ADEQUACY OF UTAUT MODEL IN PREDICTING STUDENTS' ADOPTION OF E-LEARNING IN A HIGHER EDUCATION INSTITUTE

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ABSTRACT

This analysis explores the variables that could impact students in the higher education system's intent and use behaviour in e-learning.

Acceptance of the e-learning environment is an up-to-date research pattern in the information system's (IS) acceptance domain. E-learning and training are becoming increasingly popular worldwide, reducing the temporal and spatial problems associated with traditional forms of education. The key reasons driving online learning are increasing access to quality education, enhancing the quality of education and lowering costs, and enhancing education's cost-effectiveness.

In the higher education system, the adoption of an e-learning system is relatively poor. As a result, investigating what factors could lead to acceptance is crucial to develop student's learning experiences and skills. The research aim is to investigate the elements that influence students' acceptance and use of distance-learning systems in higher education.

The conceptual approach for this research was based primarily on a unified theory of acceptance and use of technology and its modification. Derived variables included work-life quality, facilitating condition, hedonic motivation, personal innovativeness, social influence, habit, effort expectancy, and performance expectancy. Their impact on behavioural intent and use behaviour has been studied. The instrument was built using validated items from previous literature.

The proposed study model was tested using an SEM (Structural Equation Modeling) approach. Data was collected from 524 undergraduate and graduate students at the higher education institute using a digital survey. SmartPLS 3 software was used to evaluate the results.

The findings reveal that social influence, facilitating condition, Personal innovativeness, performance expectancy, and work-life quality significantly positively impacted students' adoption of e-Learning. However, effort expectancy (effort required) and hedonic motivation (enjoyment) were not influencing the behavioral intention to use e-learning.

***Keywords* — UTAUT, E-learning, Digital learning, Distance learning.**

1. INTRODUCTION

E-learning is a term that is often used to refer to the deliberate use of digital communication and information technologies to teach and learn. This education method and learning are also referred to by different names, such as online learning, web-based learning, distance learning, etc.

E-learning is a broad term that includes much more than online learning, distance learning, or web learning. Because the letter "e" stands for electronic, e-learning refers to any educational activity performed electronically, synchronously or asynchronously, by individuals or groups utilizing networked or stand-alone electronic devices.

There are different types of e-learning such as text-Based, in which the material is straightforward at this level and contains text, pictures, audio, and exam questions. Compliance training is an excellent example of text-based e-learning.

An interactive e-learning course is essentially similar to a text-based one, except that greater emphasis has been put on interaction to aid learning. Additionally, there is a higher emphasis on visuals, most of which are expected to include an interactive component.

Simulation-based distance education is highly interactive and largely reliant on graphics, video, and audio. Notably, bespoke simulations are often used to assist in learning acquisition, and these simulations may contain 3D components.

Students must be engaged in their work to enhance learning results. E-learning allows students to develop become critical thinkers, learners, and risk-takers in a safe setting. Students are not required to depend on their instructors. They may be self-sufficient. Learning may occur anywhere, at any time, and in any manner. It motivates pupils to demand more from their education. Once created, the course may be repeated indefinitely, at any number of locations, and for any learners, thus lowering the total cost. It shortens the learning process by delivering instruction in tiny consumable pieces directly to the learner's fingers. It guarantees that distribution is uniform across all places and times.

1.2 DISTANCE LEARNING

Distance learning was first proposed in 1840, and in a few years, distance learning services were available in Germany, UK, Japan, and the USA. By using synchronous and asynchronous ways, distance learning has become increasingly important, allowing no bound to the distance and time (Williams and Shea, 2003). Through the rise in popularity of the system, different technology was used to guide students that were not in contact with an instructor. Distance learning has led to many higher educational institutions implementing courses on the internet that have provided an opportunity to meet the demands for education has been extended worldwide because it facilitates versatility at any time regardless of background and availability to learners and educators at any time (Canaran and Mirici, 2020). Distance learning provided the opportunity to undertake diverse types of courses such as graduate, undergraduate, professional, and training via the internet in real-time and from anywhere.

The majority of distance learning environments at higher education systems are asynchronous and synchronous practices and tasks. Students in synchronous activities participate in immersive and concentrated activities to assist them in developing a basic knowledge of technologically-enhanced teaching, course technology use, and successful online design. Quizzes, team job assignments, group conversations, suggestions, and projects, on the other hand, are examples of collaborative practices and responsibilities. Asynchronous events and projects are also carried out using immersive video-based activities.

When it comes to distance learning, the most well-known descriptor is "distance education." It's a term that's often used to describe the initiative to provide learning opportunities to people who live far away. According to the related literature, various scholars and academics have used contradictory distance education and distance learning concepts over the past two decades. A proposed term established the dissemination of educational content, using print and electronic media, as computers became more important in the distribution of education (Moore, 1990). A teacher who was geographically positioned in a different location than the learner and potentially delivering the guidance at additional hours as part of the educational implementation. Dede (1996, p. 1) expanded on the concept by comparing standard pedagogical approaches and referring to the lesson as "teaching by saying." According to the idea, distance education creates dispersed learning resources by using emerging media and related interactions. Both of these concepts acknowledged the developments in the industry and contributed to emerging innovations that were becoming available. Much more, according to Keegan (1996), the term "distance education" is an "umbrella" term, with terms such as "correspondence education" and "correspondence research," that might have been used interchangeably in the past, being expressly described as a potential descendant of distance education.

1.3 UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY

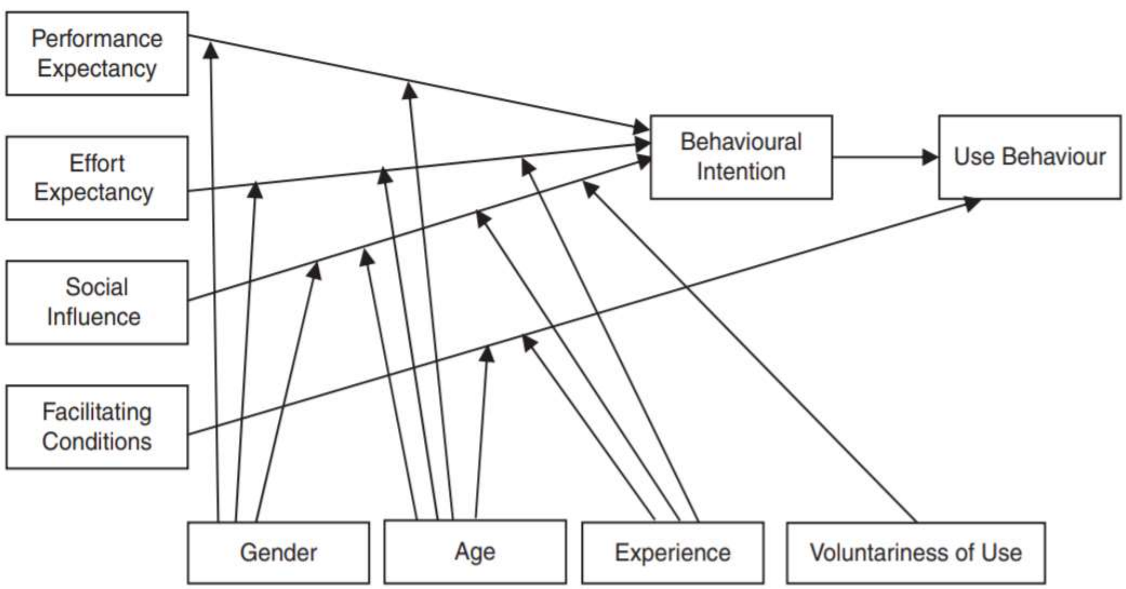
Technology adoption studies have been conducted for over two decades. They have used various models and theories to test these experiments using different analysis units in other contexts. The conclusions of these studies differ. Eight theories and models were unified by the developers of the UTAUT model, including Action Theory of Justification (Fishbein & Ajzen, 1975), Social Cognitive Theory (SCT) (Wilson, 1978), Technology Acceptance Model (TAM) (Davis, 1989), Theory of Planned Behavior (TPB) (Ajzen, 1985), Model of PC Utilization (MPCU) (Thompson et al., 1991), Motivational Model (MM) (Davis et al., 1992), TAM and TPB (C-TAM-TPB) (Taylor & Todd, 1995) and Invention Diffusion Theory (IDT) (Moore & Benbasat, 1991).

