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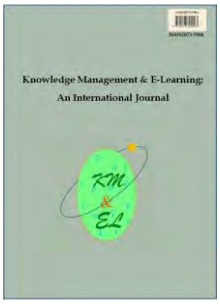

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Novel extension of the UTAUT model to assess e-learning adoption in higher education institutes: The role of study-life quality

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Abstract: The study aims to improve the existing unified theory of acceptance and use of technology (UTAUT) framework to understand the adoption of e-learning platforms in developing countries and to understand the relevance of the quality of study life among students. The constructs for the UTAUT model were chosen based on the e-learning study context and expanded with the variable study-life quality. The expanded model was tested with empirical data collected from graduate and post-graduate students of higher education institutes. The hypotheses testing and adequacy of the expanded model were analysed using structural equation modeling using SmartPLS v 3.2.8. The study's findings indicate that nine out of the twelve hypothesized paths significantly influenced students' engagement with e-learning platforms, and a total of six significant variables explained a variance of 65.8% of the dependent variable behavioral intention. The variable study-life quality had the highest β coefficient value of 0.380, indicating that it is the most significant factor for e-learning adoption in this study setting. The study adds to the publication on adoption theories by providing an expanded UTAUT framework that is empirically tested.

Keywords: Adoption theory; Online learning; SmartPLS; UTAUT; MOOCs

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1. Introduction

Education is the cornerstone of developing a country's human resource base and has a substantial and positive impact in its socioeconomic structure. Developing nations need to invest in enhancing their education system since it drives growth and economic competitiveness on a national and international scale (Mukherjee, 2016). Higher education institutions have shown persistent interest in improving students' academic performance in recent years through cutting-edge technology that provides fresh approaches to generating and delivering university education (Kim et al., 2019). The rapid growth of information technology (IT) and the need for high-quality education have fueled the rapid growth of e-learning (El-Masri & Tarhini, 2017; Oh & Yoon, 2014). It has made quality education accessible and affordable to all sections of society. E-learning systems have become critical attributes as institutions compete to reduce expenses, attract more students, and satisfy their academic requirements (Arpaci, 2015). The rise of the e-learning market is also evident from the fact that the e-learning market is projected to develop at an average cumulative growth rate of 7.07% to reach 65.41 billion dollars by 2023 (Research and Markets, 2018).

The assumption that students are digital natives suggests that they should be familiar with and comfortable with an academic e-learning environment when participating in one. But research has shown that e-learning and student satisfaction are not always positively correlated (Long et al., 2019; Martinez et al., 2020), and dropout rates tend to be 10-20% higher than offline learning (Patterson & McFadden, 2009). Understanding how people embrace e-learning technology and how it influences every element of teaching and learning is critical for the successful adoption of e-learning (Al Mulhem, 2020). Developing countries face far more significant barriers despite investments in infrastructure and training due to the shortage of personnel, inadequate technological adoption, and insufficient institutional participation and information sharing (Kim & Park, 2018; Ogbodoakum et al., 2022). Since institutes want to make the most of online learning, knowing what influences user adoption, retention intentions, and learning outcomes of online learning is essential (Panigrahi et al., 2018).

Research has tested various technology adoption theories to examine the variables that facilitate or impede student acceptance of e-learning platforms (Anthony et al., 2022; Porter et al., 2016). The Unified Theory of Acceptance and Use of Technology (UTAUT), which is deemed to have a higher explanatory power compared to other models, was also tested in the e-learning context, and its adequacy is proved by many researchers (Olasina, 2018; Yoo et al., 2012). The studies have indicated that students' successful acceptance of e-learning platforms varies according to demographic groups, societies, and cultures and is often influenced by several behavioral and organizational factors (Tarhini et al., 2017; Venkatesh et al., 2012; Venkatesh & Zhang, 2010). Given the contextual changes, using existing theories and constructs is inadequate to detect problems connected to e-learning usage intentions. To overcome this limitation and gain more insights regarding e-learning adoption in a developing nation, the adequacy of other variables must be examined. The experience of online learning and their effect on the life of students is an important factor that has not been examined along with the UTAUT variables.

The life of a student is complicated as it is. They must balance the competing expectations of their parents, friends, lovers, and other people while still fulfilling their academic requirements. They could even suffer unforeseen financial and health issues. Their ability to appropriately balance those issues will determine how successful their education will be. The perceived quality of study life is a key variable that indicates the well-being of a student. It encompasses a lot of issues ranging from student experience, teaching and faculty-student relations, program standards, institutional effectiveness, student services and learning environment (Benjamin, 1994). The quality of student life can influence student outcomes in terms of academic performance and satisfaction. It should therefore be a key factor in understanding student experiences and outcomes.

