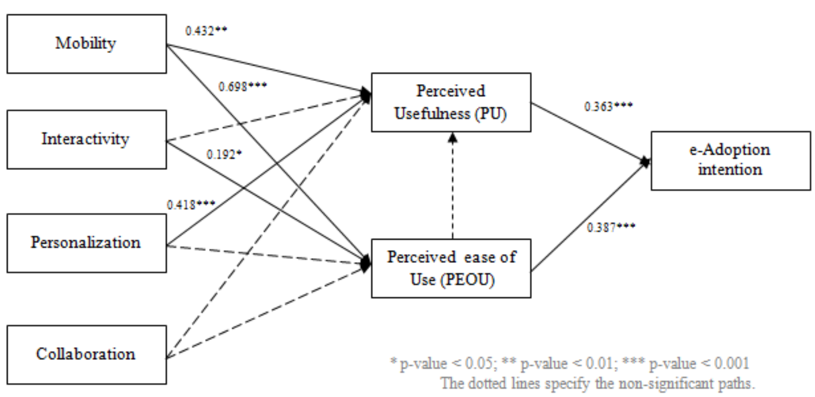

Figure 7: Path Diagram - Hypotheses Testing

Table 7 : Hypothesis Testing Results

Hypotheses		Path values
H1	PU ----> eAI	0.363***
H2	PEOU ----> eAI	0.387***
H3	PEOU ----> PU	0.081
H4	Mob ----> PU	0.432**
H5	Mob ----> PEOU	0.698***
H6	Int ----> PU	0.095
H7	Int ----> PEOU	0.192*
H8	Per ----> PU	0.418***
H9	Per ----> PEOU	0.028
H10	Col ----> PU	0.051
H11	Col ----> PEOU	0.067

*p<0.05; **p<0.01; ***p<0.001

Table 6 shows that faculty members presented more dependence on PEOU (0.387) than PU (0.363). Mobility (Mob) was having stronger dependence on PEOU (0.698) in comparison with PU (0.432). Moreover, Interactivity (Int) showed non-significant relationship with PU (0.095) but illustrated dependency upon PEOU (0.192). Personalization (Per) was significantly dependent on PU (0.418). There was no significant relationship found between PU and PEOU. Collaboration was holding no significant relationship with PU and PEOU while personalization had non-significant impact on PEOU.

Conclusions and Discussions

As suggested by the results of this study, smart learning is suitable mean of learning in higher education. In comparison with e-Learning and m-Learning, it expounds mobility, interactivity, collaboration and personalization beneficial to learning in higher education. Thus, smart learning is suggested to be adopted by higher education institutions, their faculty member for teaching, and also by students for meaningful learning. Perceived usefulness (PU), Perceived ease of Use (PEOU), and Mobility (Mob) are three most valuable and worthy indicators which enhance the tendency of acceptance of smart learning. e-Adoption of smart learning is desirable and recommended for higher education institutions, higher education faculty, and students of higher education so that appropriate measures may be take to establish smart learning infrastructure and smart learning environments to pave higher education according to novel patterns of learning.

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