"The researchers' unification combines all the constructs from eight models to four determinants that predict intentions and use. The four constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, are direct determinants of behavioral intention and ultimately use behavior (Venkatesh et al., 2003)."

"Venkatesh et al. (2003) stated the performance expectancy (PE) is the degree to which an individual believes that using the system will help them to attain gains in job performance. Effort expectancy (EE) is the degree of ease associated with the use of the system. Social influence (SI) is how an individual perceives that important other believe they should use the new system. Facilitating conditions (FC) are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system."

Fig. 1 shows the UTAUT model proposed by Venkatesh et al. (2003). Over the years since its creation, UTAUT has been popularly used as a conceptual perspective for technology adoption and integration analysis by authors who have conducted observational studies of user intent and behavior. At the time of writing, the leading research by Venkatesh et al. (2003) was highlighted more than 30,000 times, with UTAUT addressing various technologies with various control factors (e.g., revenue, sex, experience, ability to use, and schooling).

However, to adopt online learning or different technology in the education sector, various research papers are published regarding adopting online learning by modifying the UTAUT model Lee et al. (2003).



Source: Venkatesh *et al*. (2003)

Fig. I UTAUT Model

2. REVIEW OF LITERATURE

Despite the tremendous growth of the online learning system, one cannot take advantage if one is not going to the system. There are more benefits of using an online learning system, but the efficacy of the system cannot fully be utilized if no one adopts the system.

The successful implementation of an online learning system depends upon the acceptance and use of the system. So it is essential to know the different factors that will affect the adoption of the online learning system (Tarhini et al., 2014).

Hence to the adoption of an e-learning system is not simply a technological solution. Still, it is the implementation of different factors that will help design the system, such as social factors, cultural factors, individual or personal factors, and technological factors, etc. (Tarhini et al., 2014)(Liaw & Huang, 2011)(Sun & Zhang, 2006).

A study was conducted by Valenta et al. (2015), with 2000 law students, in which both the traditional and e-learning systems were investigated. The researcher compared the two results of the experiment, one with conventional settings and another with the e-learning setting. The study found no adverse effect on the student performance who were first-time users of e-learning systems (Moravec et al., 2015).

Another research was carried away using the Cohens model by Mothibi (2015). The data were collected from the 15 documents to study the impact of the ICT-based e-learning system on the students' achievements. The study found a positive and significant impact of the e-learning system and the students' accomplishments (Mothibi, 2015).

A study was carried out in which mobile learning (m-learning) was used for enterprise resource planning (ERP) systems by Scholtz and Kapeso (2014). The m-learning adoption was tested by using the Technology Adoption Model (TAM), in which the impact of the performance expectancy and effort expectancy on behavioral intention was studied. The results found positive and significant of both PE (Performance Expectancy) and EE (Effort Expectancy) on BI (Behavioral Intension) (Scholtz & Kapeso, 2014).

Teo (2014) conducted research in which teacher satisfaction with the e-learning system was tested. Different factors were analyzed by using the technology adoption model. Three hundred eighty-seven teachers were sampled to study the effect of PE, EE, FC (Facilitating Conditions), course delivery, and course condition was tested. The research shows that, except FC, all other factors contributed to teachers' satisfaction with the e-learning system (Teo, 2014).

The adoption of e-learning (digital) devices for children through the perspective of parents was studied in the Korean context by Park et al. (2019). Responses from 153 parents were collected and The UTAUT model was used to find the correlation between the different factors such as PE, EE, BI, and UB. The study found a significant relation present between PE and BI as well as between EE and BI (Park et al., 2019).

Different modification of UTAUT model is used in literature for other objectives. The adoption of e-learning in university is tested in the Sri Lankan context by using the UTAUT3 model. Gunasinghe et. al (2019) attempts to determine the adequacy of the UTAUT3 model by using different factors such as PE, EE, SI, FC, habit (HB), BI, and Personal innovativeness (PI). The final sample of the study contains 441 academicians from various universities in Sri Lanka. The result shows that except for PI and SI, all other factors contribute to the e-learning system's adoption (Gunasinghe et al., 2019).

Similarly, another model developed to study the adoption of e-learning systems in HEI, named fuzzy DETAMEL, combines TAM and UTAUT model. This model contains five core factors: information quality, task–technology fit, system quality, utility value, and usefulness that influence users' e-learning continuance satisfaction. It was carried out in the Malaysian context by Al-Samarraie et al. (2018). The authors discovered that both lecturers and learners at higher education institutions regarded information quality, task–technology fit, system quality, utility value, and usefulness as critical variables affecting e-learning continuation satisfaction (Al-Samarraie et al., 2018).

Tarhini and El-Masri (2017) researched the adoption of e-learning in a developed country (USA) and a developing country (Qatar). The author tries to examine the results of previous research, which indicates that the Arab world's adoption of e-learning is still in its infancy compared to other western/developed nations by using the UTAUT model. The study found that PU, HM, habit, and trust significantly impact BI, but Price Value does not. The findings show that both Qatari and American students are open to using e-learning technologies to aid their educational experience. Whereas price value is a significant predictor of BI, PU, HM, habit, and trust are not. In developing nations, PE and SI contribute to increased students' use of e-learning systems, while FC is the determining factor in developed countries. Trust is a critical factor in the uptake of e-learning (El-Masri & Tarhini, 2017).

Different factors may contribute to the adoption of e-learning. The researcher developed a model by analyzing frequently utilized external variables. Using the combination of TAM and UTAUT, Abdullah and Ward (2016) created a model named GETAMEL (General Extended Technology Acceptance Model for E-Learning. The objective of the study was What effect do external variables have on PE and EE? The result shows that EE for e-learning systems is predicted by several factors, the most significant of which is students' self-efficacy. Other factors that were shown to be significant include enjoyment, experience, computer anxiety, and subjective norm. Students' perceived utility (PU) in e-learning systems is predicted most strongly by their enjoyment, followed by Subjective Norm, Self-Efficacy, and Experience (Abdullah & Ward, 2016).

According to their need, researchers modified the UTAUT model. A similar case was observed in which Uğur and Turan (2018) tries to find the adoption of the e-learning system in HEI by investigating the effect of factors such as system interactivity (SIN) and area of scientific expertise (AOSE) on the adoption of e-learning. The study was carried out in Turkey in which the author found out both the PE and EE have a significant impact on the use behavior of an e-learning system along with system interactivity. At the same time, the author found that there is no relation between the area of scientific expertise and intention to use the e-learning system (Uğur & Turan, 2018).

Khechine and Augier (2019) try to find the adoption of the social media platform for learning purposes in the higher education system by using the UTAUT2 model. The objective of the study is to use social media in LMS (learning management system). For this study, the authors recruited undergraduate students to take part in the research. In the instance of the survey, students' participation was entirely optional. Different factors were analyzed, such as PE, EE, SI, FC, BI, anxiety, attitude, and autonomy. The findings indicate that FC and attitudes were the most important predictors of behavioral intention to use social media platforms to learn (Khechine & Augier, 2019).

According to Daniel (2015) and Sivathaasan (2014), many surveys have shown that most higher education institutions in developed countries with already built distance-learning programs are not competitive due to several challenges (Makokha & Mutisya, 2016) (Queiros & (Ruth) de Villiers, 2016). As a result, it is critical to explore and recognize the key factors that affect distance-learning adoption in HEI. A greater understanding of the considerations aids institution management in making the most appropriate allocation of the budget.

Furthermore, e-learning has progressed; as a result, several Massive Open Online Courses (MOOCs) are oriented towards a series of videos with a platform that employs certain standards during the learning process. Still, they do not promote flexible and customized learning. These characteristics and the uniformity of the training process are among the most recent challenges that distance learning has encountered (Daniel et al., 2015).

According to the research of Aguti et al. (2015), readers' types, like students and teaching staff, students' years of study, and user categories (Teacher, Associate Professor, Professor, and learners), have shown a substantial variation in their attitudes toward using electronic information services. Sex, on the other hand, has almost identical levels of view, which is negligible (Sivathaasan et al., 2014).