The research questions this study puts forward are i) What are the primary factors determining e-learning adoption among students of higher education institutes in a developing country? And ii) Is the overall experience of online learning relevant to students? To answer the stated research question, this study extended the UTAUT model with the variable study-life quality and tested it among graduate and post-graduate students of higher education institutes across South India. The research was done during the COVID-19 pandemic when universities resorted to e-learning to prevent any disruption in the learning process. The literature review is detailed in section 2, the theoretical framework and hypothesis are established in section 3, the methodology in section 4, data analysis in section 5, the discussion in section 6 and theoretical and practical implications in section 7, followed by the conclusion and future directions in section 8.

2. Literature review

Technology adoption studies have been conducted for over two decades, and many have proposed technology acceptance theories to study user acceptance of novel technology. The disciplinary underpinnings of the proposed theories constrained the applicability of these theories to certain contexts. To give a comprehensive grasp of technology adoption, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), which was a unification of eight adoption theories that include 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 UTAUT theory offered a variety of perspectives on the adoption and implementation of technology since the theory took into account various domains. The UTAUT model, which comprised four variables, was extended by Venkatesh et al. (2012) (named UTAUT-2) by adding three more determinants to enhance the explanatory power while testing information systems' acceptance in consumers (Venkatesh et al., 2012). Farooq et al. (2017) added one more variable and claimed that the UTAUT-3 framework had an explanatory power of 66% in predicting technology acceptance. The UTAUT model has proved to be a reliable research instrument that predicts adoption behavior, and it has proved adept in predicting technology adoption by 70%, which is better than other models (Schaper & Pervan, 2007).

Many researchers have been able to comprehend technology adoption due to substantial replication, applications, and integration of UTAUT, but there is still a need for a methodical analysis and conceptualization of the essential factors that are relevant to a certain context (Venkatesh et al., 2012). Studies have recommended using context-specific constructs that consider characteristics pertaining to users and the technology being considered. The UTAUT framework was extended using determinants like personal traits (Barnett et al., 2015), ICT competency (Aslan & Zhu, 2018), attitude (Dwivedi et al., 2019), anxiety (Maican et al., 2019), self-efficacy (Long et al., 2019), and experience (Dedeoglu et al., 2017). The explanatory power is bound to change according to the context of application, i.e., the technology acceptance under study and the population demographic in question.

The literature survey revealed that many researchers studied and adopted the UTAUT framework in e-learning. In their study, Chen and Tseng (2012) tested the UTAUT model on junior high school teachers in Taiwan and discovered positive effects on the variables perceived usefulness and perceived ease of use. Campbell and Ma (2016) discovered that system exposure and technological innovation impacted how well e-textbooks were received. Yatigammana et al. (2014) found that observability and comparative advantage significantly influence attitudes and intentions about the usage of e-learning in Sri Lanka. According to Mtebe (2014) the factors that greatly affected students' adoption of mobile learning solutions in East Africa's higher education were effort expectancy, performance expectancy, social influence, and facilitating conditions. In their research on the adoption of e-textbooks, Hsiao and Tang (2014) looked at five theoretical adoption models, including the UTAUT model. They discovered that the UTAUT model had the highest explanatory power of all the tested models, demonstrating its reliability for online learning. Quality, trust, academic self-efficacy, quality of work life and sense of community were other variables found in the literature that significantly impacted e-learning adoption (Masa'deh et al., 2016; Tarhini et al., 2013; Wang, 2014).

Tarhini et al. (2014) have used the variable quality of work life in an extended TAM model to study the adoption of e-learning in Lebanon. Though the variable quality of work-life has been used to improve the TAM model in the information systems domain, Tarhini et al. (2014) was the first to use this variable in the context of education. The authors in the current study postulate that the second research question, which tries to understand the students' overall experience while using the e-learning system, could be evaluated using the quality of work-life variable. The authors found no studies where the quality of work-life was used in conjunction with the variables of the UTAUT model. So, considering the explanatory power of the model and the relevance of the UTAUT variables in the study context, the authors decided to extend the UTAUT model with the variable study life quality to answer the research questions.

3. Theoretical framework

The main objective of the study is to examine the primary factors determining e-learning adoption among students of higher education institutes in a developing country and to examine the relevance of e-learning experience to students. To achieve the stated objective, the authors chose the UTAUT framework, supported by previous studies examining e-learning adoption (Olasina, 2018). The UTAUT framework was extended with the variable study life quality which is similar to the variable quality of work life used by Tarhini et al. (2014). This variable was added with the belief that adopting e-learning would enhance the quality of student life, including the ability to connect with classmates and instructors while saving money on the cost of downloading materials (Tarhini et al., 2013). The proposed model had eight independent variables that are hypothesized to impact behavioral intention and use behavior significantly. Since the variables like age, gender, voluntariness and experience did not have notable variations among the students the moderating effect of these variables was not examined in this study. Many similar studies have excluded the moderators while adopting the UTAUT framework (Alalwan et al., 2015; El-Masri & Tarhini, 2017; Morosan & DeFranco, 2016).

The extended UTAUT framework is illustrated in Fig. 1, and it has the following determinants:

Performance expectancy (PE)

Performance expectancy is the expectation of the student that the e-learning platform will help him enhance his academic performance. Previous studies support the notion that users will see technologies favorably if they help them with their tasks (Davis, 1989; Venkatesh et al., 2003). Hence it is hypothesized in this study that:

> ***H1***: Performance expectancy positively influences students' behavioral intention to use e-learning systems

Effort expectancy (EE)

Effort expectancy is the intended usability of the e-learning platforms. Studies have shown that if the user believes that the technology is easy to use and trouble-free, they will adopt it (Venkatesh & Zhang, 2010). Hence it is hypothesized that:

> ***H2***: Effort expectancy positively influences students' behavioral intention to use e-learning systems

Social influence (SI)

Social influence is the influence of the faculty and peers on the student to utilise the e-learning platform. Most information system (IS) empirical studies indicated that SI was a significant predecessor to BI (El-Masri & Tarhini, 2017; Tarhini et al., 2013; Venkatesh & Zhang, 2010). Here in the e-learning context, it is believed that students will consult each other and their instructors on the available e-learning systems and their efficacy before adopting them. Accordingly, the following hypothesis was postulated that:

> ***H3***: Social influence positively influences students' behavioral intention to use e-learning systems

Study-life quality (SLQ)

Study life quality is the motivation and satisfaction that students receive as part of their student life when using the e-learning platform. Tarhini et al. (2013) in their study on e-learning adoption, has supported the fact that quality of work life is an essential antecedent to BI. It is believed that if students feel and think utilising technology would enhance their quality of working life, they will tend to adopt it. Therefore, it is hypothesized that:

> ***H4***: Study life quality positively influences students' behavioral intention to use e-learning systems

Hedonic motivation (HM)

Hedonic motivation is the joy while engaging with the e-learning platform. Research in the IS and marketing sectors has revealed that the perceived hedonic character of a system can enhance the intention to use the system (Brown & Venkatesh, 2005; Venkatesh et al., 2012). Hence it is hypothesized as:

> ***H5***: Hedonic motivation positively influences students' behavioral intention to use e-learning systems

Personal innovativeness (PI)

Personal innovativeness is the character attribute that makes students try out new technology. The research by Masadeh et al. (2016) shows that in successful integration scenarios, students' readiness to adopt new information technologies significantly influences their choice of technology. Gunasinghe et al. (2019), in their study, have found a significant effect of PI on both behavioral intention and use behavior. Ngafeeson and Sun (2015) also reported a positive influence of PI on the intention to use. Accordingly, it is hypothesized in this study as:

> ***H6***: Personal innovativeness positively influences students' behavioural intention to use e-learning systems

> ***H7***: Personal innovativeness positively influences students' use behaviour of the e-learning system

Facilitating conditions (FC)

Facilitating conditions refer to the institutional resources that make the e-learning platform easier to utilise. Various studies have found this variable's significant effect on user intention and actual usage (Gunasinghe et al., 2019; Venkatesh et al., 2003, 2012). Hence it is hypothesized as:

> ***H8***: Facilitating conditions positively influences students' behavioral intention to use e-learning systems

> ***H9***: Facilitating conditions positively influences students' use behavior of the e-learning system

Habit (HA)

Habit is the instinctive utilisation of the e-learning platform because of prior experience. Habit establishes a psychological commitment to a specific behavior and frequently prevents modifications to real activity. Studies have shown the positive influence of the variable habit on both user intention and actual use of technology (Gunasinghe et al., 2019; Venkatesh et al., 2012). Hence it is hypothesized as:

> ***H10***: Habit positively influences students' behavioral intention to use e-learning systems

> ***H11***: Habit positively influences students' use behavior of the e-learning system

Behavioral intention (BI) to use

Behavioral intention is the students' willingness to adopt the e-learning platform and is proven in many studies to directly effect actual use behavior (Davis, 1989; Gunasinghe et al., 2019). Accordingly, it is hypothesized as:

> ***H12***: Behavioral Intention positively influences students' use behavior of the e-learning system

Use behavior (UB)

Use behavior refers to the degree to which e-learning systems are really used.