If we considered different factors that affect the adoption of e-learning, factors such as social influence, effort expectancy, self-efficacy, and performance expectancy would influence behavioral intention to use the technology whereas self-efficacy alone influences the actual use of the technology (Lwoga & Komba, 2015).

ICT (Information and Communications Technology) infrastructure barriers, an unfriendly e-learning user interface, inadequate ICT rules, a lack of technological support, limited expertise, insufficient knowledge, disinclination to reform, and time constraints to plan the content for the application of the distance-learning framework were all listed as challenges for using distance-learning. Since the emergence of e-learning technology, universities' use of e-learning platforms to encourage mixed learning has increased significantly (Aguti et al., 2015).

The various component that influenced students' adoption of distance-learning programs were explored by Salloum et al. (2019). The research introduced a new paradigm that looked at the influence of innovativeness, consistency, confidence, and expertise as main determinants of e-learning adoption (Salloum et al., 2019).

According to the findings of Jayatilleke and Gunawardena (2016), the model's ability to analyze information creation in various communication tools is insufficient. The study went on to say that it's essential to rethink how learning is orchestrated and that some aspects of the paradigm in question need to be redefined (Lucas et al., 2014).

Furthermore, according to Strachan and Liyanage (2015), ongoing education and experimenting with innovative communication approaches will help improve learning while also the respect, teamwork, and value between teachers and students. There are powerful strategies for presenting interface content in an online environment that can help students reach higher levels of education satisfaction and intellective comprehension of the pedagogical essentials (Tîrziu & Vrabie, 2015).

E-learning was created and intended specifically for those involved in education but unable to commute and liberate them from the four walls of classroom operations, allowing them to access information conveniently(Naidu, 2014)

3. THEORETICAL FRAMEWORK

The research aim is to investigate the elements that influence students' acceptance and use of e-learning systems in higher education institutes. To check the adequacy of the proposed UTAUT model which is based on the UTAUT2 model given by Venkatesh et al. (2012), it is necessary to investigate the correlation between different variables. The following fig. 2, show the theoretical UTAUT model used in this study, to investigate the influence of 10 variables in the adoption of e-learning. The eight independent variables are hypothesized to check the influence on the two dependent variables behavioral intention (BI) and use behavior (UB). The different variables used in this study are given below.

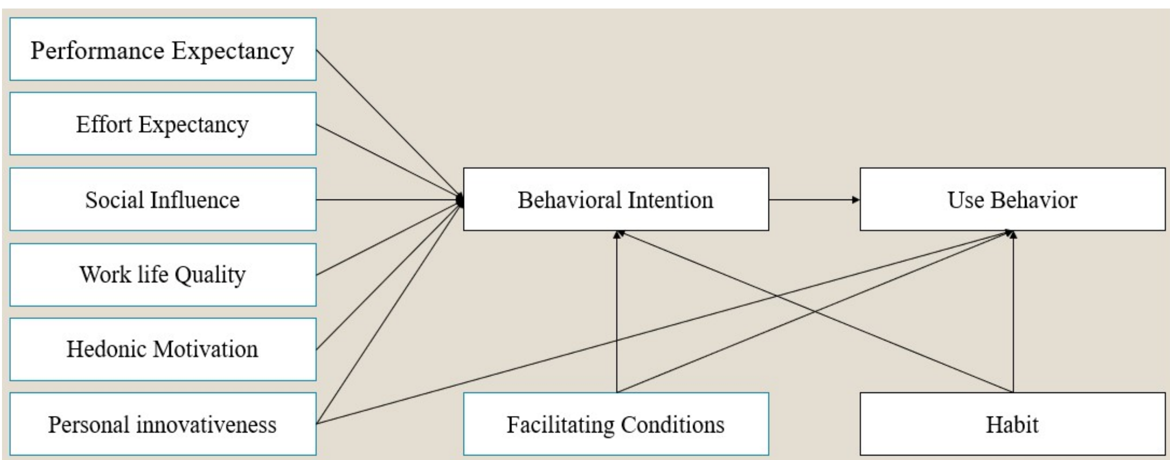


Fig. II Theoretical Model

PERFORMANCE EXPECTANCY

PE is described as the user's expectation that targeted technology can enhance their efficiency to achieve work-related gains (Venkatesh et al., 2012). In this research, Performance expectancy relates to the student's assumption that e-learning would be helpful for them all to do a job more accurately and efficiently. It is then hypothesized that;

H1: PE has a significant positive impact on BI.

EFFORT EXPECTANCY

EE is a person's assumption that the system is easy to use (Venkatesh et al., 2012). In the background of this analysis, Effort expectancy corresponds to the student's belief that e-Learning systems are simpler to use. It is then hypothesized that;

H2: EE has a positive impact on BI.

SOCIAL INFLUENCE

SI refers to the presence or action of others people on the individual's attitudes or opinion on the use of an e-learning system (Venkatesh et al., 2003). In the context of this research, "social influence" refers to external pressures that impact students understanding of e-learning. It is then hypothesized that;

H3: SI has a positive impact on BI.

WORK-LIFE QUALITY

WLQ refers to someone's perception of confidence that their quality of work will increase by using technology; In this scenario, the e-learning approach is intended to maximize students' educational experience by saving time and expenses through downloading learning materials and literature or communicating with their schoolmates (M. Ali et al., 2018). Although Multiple studies on technology acceptance have examined the value of WLQ, in the Indian context, the Number of Research based on the e-learning area is minimal (Tarhini, Deh, et al., 2017a); thus, this research seeks to test the effect of work-life quality on the acceptance of the e-learning system. The following theory, then, is proposed;

H4: WLQ has a positive impact on BI.

BEHAVIORAL INTENTION

The BI defines consumers' willingness to consider e-learning programs in this study's context (Venkatesh et al., 2003). Behavioral intention means students plan to use e-learning programs from the present way of learning to the future. It is called a predecessor to the behavior of users. It indicates the willingness of users to carry out a particular behavior. Previous research has shown that individuals' actual use of electronic systems is directly impacted positively by the intention to use those systems and in the sense of e-learning systems (Venkatesh et al., 2003, 2012). It is, therefore hypothesized, in this study, that:

H5: BI has a positive impact on use Behavior.

FACILITATING CONDITIONS

Facilitating conditions talk about their perception that there are institutional assistance and resources to aid with technologies (Venkatesh et al., 2012). Operational support and facilities that support the use of the system are usually classified under Facilitating conditions. Facilitating conditions influences both user intent (Venkatesh et al., 2012) and real use (Venkatesh et al., 2003, 2012). It is, therefore hypothesized, in this study, that:

H6a: FC has a positive impact on BI.

H6b: FC has a positive impact on use behavior.

HEDONIC MOTIVATION

HM is explained as "the enjoyment that comes from the use of technology" (Venkatesh et al., 2012). It tests the pleasure and amusement of the user (Venkatesh et al., 2003). This factor was introduced to the UTAUT2 model by Venkatesh et al. (2012). The following theory is thus being proposed:

H7: hm has a positive impact on bi.

HABIT

A person's habit means reaction, which is instinctively or automatically because of previous experience (Venkatesh et al., 2012). Habit describes the experience, but experience alone is not enough to construct a habit independently (Venkatesh et al., 2012). Habit is considered to profoundly impact both the purpose of the user and the actual application of technology. It is also hypothesized.

H8a: HB has a positive impact on BI.

H8b: HB has a positive impact on UB.

PERSONAL INNOVATIVENESS

"Farooq et al. (2017) acknowledged personal innovativeness as a healthy character attribute that makes a person want to pursue modern technologies". PI affects the actions of both consumer intent and technology use. Different researchers have also verified that personality characteristics such as PI influence the acceptance of technology, especially in IT (Gunasinghe et al., 2019). It is also hypothesized that,

H9a: PI has a positive impact on BI.

H9b: PI has a positive impact on UB.