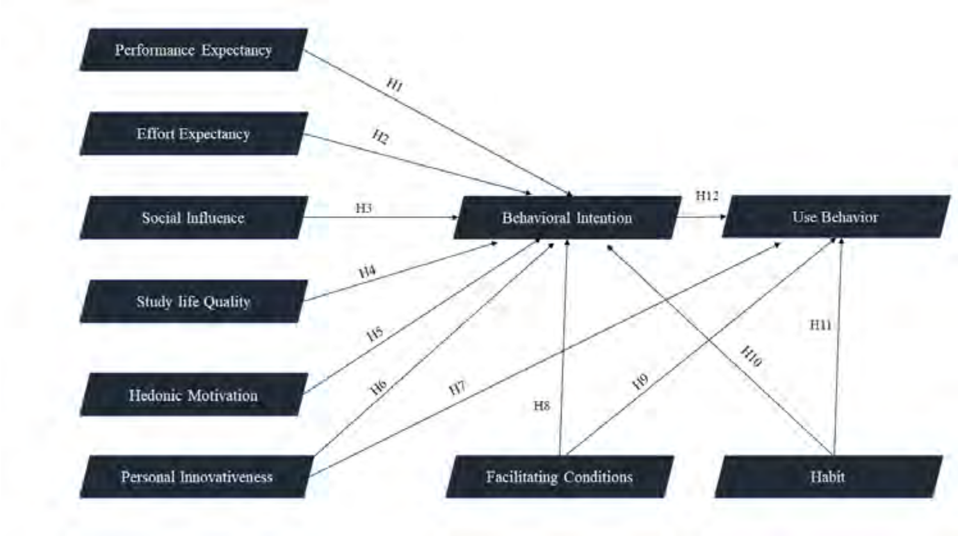

Fig. 1. Theoretical framework

4. Methodology

To gather responses, a survey was built and distributed using Google Forms. The initial part of the questionnaire gave a brief of the study and then gathered the demographic data of the respondents. The main part of the questionnaire had thirty-four items capturing UTAUT variables, altered to fit the context of e-learning, on a five-point Likert scale. Five items corresponded to PE, four to EE, four to SI, four to FC, three to HM, four to HA, three to SLQ, three to PI, and four to BI (Venkatesh et al., 2003; Venkatesh & Zhang, 2010). The third part had three questions that captured the user behavior and had an open-ended question asking relevant suggestions from the respondents. The questionnaire was put through a focus group study to ascertain the level of comprehension and the time required for completion of the questionnaire. Minor changes, wherever necessary, were made based on their feedback to improve understanding, and the time needed for completing was estimated to be around seven minutes. The instrument (Appendix I) was then subjected to actual data collection.

The data for the full-scale survey was collected from the students of various technical institutes in the southern part of India. It was found that technical institutes had more e-learning platform users than other institutes. The snowball sampling method was employed to collect the responses. The invitation to the survey explaining the nature of the study and a link to the questionnaire was mailed to graduate and post-graduate students who are current users of e-learning platforms. They were then asked to refer their friends or relatives to help with the data collection. The survey respondents were instructed that the study was based on the voluntary adoption of the e-learning platform and not the forceful shift due to COVID-19. A total of 524 valid responses were gathered from January 2021 to March 2021.

5. Data analysis

Structural Equation Modeling (SEM) was performed to test the hypotheses and to determine whether the proposed UTAUT model was adequate. SEM is a statistical technique for analysing and estimating causal links that distinguishes between structural and measurement models and explicitly takes measurement error into account. (Henseler et al., 2009). This is also congruent with Hair et al. (2017) proposal that the measurement models be investigated independently before the structural model is evaluated. SEM is the most frequently used statistical modeling tool in behavioral studies that are explanatory in nature (Blunch, 2013). The software SmartPLS (v 3.2.8), which is based on the Partial Least Square (PLS) SEM approach, was used to assess the data. PLS-based SEM was chosen since it is the one best suited for predictive purposes (Briz-Ponce et al., 2017; Jr. et al., 2017). The PLS-SEM, a variance-based SEM technique, has a regression-based approach that maximizes the residual variance of the dependent variables. The PLS comprises two components: the measurement model and the structural model. The measurement model explains how the variables interact to reflect the theory that is being suggested and evaluates the value of the variables, whereas the structural model assesses the interconnections between the variables (Hair et al., 2011). Additionally, the bootstrap technique was utilized to determine the significance of coefficients and route load.

5.1. Respondents' demographic information

Table 1 and Fig. 2 represents the respondents' profiles. Out of the 524 responders, 415 (79%) were male, and 109 were female (21 %), 104 were post-graduates (20 %), and 420 were undergraduates (80 %). Most of the responders were in the 20 to 22-year age range. (65 %). Other respondents were distributed as 20% in the age group of 20 to 22 years and 15% below 20 years. Though the sample is not uniformly distributed across each demography, the authors consider this a fair illustration of the student population in a technical higher education institute in India regarding gender ratio, age group and undergraduate-to-postgraduate ratio (Deccan Herald, 2022). The authors discovered no statistically significant changes in the usage behavior of the respondents in connection to their demographics.

Table 1
Demographic information of residents

Variable	Frequency	Percentage
Gender		
Male	415	79
Female	109	21
Type of degree		
Undergraduate	420	80
Post-graduate	104	20
Age group		
Below 20 years	79	15
20 to 22 years	104	20
Above 22 years	321	65

Fig. 2. Respondents profile

5.2. Measurement model: Reliability and validity

This study adheres to the standards outlined by Fornell & Larcker (1981) and Hair et al. (2017) which specifies that every factor loading should be more than 0.7 and significant at the 5% level. Table 2 indicates that the factor loadings of all items obtained from SmartPLS meet this criterion. It is also essential to assess the internal consistency reliability since the survey was based on a 5-point Likert scale. Reliability measures include Cronbach's alpha and composite reliability (CR). The Cronbach's alpha values shown in Table 3 are greater than the cutoff point of 0.7, which Nunnally (1968) recommended for an explanatory study. The study shows strong internal consistency reliability as the values of CR varied from 0.857 to 0.935, which is compatible with the value suggested by Hair (2009).

Convergent validity indicates how closely the items are connected to the variable. Average Variance Extracted (AVE), which must have values of 0.5 or greater, provides a measure of convergent validity (Bagozzi & Yi, 1988). Table 4 indicates that all values of AVE are higher than 0.5, which shows that the model has convergent validity.

The HTMT (Heterotrait-Monotrait) ratio of correlations shows the distinctiveness of the variables are from one another, and it is an indicator of discriminant validity (Henseler et al., 2014). The HTMT value should be below 0.85 to exhibit good discriminant validity (Kline, 2011). The outputs listed in Table 5 indicate that the model has sufficient discriminant validity.

Table 2
Factor loadings

Constructs & items	Factor loading	Confidence interval 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
SLQ1 <- SLQ	0.873	0.850	0.892
SLQ2 <- SLQ	0.733	0.697	0.776
SLQ3 <- SLQ	0.849	0.823	0.869

Table 3
Model reliability measures

Constructs	Cronbach's alpha	Confidence interval Lower bound	Upper bound	Composite reliability	Confidence interval 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	0.870	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
Study-life quality	0.758	0.72	0.79	0.86	0.841	0.877

Table 4
Values of average variance extracted (AVE)

Constructs	Average variance extracted	Confidence interval Lower bound	Upper bound
Behavioral intention	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
Personal innovativeness	0.702	0.668	0.732
Social influence	0.757	0.730	0.782
Use behavior	0.744	0.715	0.771
Study-life quality	0.673	0.644	0.706

Table 5
Heterotrait-monotrait ratio

	BI	EE	FC	HA	HM	PE	PI	SI	UB
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	
SLQ	0.888	0.673	0.408	0.587	0.764	0.839	0.570	0.647	0.066

The goodness of fit of the proposed structural model was assessed. All goodness of fit estimates was above the cut-off value, as indicated in Table 6.

Table 6
Goodness of fit measures

Measure	Estimate	Threshold	Interpretation
$\chi 2$ /df	2.035	1 to 3	Excellent
NFI	0.900	> 9	Excellent
RMSEA	0.045	< 0.06	Excellent
SRMR	0.030	< 0.08	Excellent

5.3. Structural model assessment

The interrelationship between the variables, the R^2 value and the goodness of the structural model are estimated for the statistical evaluation of the proposed model. The path coefficients are shown in Table 7. All the hypotheses except H2 (effort expectancy influencing behavioral intention), H5 (hedonic motivation influencing behavioral intention), and H11 (habit influencing use behavior) are supported.