PRICE VALUE

This variable tends to be accurate in a customer context as price value refers to a person's cognitive trade-off between the distinguished advantages of using technology and the price value expended on using it. In market cognition, where the expected rewards are more significant than the perceived costs, PV takes on a favorable meaning, positively impacting the behavioral purpose of using the device or device. This factor has no importance in the present research, as e-learning is available free of cost to all HEI academics. PV is thus regarded as a constant, and in this analysis, its importance is not hypothesized.

4. METHODOLOGY

This study is a quantitative study based on a survey questionnaire (Appendix). The quantitative methodology helps the research worker analyze the associations between the factors described in theory and provide data to accept or reject the hypotheses. Research interested in hypothesis testing typically describes such interactions or assesses the distinction between classes of the variables in a given case (Sekaran and Bougie, 2010).

4.1 PARTICIPANTS AND PROCEDURE

NIT Calicut undergraduate and postgraduate students were included in the sample of this research report. The institute has over 4000 postgraduate and undergraduate students. It was appropriate to follow the snowball sampling procedure for the pilot analysis. Using Google Form, the questionnaire was made available as an anonymous survey Weblink was shared among undergraduate and postgraduate students via e-mail and messenger.

4.2 INSTRUMENT DEVELOPMENT

Constructs and items have been taken from prior literature for the instrument of this analysis. A total of 12 constructs and 55 items have been made. The constructs Knowledge, Self-Efficacy, Mood, Computer/mobile Discomfort, Cognitive Involvement, and suggested constructs were taken from the literature.

The focus group conversations played a significant role in the questionnaire formulation. They helped define the relevant constructs and items to be used in the questionnaire, the number of choices provided to respondents, and the details needed to frame the questionnaire better. The relevance of the responses from the focus group in creating this questionnaire is evident. E.g., a variety of difficulties were faced in the first draft of the questionnaire: most notably, a lack of consistency in presenting the problem and the absence of one attribute, i.e., the quality of work life.

The target group for the participants was undergraduate and postgraduate students. That made it possible to make necessary changes to the questionnaire's frame provided in the draft questionnaire. Consequently, during the duration of the focus group, different revisions were made to the draft questionnaire. These covered the simplification and explanation of the questionnaire's most difficult sections. Following input and suggestions from the focus group workshops, the questionnaire's final draft was created through an instructor's supervision.

The constructs BI, PE, and FC were calculated using four, four, and three items, respectively (Venkatesh et al., 2003). There were four items used by SI, EE (Venkatesh et al., 2003), and three items used by WLQ (Kripanont, 2007). Three items were used by HM and UB (Venkatesh et al., 2012), while HB used three items. The constructs HM, EE, FC, PI, HB, SI, WLQ, BI, and PE used a five-point Likert scale, where one corresponds to strongly disagreed, and five corresponds to strongly agree. The three-item UB structure was measured as UB1 (measures the frequency of the use of e-learning system in a week) ranging from one day in a week (1) to daily (5), UB2 (measures the frequency of the use of e-learning system in a day) was measured (1) for less than one hour to (5) for more than five hours, and UB3 measured extremely infrequent as 1 to extremely frequent as 5.

5. DATA ANALYSIS

The use of Structural Equation Modeling (SEM) methods is critical in this study. There are two kinds of SEMs, variance-based and covariance-based (Hsu et al., 2006). The SEM method is described as “one of the most frequently utilized statistical modeling tools in behavioral sciences. (Blunch, 2017)" SEM may alternatively be thought of as a hybrid of factor and regression analysis or path analysis. Both methods exhibit a high degree of resistance to skewness, although variance-based SEM techniques are often more precise in small-scale situations or for predictive purposes (Briz-Ponce et al., 2017). The PLS is composed of two components: the measurement model (generally referred to as the outer model) and the structural model (also called the inner model). The outer model characterizes all components to assess their validity and reliability, whereas the inner model assesses the connections between the various model constructs (Hair et al., 2011). Additionally, the bootstrap technique was utilized to determine the significance of coefficients and route load. Fig. 3, shows the data outline of data analysis method.

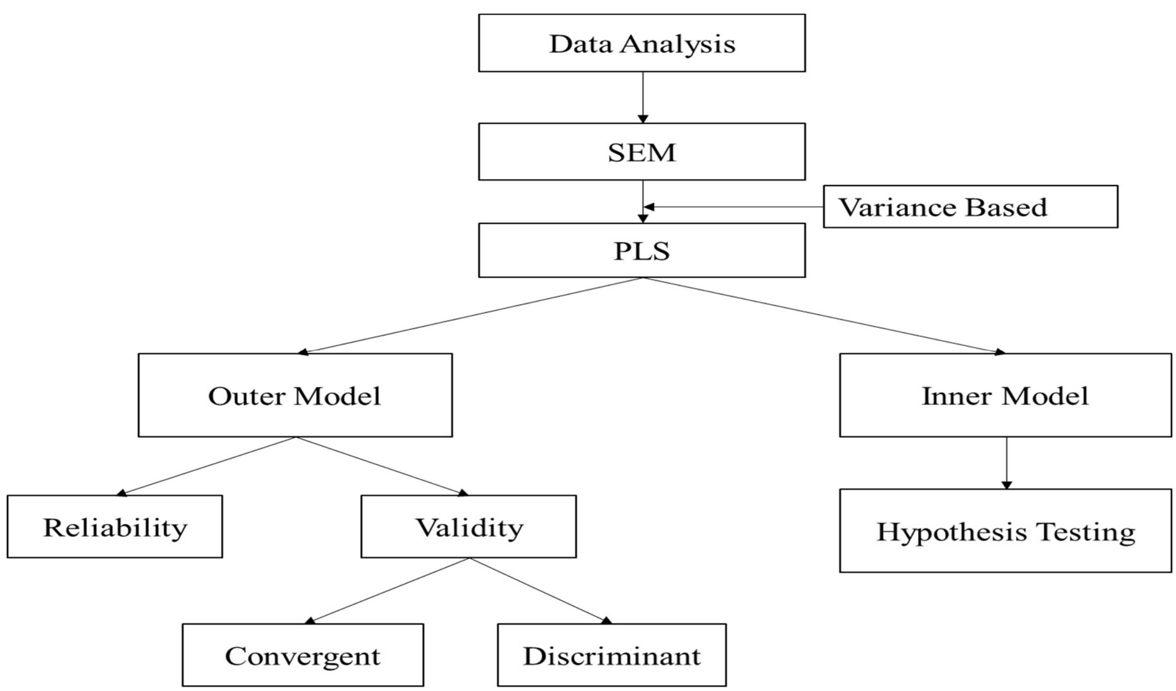


Fig. III Data Analysis Method

5.1 RESPONDENTS’ PROFILE

To learn more about the demographics of the respondents, descriptive statistics were used. Table 1, shows that out of the 524 responders, 415 (79%) were male, and 109 were female (21 %). Respondents include both undergraduate and postgraduate students from the institute. Out of the 524 respondents, 104 were postgraduates (20 %), and 420 were undergraduates (80 %). The majority of the respondents are between the age group of 20 to 22 years (65 %), 20 percent are above 22 years, and 15 percent are below 20 years. Fig. 4, shows the Pie chart for respondents' profile.