Fig. 3 represents the path coefficients and R2 value of each factor. The findings indicate that nine out of the twelve hypothesized paths were significant in predicting students' adoption of e-learning platforms. The independent variables performance expectancy, social influence, facilitating conditions, study-life quality, habit, and personal innovativeness accounted for 65.8% variance of the dependent variable behavioral intention. Additionally, behavioral intention, personal innovativeness, and facilitating conditions explained 7.1% variance of the dependent variable use behavior.

Table 7
Model hypothesis

				Path Coefficient	Standard Deviation	*t*- Statistics	*p* Value
H1	PE	⟹	BI	0.202	0.043	4.652	0.042
H2	EE	⟹	BI	0.007	0.042	0.155	*0.438*
H3	SI	⟹	BI	0.105	0.035	3.015	0.012
H4	SLQ	⟹	BI	0.380	0.045	8.523	0.024
H5	HM	⟹	BI	0.032	0.047	0.681	0.012
H6	PI	⟹	BI	0.101	0.038	2.638	*0.445*
H7	PI	⟹	UB	0.224	0.063	3.531	*0.248*
H8	FC	⟹	BI	0.086	0.038	2.261	0.000
H9	FC	⟹	UB	0.124	0.062	1.990	0.004
H10	HA	⟹	BI	0.110	0.049	2.251	0.000
H11	HA	⟹	UB	0.009	0.062	0.139	0.001
H12	BI	⟹	UB	-0.087	0.050	1.728	0.000

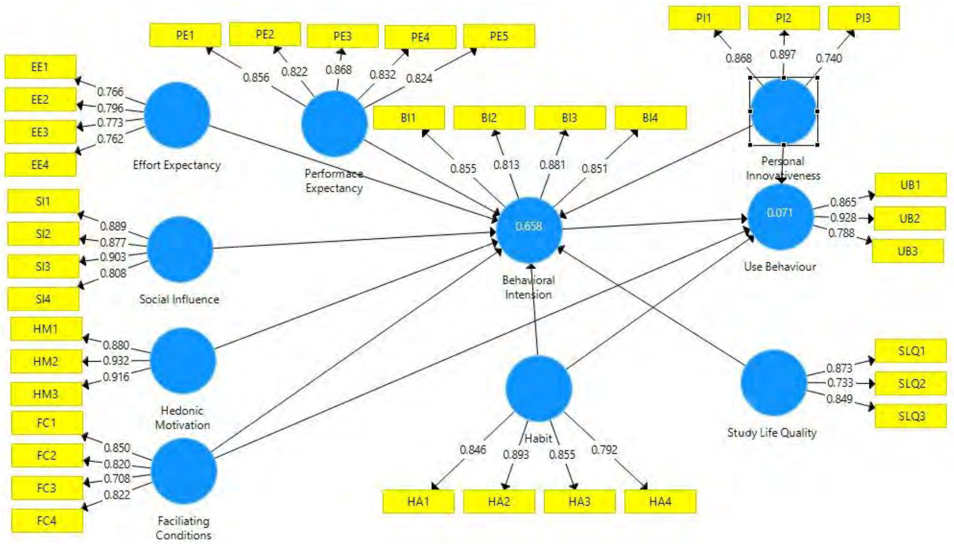

Fig. 3. Structural model obtained from SmartPLS

6. Discussion

The study explored the variables that could affect students' behavior when using e-learning technologies at higher education institutions. This study's theoretical framework is an expanded version of the UTAUT framework. This research examined the impact of different variables such as effort expectancy, performance expectancy, social influence, facilitating condition, study-life quality, personal innovativeness, habit, and hedonic motivation on the behavioral intention of users to use e-learning and their accompanying effect on how users of e-learning platforms behave. The findings indicate that nine out of the twelve hypothesized paths were significant in predicting students' adoption of e-learning platforms. The variable study-life quality had the highest β coefficient value of 0.380, indicating that it is the most significant factor for e-learning adoption in this study setting. Other factors like performance expectancy (hypothesis 1 (PE→BI), β coefficient 0.202), social influence (hypothesis 3 (SI→BI), β coefficient 0.105), facilitating conditions (hypothesis 8 (FC→BI), β coefficient 0.086), habit (hypothesis 10 (HA→BI), β coefficient 0.110) and personal innovativeness (hypothesis 7 (PI→BI), β coefficient 0.101) were also found to be strong determinants of e-learning platform usage behavior. Further, the factors like behavioral intention (hypothesis 12, β coefficient -0.087), personal innovativeness (hypothesis 7 (PI→UB), β coefficient 0.101) and facilitating conditions (hypothesis 9 (FC→UB), β coefficient 0.124) are found to be significant determinants of the dependent variable use behavior. Contrary to the findings of Farooq et al. (2017), the factors effort expectancy and hedonic motivation were not significant in predicting students' willingness to use e-learning platforms.