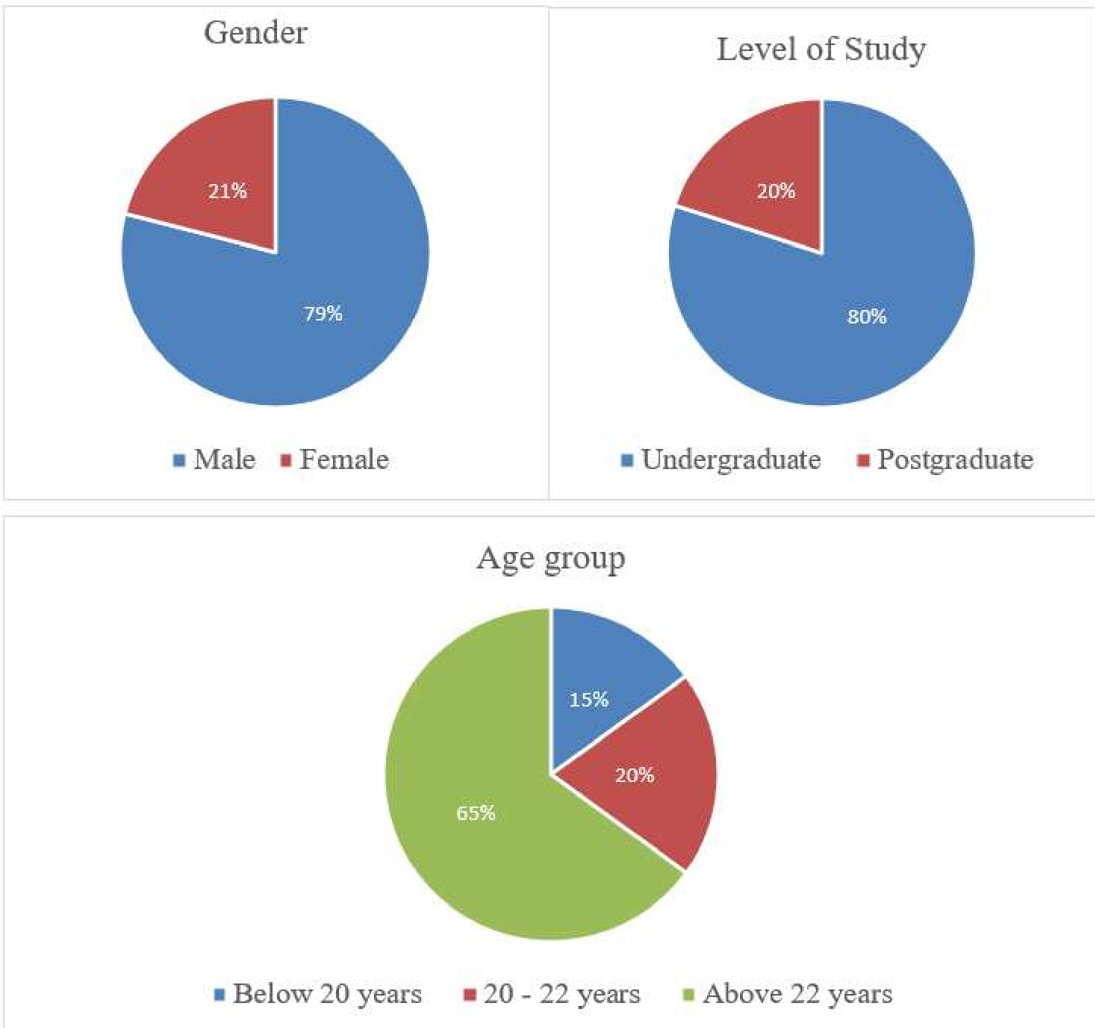


Fig. IV Pie chart for respondents' profile

Table I Demographic profiles of respondents

Variable	Frequency	(%)
Gender		
Male	415	79
Female	109	21
Type of degree		
Undergraduate	420	80
Postgraduate	104	20
Age Group		
Below 20 years	79	15
20 to 22 years	104	20
Above 22 years	321	65

5.2 CONFIRMATORY FACTOR ANALYSIS

In CFA assessment, the goodness of fit and constructs validity is used. There are many criteria used to assess the goodness of fit model (Hair et al., 2011). Generally, χ^2 was used for the assessment of goodness of fit. But it is not a good criterion for the goodness of fit assessment because the χ^2 value is too sensitive for a large sample size (Hu & Bentler, 1999). Hence, the χ^2 /df criterion is considered for the goodness of fit assessment, where df is degrees of freedom. Other measures are also used for goodness of fit, such as NFI (Normed Fit Index), RMSEA (Root Mean Squared Error), and SRMR (Standardized Root Mean Squared Error) (Hu & Bentler, 1999). Based on Table 2, the different criteria with threshold are given, and the measured value is within recommended ranges, proving that the model fit is good.

Table II Model fit measures

Measure	Estimate	Threshold	Interpretation
$\chi2$ /df	2.035	Between 1 and 3	Excellent
NFI	0.900	>9	Excellent
RMSEA	0.045	<0.06	Excellent

SRMR	0.030	<0.08	Excellent

5.3 OUTER MODEL: VALIDITY AND RELIABILITY

The outer model does exploratory study to determine the scale's reliability and constructs validity (Briz-Ponce et al., 2017). The outer model's reliability and validity are assessed using item discriminant validity, convergent validity, and reliability. "Reliability" refers to the degree to which a set of instrument items selected for a given construct measures the same construct consistently across occasions, while "validity" refers to the degree to which the chosen instrument items for a given construct are a good measurement of the construct (Sabah, 2016). Reliability measures include Cronbach's alpha, factor loadings, and composite reliability (CR); convergent validity measures include Average Variance Extracted (AVE) and CR; and discriminant validity measures include HTMT (Heterotrait–Monotrait ratio). To verify the given measurement, the SmartPLS software was used. The following criteria were utilized to do this (Briz-Ponce et al., 2017):

- All indicators' factor loads should be significant and more than 0.5.;
- At a minimum, factor loads should be 0.7, and the t-statistic should exceed the ±1.96 threshold of 5%;
- The lower bound of the confidence interval must be greater than 0.7.

According to Table 3, the factor loadings observed in this research are significant at the 5% level, having more than 1.96. Additionally, the factor loads are greater than 0.7, meeting both the first and second criteria.

The survey employed in this study is a 5-point Likert scale. As a result, an evaluation of reliability is crucial. Two techniques are utilized to determine reliability: Cronbach's alpha and composite reliability (or CR) (Hair et al., 2011). Cronbach's alpha coefficient is determined using the Cronbach's alpha technique, which was established in (Cronbach, 1951). This number may range between [0,1], and the closer it is to 1, the more internal consistency there is. The alpha acceptance value varies according to the kind of study (Hundleby & Nunnally, 1968). In exploratory investigations, the alpha coefficient must be at least 0.7. CR is the second technique for calculating internal consistency reliability. CR determines a criterion's internal consistency. "It corresponds to the total amount of scale score variation explained by all underlying constructs. (Sabah, 2016)" This metric is comparable to Cronbach's alpha but is computed differently. While the alpha coefficient assumes that all things have the same.

Table III Factor loadings

		Confidence interval	
	Factor Loading	**Lower Bound**	**Upper Bound**
BI1 <- BI	0.855	0.831	0.875
BI2 <- BI	0.813	0.776	0.842
BI3 <- BI	0.881	0.860	0.898
BI4 <- BI	0.851	0.824	0.874
EE1 <- EE	0.766	0.719	0.804
EE2 <- EE	0.796	0.758	0.826
EE3 <- EE	0.773	0.734	0.805
EE4 <- EE	0.762	0.711	0.801
FC1 <- FC	0.850	0.819	0.874
FC2 <- FC	0.820	0.778	0.851
FC3 <- FC	0.708	0.650	0.751
FC4 <- FC	0.822	0.784	0.853
HA1 <- HA	0.846	0.810	0.874
HA2 <- HA	0.893	0.868	0.912
HA3 <- HA	0.855	0.823	0.879
HA4 <- HA	0.792	0.757	0.820
HM1 <- HM	0.880	0.850	0.903
HM2 <- HM	0.932	0.917	0.943
HM3 <- HM	0.916	0.902	0.927
PE1 <- PE	0.856	0.832	0.876
PE2 <- PE	0.822	0.793	0.846
PE3 <- PE	0.868	0.846	0.887
PE4 <- PE	0.832	0.804	0.855
PE5 <- PE	0.824	0.793	0.849
PI1 <- PI	0.868	0.835	0.892
PI2 <- PI	0.897	0.879	0.912
PI3 <- PI	0.740	0.687	0.782
SI1 <- SI	0.889	0.869	0.904
SI2 <- SI	0.877	0.845	0.900
SI3 <- SI	0.903	0.886	0.918
SI4 <- SI	0.808	0.765	0.840
UB1 <- UB	0.865	0.825	0.895
UB2 <- UB	0.928	0.912	0.948
UB3 <- UB	0.788	0.705	0.835
WLQ1 <- WLQ	0.873	0.850	0.892
WLQ2 <- WLQ	0.733	0.697	0.776
WLQ3 <- WLQ	0.849	0.823	0.869

Weight, CR evaluates the importance of each item based on its unique significance. As a result, CR is more accurate than the Cronbach's Alpha coefficient when doing a rigorous assessment (Briz-Ponce et al., 2017). Additionally, the confidence interval is also calculated for both the technique. So, from Table 4, it is clear that the value for both criteria is larger than 0.7.

Table IV Model reliability measures

Constructs	Cronbach's Alpha	Confidence interval		Composite Reliability	Confidence interval	
		Lower Bound	Upper Bound		Lower Bound	Upper Bound
Behavioral Intention	0.872	0.853	0.889	0.912	0.901	0.923
Effort Expectancy	0.779	0.746	0.807	0.857	0.839	0.873
Facilitating Conditions	0.812	0.783	0.838	0.878	0.861	0.893
Habit	0.87	0.848	0.887	0.91	0.897	0.922
Hedonic Motivation	0.896	0.877	0.911	0.935	0.924	0.944
Performance Expectancy	0.896	0.882	0.908	0.923	0.913	0.932
Personal Innovativeness	0.787	0.753	0.816	0.875	0.857	0.891
Social Influence	0.892	0.876	0.907	0.925	0.915	0.935
Use Behavior	0.832	0.806	0.855	0.896	0.88	0.911
Work life Quality	0.758	0.72	0.79	0.86	0.841	0.877

To determine the questionnaire's validity, two techniques should be used: convergent validity and discriminant validity. Convergent and discriminant validity is defined as "the degree to which various measures of the same construct are linked" and "the extent to which different measures of distinct constructs are not related (Ooi & Tan, 2016)." The AVE value should be more than 0.5 (Briz-Ponce et al., 2017)(Yeap et al., 2016). "AVE quantifies the amount of variation captured by a construct in comparison to the variance attributable to random measurement error. (Sabah, 2016)" Table 5, summarizes the Convergent validity findings. As a consequence of these findings, it can be stated that the questionnaire's convergent validity and reliability have been established. The discriminant validity of AVE is determined by comparing its square roots to the correlation coefficients of the components (Lwoga & Komba, 2015).

Table V Model Convergent validity measures

Constructs	Average Variance Extracted (AVE)	Confidence Interval	
		Lower Bound	Upper Bound
Behavioral Intension	0.723	0.695	0.752
Effort Expectancy	0.600	0.567	0.630
Facilitating Conditions	0.643	0.606	0.673
Habit	0.718	0.684	0.748
Hedonic Motivation	0.828	0.802	0.849
Performance Expectancy	0.707	0.682	0.733
Personnal Innovativeness	0.702	0.668	0.732
Social Influence	0.757	0.730	0.782
Use Behavior	0.744	0.715	0.771
Work-life Quality	0.673	0.644	0.706

In general, the HTMT (Heterotrait–Monotrait ratio) criteria should be employed to demonstrate discriminant validity in PLS-SEM (PLS-SEM, 2015). The heterotrait-monotrait correlation ratio (HTMT) is a novel technique for evaluating discriminant validity in partial least squares structural equation modeling, a critical component of model assessment. Without establishing discriminant validity, researchers cannot be confident that the findings supporting postulated structural pathways are genuine or are the product of statistical inconsistencies. The HTMT criteria surpass established methods for determining discriminant validity, such as the Fornell-Larcker criterion and (partial) cross-loadings, which are generally ineffective at detecting a lack of discriminant validity. According to guidelines, the HTMT value for constructions should be less than 0.9. from Table 6, it is clear that all values are below 0.9, which guaranty the discriminant validity.

Table VI Model discriminant validity measures (HTMT ratio)

	BI	EE	FC	HA	HM	PE	PI	SI	UB
BI									
EE	0.672								
FC	0.518	0.714							
HA	0.658	0.763	0.789						
HM	0.648	0.664	0.411	0.556					

PE	0.791	0.682	0.410	0.581	0.643				
PI	0.627	0.628	0.563	0.663	0.443	0.574			
SI	0.642	0.530	0.247	0.489	0.600	0.710	0.455		
UB	0.101	0.128	0.219	0.167	0.069	0.068	0.267	0.074	
WLQ	0.888	0.673	0.408	0.587	0.764	0.839	0.570	0.647	0.066

5.4 INNER MODEL ASSESSMENT

Based on the substantive theory, an inner model explains the connection between latent variables (Briz-Ponce et al., 2017). To evaluate the inner model, the path coefficient, t-statistic, the p-value is considered for hypothesis testing, and R^2 (explained variance). R^2 values of 0.75, 0.5, and 0.25 suggest that the model is substantial, moderate, or weak, respectively (Hair et al., 2011). The R^2 value greater than 0.35 indicates a significant model (Muller & Cohen, 1989).

Table VII Results of hypotheses testing

	Path Coefficient	**Standard Deviation (STDEV)**	**t- Statistics**	**p Value**
BI -> UB	-0.087	0.050	1.728	0.042
EE -> BI	0.007	0.042	0.155	0.438
FC -> BI	0.086	0.038	2.261	0.012
FC -> UB	0.124	0.062	1.990	0.024
HA -> BI	0.110	0.049	2.251	0.012
HA -> UB	0.009	0.062	0.139	0.445
HM -> BI	0.032	0.047	0.681	0.248
PE -> BI	0.202	0.043	4.652	0.000
PI -> BI	0.101	0.038	2.638	0.004
PI -> UB	0.224	0.063	3.531	0.000
SI -> BI	0.105	0.035	3.015	0.001
WLQ -> BI	0.380	0.045	8.523	0.000

Table 7, displays the result for path coefficient, t-statistic, and p-value. To accept the null hypothesis the path coefficient should be positive, the t-statistic value should be larger than 1.96, and the p-value should be less than 0.05 to found statistical significance.

Based on Table 7, the correlation between the paths of all constructions. As expected, all t-values exceed 1.96 at the 5% level, except the relationships between EE and BI, HM and BI, and HB and UB. As a result, all hypotheses except H2, H7, and H8b are accepted.

That means the PE, EE, SI, WLQ, FC, and PI were shown to have statistically significant relationships with the BI of e-learning systems.

Also, there is a statistically significant relationship between BI and UB, FC and UB, and PI and UB.

Figure 5 shows the model developed in smart pls software with factor loading and R^2 value. As shown in Figure 5, PE, SI, FC, WLQ, and PI all affected students' BI to use e-learning systems in their respective order of impact and explained 65.8% of the variation in behavioral intention to use e-learning systems. Additionally, BI, PI, and FC impacted the usage of e-learning systems in their respective order of effect and accounted for 7.1% of the variation in this use behavior.

As a result, the theoretical model presented in this research was insufficient (R^2 = 0.07) to explain students' adoption of e-learning at an HEI. At the same time, the model presented in this research is the substantial model (R^2 = 0.658) to explain the students' BI to adopt the e-learning system.