The result indicates the significance of the factor 'performance expectancy' which is similar to earlier studies in e-learning adoption (Ali et al., 2018; Gunasinghe et al., 2019; Wang et al., 2020). It is quite evident that if the students believe that utilising the e-learning platforms would enhance their academic achievement, they will be motivated to utilise it. Hence, academicians and administrators should ensure that students are well informed of the usefulness of the platform and provide helpful content. The adoption generally tends to be higher if the platform is more user-friendly, less complex, and timesaving than the traditional system. But in the current study, effort expectancy was an insignificant factor, which contradicts the findings of previous studies on e-learning adoption (Farooq et al., 2017; Gunasinghe et al., 2019). This might be because internet and technology usage has become more common and shifting to a new platform is no longer an uphill task.

The role of teachers, administration and their peers is also essential for adopting e-learning platforms. Similar to prior research, the result shows that social influence directly influences behavioral intention to utilise e-learning platforms (Briz-Ponce et al., 2017). Peers and teachers alike can influence the perception and attitude of a student toward e-learning. The effect of social influence on a person can vary based on culture, age, and education (Masadeh et al., 2016). It is always recommended that teachers elucidate the advantages of e-learning platforms to their students and also lend assistance whenever they can. They can even convince early adopters to assist others if required. Once a certain number of users have been attracted, there will be an exponential increase in new users. (Tarhini et al., 2014).

The variable study-life quality was the most important predictor of behavioral intention to utilise e-learning platforms. The implementation of an e-learning platform streamlines the learning process and reduces costs, which will enhance the study life of the students (Ali et al., 2018; Tarhini et al., 2014). This factor is very relevant in the Indian context since educators and parents expect students to put in a lot of time for their studies at the expense of leisure activities. This can adversely impact the mental health of the students. Adopting e-learning platforms can help students counter this difficulty and help them find time for leisure.

Similar to other studies in the area, facilitating conditions significantly affected both behavioral intention and use behavior (Masadeh et al., 2016). The administration has to ensure that students have all the required facilities, access, and help for e-learning platforms. Past research has shown that providing students with the skills and motivation to utilize e-learning platforms and integrating e-learning systems into existing conventional settings would guarantee widespread usage of these systems by students (Ambarwati et al., 2020).

According to this research, habit is a crucial variable in the penetration of e-learning platforms, which corroborates previous findings (Jin et al., 2021; Tandon et al., 2022). More frequent and consistent use of e-learning platforms by students will encourage them to use them regularly. The administrators should provide adequate training and support until the user finds the experience enjoyable and ultimately develops a habit of using the platform. In addition, studies have shown that an appropriate intervention strategy positively affects the willingness to utilise an e-learning platform (Cobos & Ruiz-Garcia, 2021). The study, however, found no substantial effect of the variable habit on e-learning use behavior. Further, studies also reveal that students prefer taking offline classes when it comes to difficult courses (Jaggars, 2014; Martinez et al., 2020). It indicates that it is difficult to predict the frequency of use based on habit.

The study found no substantial impact of hedonic motivation on behavioral intention, indicating that the students need no external influences to use the e-learning platform. But this result differs from those obtained in previous studies, which concluded that greater adoption requires user enjoyment and motivation (Gunasinghe et al., 2019). This might be because although many people agree on the general notion of perceived enjoyment in e-learning, it cannot be generalized to the entire population. Also, enjoyment might not be a deciding factor in using e-learning systems for the population under study. Personal innovativeness significantly impacted behavioral intention and use behavior. Students generally have an inbuilt sense of curiosity for novel technology. So, if they are provided access to a new technology, they tend to adopt it readily. The administration can take steps to introduce novel technologies that will refresh the student experience. The literature has previously shown a link between behavioral intention and actual behavior (Gunasinghe et al., 2019; Xu et al., 2021). The current research also exemplifies the theory that behavioral intention is an immediate antecedent to actual use behavior. It reveals the user's willingness to perform a specific behavior. Hence it can be said that higher the intention higher is the actual use.