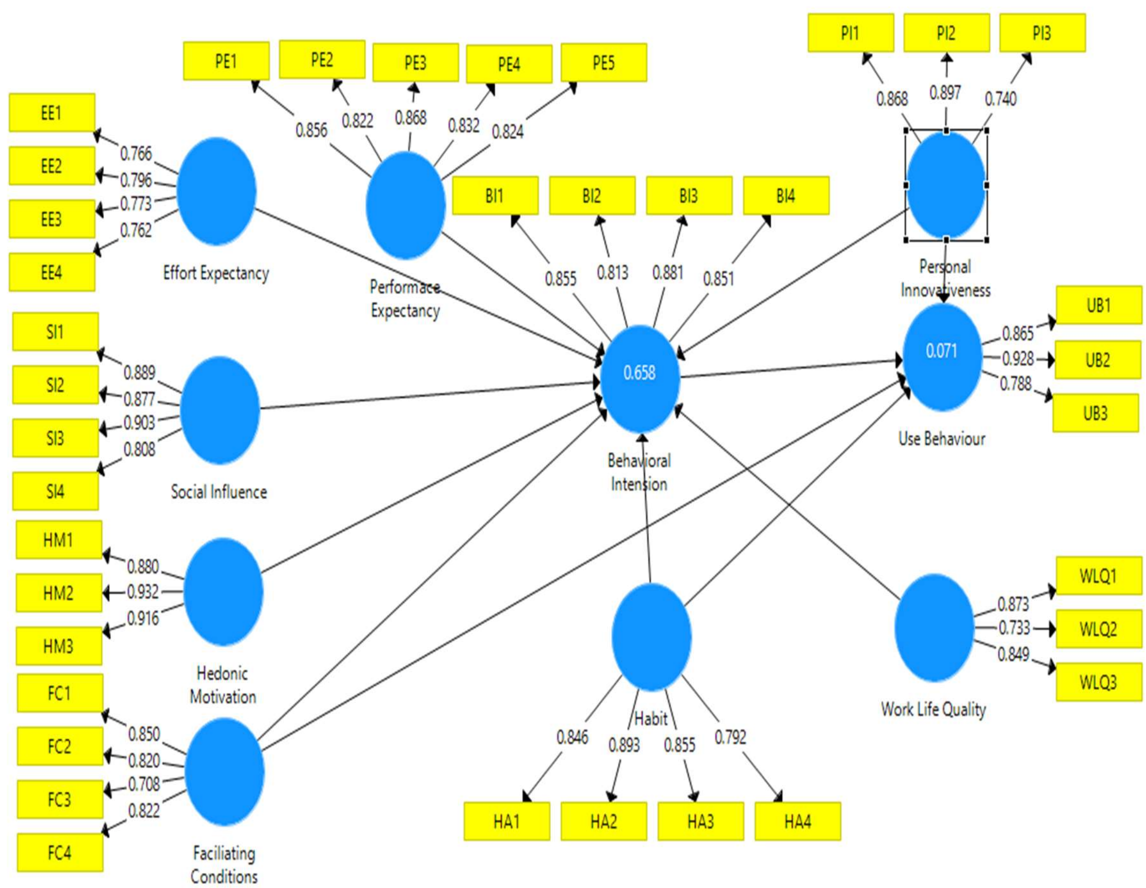


Fig. V Model developed in smart pls software

6. DISCUSSION

In this research study, the theoretical model developed is the combination of different TAM (Technology Acceptance Model) and UTAUT models used in literature such as UTAUT 2 (Park et al., 2019)(El-Masri & Tarhini, 2017), UTAUT 3 (Gunasinghe et al., 2019), GETAMEL (Rizun & Strzelecki, 2020), etc... In this research, different variables such as effort expectancy, performance expectancy, social influence, facilitating condition, work-life quality, personal innovativeness, habit, and hedonic motivation on behavioral intention are examined. Moreover, behavioral intention, facilitating condition, habit, and personal innovativeness on actual use behavior of e-learning are also analyzed.

This result is consistent with previously published research on the subject. Thus, research demonstrates that learners first determine if utilizing online learning platforms met their study needs or were relevant to their study process before contemplating using such technology in their study. Learners have been shown to view online learning platforms as more beneficial when they find that such technology is superior to conventional learning methods that do not involve online learning platforms (Fung Choy & Quek, 2016). The present study investigated how to increase students' academic performance and satisfaction using the suggested approach.

Thus, the following section will give some implications on how to improve the students' academic performance and satisfaction

The direct impact of performance expectancy on behavioral intention to use technology

Performance expectancy refers to how students' performance will increase by using the proposed e-learning system. So this hypothesis gives the relation between intention to use a system and performance expectancy.

If university students think that using e-learning technologies would enhance their learning process or performance, they will utilize them. As a result, teachers, and lecturers should ensure that the system's contents are more valuable and current, better meeting the requirements of students. This result is consistent with prior e-learning research findings (M. Ali et al., 2018)(Tarhini et al., 2014)(Tarhini, Hone, et al., 2017). This result exemplifies academics' view that if they discover that e-Learning is more effective in delivering education than conventional teaching, they will expand their use of e-Learning for course delivery. Thus, higher education administration should constantly educate and remind employees about the advantages of e-Learning via group discussions, seminars, and training.

The direct impact of social influence on behavioral intention to use technology

The second significant factor in this study is social influence, which primarily relates to how individuals perceive how others expect them to use a system. The views of their counterparts may affect an undergraduate. Additionally, the impact of lecturers or instructors on the use of e-learning tools will affect. The current study's results on the effects of SI are consistent with previous research (Salloum et al., 2019)(Fung Choy & Quek, 2016)(S. Ali et al., 2018a). Consequently, professors and teachers should engage students in using e-learning systems, and students should be urged to do the same for their peers.

In the context of e-learning, peers' and instructors' perspectives may influence other participants' attitudes and views. Social impact directly affects students' behavioral intention to utilize an e-learning system, the findings indicate. Indeed, the effect of social influence on a person varies according to various variables, including culture, age, and education (Masa'deh et al., 2016). It is thus recommended that instructors inform students that participation in the e-learning system is essential and that practitioners convince users who are already acquainted with the plan to assist in marketing it to new users. Thus, once a critical mass of e-learning users is reached, the number of subsequent e-learning adopters is expected to increase quickly (Tarhini et al., 2014). This stresses the need to develop implementation methods that get buy-in from the broader social context.

The direct impact of work-life quality on behavioral intention to use technology.

WLQ is another construct to influence students in their BI to use e-learning systems,

Work-life quality refers to getting more time for creative thinking as well as for leisure.

This case implies that when students use an e-learning system, the quality of students' academic life will improve in saving money, time, etc. (M. Ali et al., 2018). Due to the e-learning system, students get more time for different extracurricular activities(M. Ali et al., 2018)(Tarhini et al., 2014).

The direct impact of facilitating condition on behavioral intention to use technology and on use behavior.

Additionally, the results indicate that FCs and BI substantially impact students' e-learning system use behavior. This result corroborates previous research (S. Ali et al., 2018a; Masa'deh et al., 2016). As a result, authorities may take a variety of actions. They may upgrade the campus's technological infrastructure by increasing internet speed and adding additional Wi-Fi access points. Can negotiate with the country's mobile network providers to offer low-cost Internet data bundles for university students through dedicated dongles. Again This result implies that administration at higher educational institutions should provide required infrastructure (e.g., Wi-Fi), support services (e.g., help-line), and easy access to e-Learning resources to academic staff. These facilitations will enable a broader audience to embrace e-Learning as a mode of instruction. All of these factors would serve to increase students' use of e-learning technologies. Thus, the overall results indicate that providing students with the skills and motivation to utilize e-learning systems and integrating e-learning systems into existing conventional settings would guarantee widespread usage of these systems by students.

The direct impact of habit on behavioral intention to use technology.

The term "habit" refers to the perceptual structure associated with frequently and consistently doing an action. The findings indicate that habit is another significant predictor of behavioral intention (Adedoja et al., 2013)(Abu Bakar & Abdul Razak, 2014)(Elkaseh et al., 2015)(Masa'deh et al., 2016). In other words, if users develop a habit of using the system and perceive the e-learning system to be enjoyable to use, they are more inclined to do so.

People who utilize e-learning services more often engage in a more interactive learning environment (Lewis et al., 2013). Thus, management should educate users on the advantages of e-learning services and offer both on- and off-line assistance in addition to training until users reach a stage when technology use becomes a significant element of their educational experiences. When students develop a habit of using e-learning services, they are more inclined to utilize the system. As a result, habit plays a crucial role in broadening the breadth and generalizability of UTAUT2 in the e-learning environment.

The direct impact of Personal Innovativeness on behavioral intention to use technology and on use behavior.

Personal Innovativeness substantially impacted both BI and UB, consistent with UTAUT-3 results, showing its efficacy in explaining academicians' e-Learning adoption in HEI. This conclusion contradicts Lu et al. (2005) findings on the impact of SI and personal innovativeness in information technology (PI) on wireless internet service uptake. The authors discovered that personal innovation in information technology did not predict consumers' willingness to adopt wireless internet services through mobile phones. Another explanation for the importance of PI may be the intended respondents' educational levels. Thus, it is more probable that technology usage is a logical choice based on available knowledge rather than an intuitive one. As a result, the adoption of e-Learning occurs as a result of curiosity or bravery. Another evidence for this behavior via their research of the impact of lecturers' innovativeness in information technology (PI) on their willingness to use VLEs. Thus, it was determined that SI or PI is predictive of e-Learning uptake in HEIs (Gunasinghe et al., 2018). So, the institute should introduce new things at a specific interval that will refresh the student.

The direct impact of behavioral intention to use technology on actual use behaviour.

The connection between intention to behave and actual behavior was found to be strong, as previously verified (Shen & Shariff, 2016)(Adam Wong, 2018)(Šumak & Šorgo, 2016). The findings indicate that the higher the intention, the larger the actual use. Thus, Higher education institutions should encourage e-Learning as a complement to traditional classroom instruction.

Three hypotheses are rejected. In the first one, there is no significant impact between effort expectancy and behavioral intention. That implies that it is the easiness of a system is not essential to the user. Whether the system is easy to use or students will use the system until their performance increases. Second, there is no significant positive impact of habit on the use behavior of a system. This means it is clear that we cannot predict the frequency of its use based on students' habitats to use an e-learning system. The last one, there is no significant positive impact of hedonic motivation on behavioral intention. There is no need for any external reason required for a student to use the e-learning system.

6.1 CONTRIBUTION AND RECOMMENDATIONS

This research adds to the body of knowledge in both theory and practice. In the context of higher education, nothing is known about the use of e-learning technologies. While previous research used segmented factors, this study sought to integrate the integrative adoption model, synthesizing many adoption theories. Although UTAUT2 has been widely utilized in non-educational contexts (Tarhini, Deh, et al., 2017b), our research added to the learning situation in the Indian domain, as Venkatesh et al. (2012) highlighted, by validating it in a diverse setting. This research expanded UTAUT2 by including two new variables, PI and WLQ, to capture additional dimensions of people's attitudes about e-learning technology adoption. This research aimed to give practitioners a clear path. The results would indicate which areas need more effort to ensure the adoption process is successful.

The suggested research model was verified using empirical data in this study. The results show that user adoption of e-Learning is strongly influenced by the user's views, experiences, abilities, and confidence rather than by the character or motivations of others. PE, FC, HA, PI, and WLQ were significant predictors of technology adoption. Thus, the research adds to the theory of information systems adoption and, more specifically, to the domain of research about the acceptance of e-Learning by academics at HEIs. The results will help HEI management, teachers and instructors, and policymakers develop and implement their online strategy and make informed choices on how to increase the acceptance of e-Learning among local HEI academics. Successful implementation of e-Learning would assist HEIs in overcoming some challenges inherent in a conventional classroom. e-Learning enables education to be delivered outside of traditional time and location constraints while also facilitating improved performance monitoring and skill development, ultimately improving output quality and institutional performance (S. Ali et al., 2018b). Thus, it is suggested that decision-makers at HEIs examine the implications of the results mentioned above when developing plans for increased e-Learning use. Regular assessment of the e-learning system will help to removes flaws. These activities may enable a broader academic audience to use e-Learning for course delivery. Based on the study's results, the first suggestion would be for administrators of higher education institutions. More attention must be paid to the course structure design to integrate online learning, founded on theories and previous literature.

Additionally, instructors and course developers must be educated and competent to accomplish the objectives of online learning platforms. Students must attend workshops and training sessions to increase their familiarity with learning management systems such as Moodle and LMS. The software alone is insufficient to provide an online learning environment that is both student and teacher-friendly. If teachers are not educated and are ignorant of using the software (e.g., Moodle) in class, the quality of education delivered to students will suffer. Educating and assessing the class teacher and modifying the software may result in a pleasant educational setting for the instructor and a good education for the student. Both student happiness and academic success are contingent upon students' previous knowledge and experience with online learning.

7. LIMITATIONS AND FUTURE DIRECTIONS

The research examined student views of e-Learning adoption solely, leaving other user perspectives (such as instructors). Additionally, this is cross-sectional research, which means that user impressions are evaluated during a particular period. However, user views of systems change with time and with experience. Additionally, the quantitative technique was utilized to gather data. As a result, the use associated with profound insights was overlooked. Thus, longitudinal studies using a mixed approach of data collecting and including academicians and students will benefit future studies.

The sampling technique used was convenient non-probabilistic sampling. As a result, this sample should not be considered a perfect representative of the total student population. The findings of this study are limited to a single higher education institution, and due to the small sample size, caution should be used about generalizability.

Future studies should use a larger sample size to account for more responses. To better understand students' adoption of e-learning systems, future research could introduce extra constructs, especially culture and trust, and the moderating effects of demographic variables through probabilistic sampling, the mix method, and longitudinal data collection. Additionally, an additional study may be performed to ascertain college students' efficiency while using e-learning technology.

8. CONCLUSION

The purpose of this research was to present a complete model based on a combination of the TAM and UTAUT frameworks and certain external variables affecting the distance education system to explain the impact of various elements. It's worth noting that although individual problems result from societal circumstances, this study attempted to concentrate on the psychological aspects of people. With the findings of this study, developers of this system, particularly in developing countries, can determine which components should be prioritized for effective deployment.

This research investigated the factors of remote learning from the students' viewpoint using the UTAUT paradigm. The suggested theoretical model was verified in the setting of a local HEI, where the research instrument matched well with actual data, allowing hypothesis testing to continue. The structural model analysis revealed that nine of the twelve predicted connections were significant predictors of distance-learning adoption.

Appendix I: Constructs and Items

Performance Expectancy (Venkatesh et al., 2003)	
PE1:	I would find e-learning system useful for my studies
PE2:	Using the E-learning system helps in accomplishing my tasks more quickly
PE3:	Using the E-learning system increases my effectiveness in learning
PE4:	Using the E-learning system increases my productivity
PE5:	Using the E-learning system makes it easier to learn course contents
Effort expectancy (Venkatesh et al., 2003)	
EE1:	The interaction with e-learning system is clear and understandable
EE2:	It is easier to become skillful at using the e-learning system
EE3:	It is easy to find information using the e-learning system
EE4:	Learning to use the e-learning system is easy
Social influence (Venkatesh et al., 2003)	
SI1:	People who are important to me think that I should use an e-learning system
SI2:	People whose opinions I value prefer that I use an e-learning system in my studies
SI3:	My lecturers think I should use the e-learning system
SI4:	My colleagues think I should use the e-learning system
Hedonic motivation (Venkatesh et al., 2012)	
HM1:	Using an e-learning system is fun
HM2:	Using an e-learning system is an enjoyable experience
HM3:	The actual process of using an e-learning system is pleasant and entertaining
Facilitating condition (Venkatesh et al., 2003)	
FC1:	I have the resources necessary to use the e-learning system
FC2:	I have the knowledge necessary to use the e-learning system
FC3:	The technological requirements needed to use an e-learning system is compatible with my current system requirements
Habit/ Internet Experience (Liao and Cheung ,2001).	
HB1:	I am comfortable using the internet for e-learning
HB2:	I am comfortable using the computer for e-learning
HB3:	I am comfortable using the e-learning software /app
HB4:	Using e-learning system has become a habit to me
Personal innovativeness (Junainah 2019)	
PI1:	I like to experiment/ try out new features and advancements in technology
PI2:	I am keen to try new features in e-learning systems
PI3:	Usually, I am the first to adopt innovative learning methods among my peers
Work-life quality (Kripanont, 2007)	
WLQ1:	Using the e-learning system helps me to have more time for a creative thinking
WLQ2:	Using the e-learning system helps me to have more time for leisure
WLQ3:	Using the e-Learning system helps improve my quality of learning
Behavioural Intention (Venkatesh et al., 2003)	
BI1:	I intend to use the e-learning system for preparing for the exam and coursework
BI2:	Given the chance, I intend to use the e-learning system to do different things, from downloading lecture notes and participating in chat rooms to learning on the Web
BI3:	In general, I plan to use e-learning system frequently for my

	coursework and other activities in the next semester
BI4:	I intend to engage in e-learning routinely
Use Behaviour (Venkatesh et al., 2012)	
UB1:	How many times do you use the e-Learning system during a week?
UB2:	How long do you use the e-Learning system?
UB3:	How frequently do you use an e-Learning System?

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