Six determinants could significantly explain 65.8% variance of the dependent variable behavioral intention. This shows that the framework proposed here is good enough to predict the dependent variable behavioral intention. However, the proposed model, with just three independent variables, was not adequate (R^2 = 0.07) to explain students' adoption of e-learning at an HEI.

7. Practical and theoretical implications

The model proposed in this study emphasises the significant relationships between elements that affect e-learning acceptance, like influence of peers and faculty, quality of study life, personal innovativeness, infrastructural availability, and habit. This research broadens our knowledge of adoption theories, particularly in higher education, by providing a modified UTAUT framework that is empirically tested. A majority of authors who created adoption frameworks have recommended testing their framework in newer contexts (Farooq et al., 2017; Wilson, 1978) and this study extends the UTAUT model to the diverse higher education setting. The factors like study-life quality and hedonic motivation were included to offer information on the influence of psychological elements on students' use of e-learning. The former was found to be a significant factor, whereas the latter was found to be insignificant in the study context. The result is helpful for managers and administrators alike for planning and fruitful implementation of e-learning platforms in developing countries. The significance of the variable study-life quality emphasizes the need for an all-around student experience, including time for co-curricular activities. Students need motivation, satisfaction, and maximum benefit in terms of time and money from their sessions. e-Learning can meet this demand to a certain extent and help them find time for leisure activities, significantly influencing their mental well-being. The e-learning platforms' successful implementation would benefit higher education institutes in overcoming the inherent shortcomings in a traditional classroom. It removes the constraints of place and time and facilitates improved performance monitoring and skill development. This will ultimately help the institute improve its service quality and student satisfaction.

Implementing the e-learning systems alone won't provide a teacher-friendly or student-friendly environment. Improper training and support will only lead to frustration and a decrease in the quality of the outcome. The management should make sure the systems are correctly installed and fully functional. This can ensure a smooth transition and ensure that the experience is enjoyable and user-friendly. The current study also showed that the students didn't care about the effort involved or the fun aspect of e-learning systems. This implies that adopting new technology in the digital age is not a labour-intensive process for students. They are ready to shift to a new platform if it enhances their learning experience despite not having much fun associated with the whole experience.

8. Conclusion and future directions

The study focused on examining the factors that affect the acceptance of e-learning in a developing country and to understand the relevance of the overall e-learning experience to the students. The UTAUT framework was extended with the variable study-life quality, and the proposed model was tested among students in South India. The data were analysed using a structural equation modeling approach, and it was found that the proposed model could explain 65.8% of the variance of the dependent variable behavioral intention and only 7% of the variance of the variable use behavior. The results show the relevance of the variable study life quality and the significance of the overall learning experience for the students. The use behavior of the respondents made it clear that students in south India favor e-learning, and once the hindrances are removed, it will have a successful acceptance among the entire population.

Although the study offered insight into the elements influencing the acceptance of e-learning in a developing nation, it only looked at the perspectives of the students. The views of other stakeholders are also equally important and should be considered for future research. This was a cross-sectional study conducted during a particular period, and the results are bound to vary since user opinions also change with time. The study was conducted when all universities shifted to online mode amidst the COVID-19 pandemic. The survey respondents were advised that the questions primarily focused on e-learning that was used voluntarily rather than e-learning that was forced upon them owing to COVID-19, yet the findings might still be marginally biased. A separate study to examine the effect of COVID-19 is needed to confirm this.

Further, since the study was quantitative, some factors that might have been relevant in the context might have been overlooked. Factors like flexibility, course quality and interaction with faculty used by Turhangil Erenler (2020) to evaluate student satisfaction can be considered when assessing use behavior. A qualitative study can shed lighter on this front. Though the moderating effect of age, gender, age, voluntariness and experience is not relevant in this study, it should be examined for a large-scale study with a vast population and different subgroups.

The three variables in the framework postulated to effect use behavior could only explain 7% of the variance. This means that other significant factors should be explored at length and tested for their significant effect on the dependent variable use behavior.

Author Statement

The authors declare that there is no conflict of interest.

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Appendix I

Constructs and items

Performance expectancy	
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	
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	
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	
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	
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	
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 for me
Personal innovativeness	
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

Study-life quality

SLQ1: Using the e-learning system helps me to have more time for creative thinking and leisure

SLQ2: Using the e-learning system helps to lower the stress level associated with learning

SLQ3: Using the e-learning system helps improve my quality of learning and improve my career prospects

Behavioral intention

BI1: I intend to use the e-learning system for preparing for the exam and coursework

BI2: Given a 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

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?

Any other suggestions?