FACTORS INFLUENCING STUDENTS' INTENTION TO USE E-LEARNING IN INDIGENOUS MEDICAL EDUCATION IN SRI LANKA

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Abstract

E-learning has emerged as a transformative approach in higher education, driven by advances in information and communication technologies. However, its adoption in Indigenous medical education in Sri Lanka remains limited compared to developed countries. This study investigates the key factors influencing undergraduate students' intention to use e-learning in this context. Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM), an integrated framework was developed to examine multiple dimensions affecting e-learning adoption. A quantitative research design was employed, collecting data from 239 undergraduates at the Faculty of Indigenous Medicine, Gampaha Wickramarachchi University, using a structured questionnaire. Convenience sampling was applied for participant selection. Findings indicate that performance expectancy, effort expectancy, social influence, accessibility, computer playfulness, system quality, information quality, and service quality significantly influence students' intention to use e-learning, whereas enjoyment showed a weaker effect. The study extends TAM with context-specific variables relevant to indigenous medical education, offering theoretical and practical insights for policymakers and educators to enhance e-learning engagement and integration in Sri Lanka's higher education sector.

Keywords: E-learning, higher education, indigenous medicine, Sri Lanka, Technology Acceptance Model-TAM, UTAUT

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Introduction

E-learning has become a core component of higher education worldwide, enabling flexible, accessible, and learner-centred education through digital technologies (Sun et al., 2023). It integrates information and communication technologies (ICT) into the teaching–learning process, allowing students to engage with content, peers, and instructors beyond traditional classroom boundaries (Al-Fraihat et al., 2020). The global COVID-19 pandemic accelerated the adoption of e-learning platforms, demonstrating their value in sustaining educational continuity (Dhawan, 2020). Despite these advancements, the successful implementation and sustained use of e-learning remain uneven across countries, institutions, and disciplines (Kebritchi et al., 2017).

In Sri Lanka, e-learning initiatives have been increasingly promoted within higher education, yet adoption levels vary across disciplines due to differences in technological readiness, institutional support, and learners' digital literacy (Perera & Hewagamage, 2021). Within the field of Indigenous medical education, which traditionally relies on face-to-face, practice-oriented instruction, integrating e-learning poses unique challenges. Students and instructors often face barriers such as limited infrastructure, low motivation, and a lack of culturally adapted content (Jayasinghe et al., 2022). Understanding the determinants that influence students' intention to use e-learning in this context is therefore critical for ensuring the effective integration of digital tools in Indigenous medical education.

Previous research on technology adoption has primarily focused on general higher education contexts, with limited attention to Indigenous or culturally specific medical education. Studies using the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have demonstrated that factors such as performance expectancy, effort expectancy, and social influence significantly affect users' technology adoption (Venkatesh et al., 2012; Davis, 1989). However, little empirical work has examined how these factors interact within the context of Indigenous medical education in developing countries like Sri Lanka.

Accordingly, this study aims to identify the factors influencing students' intention to use e-learning in Indigenous medical education in Sri Lanka by integrating constructs from TAM and UTAUT models. By doing so, the study contributes to the limited literature on e-learning adoption in culturally specific educational contexts and provides insights for policymakers and educators to enhance digital learning effectiveness.

Literature Review

The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a comprehensive framework for understanding how individuals adopt new technologies (Venkatesh et al., 2003). It emphasises four core constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions, which collectively influence behavioural intention and actual usage. Studies consistently show that PE, EE, and SI directly affect intention, while all four constructs contribute to user behaviour (Wang, 2022). UTAUT has been extensively applied in educational contexts to examine the determinants of e-learning adoption.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a widely used framework for understanding technology adoption, focusing on perceived usefulness and perceived ease of use as the primary determinants of user acceptance (Salloum et al., 2019). Abdullah and Ward (2016) conducted a comprehensive review of 107 studies over a decade, identifying 152 environmental factors influencing technology adoption. Among these, external factors such as self-efficacy, subjective norms, enjoyment, computer anxiety, and prior experience were repeatedly noted. However, only TAM's core constructs, perceived usefulness and perceived ease of use were consistently affected by these factors. While TAM is robust across diverse contexts, its explanatory power is limited in settings with unique cultural or educational characteristics, such as Indigenous medical education. Extending TAM with constructs such as perceived enjoyment, accessibility, playfulness, and system quality provides a more comprehensive understanding of e-learning adoption in these contexts.

Individual factors

Performance expectancy (PE)

Performance expectancy reflects users' beliefs that using a system will enhance their performance (Venkatesh et al., 2012). Research indicates that attitudes toward technology, perceived usefulness, and perceived ease of use are critical in shaping intentions to adopt e-learning (Murniati, 2020). PE has been shown to reliably predict adoption across various domains, including online learning, social media, and mobile banking (Alalwan et al., 2015). In this study, PE refers to students' belief that e-learning enhances academic performance.

H1 - *Performance expectancy has a positive impact on learners' behaviour intention to use e-learning.*

Effort expectancy (EE)

Effort expectancy (EE) reflects the perceived ease of use and comfort in using a system (Venkatesh et al., 2012). Systems perceived as user-friendly are more likely to be adopted, as supported by Sharma et al. (2016) and Zuiderwijk et al. (2015), who found a positive relationship between EE and learners' intention to use e-learning platforms.

H2 - *Effort expectancy has a positive impact on learners' behaviour intention to use e-learning.*

Social influence (SI)

Social influence (SI), embedded in the theory of planned behaviour, reflects the impact of peers, instructors, and social networks on technology adoption. Research indicates that learners often rely on social cues when deciding to adopt new technologies. Studies by Maldonado et al. (2010) and Venkatesh et al. (2012) highlight that SI significantly affects behavioural intention, especially when system use is mandatory rather than optional.

H3 – *Social Influence has a positive impact on learners' behavioural intention to use e-learning.*

Perceived enjoyment (PE)

Perceived enjoyment represents the satisfaction derived from using a system regardless of its performance impact (Venkatesh, 2000). Enjoyable systems enhance perceived usability and usefulness, fostering higher adoption intentions (Elkaseh et al., 2020; Ramírez-Correa et al., 2015).

H4 - *Perceived enjoyment has a positive impact on learners' behavioural intention to use e-learning.*

Perceived accessibility (PA)

Perceived accessibility (PA) refers to the ease with which learners can access and navigate an e-learning system (Al-Aulamie, 2013). When students perceive an online platform as easily accessible, it enhances both perceived ease of use and perceived usefulness, positively influencing their intention to engage with the system.

H5 - *Perceived accessibility has a positive impact on learners' behavioural intention to use e-learning.*

Perceived playfulness (PP)

Perceived playfulness (PP) refers to the learner's perception of enjoyment, curiosity, and cognitive spontaneity while interacting with an e-learning system (Venkatesh, 2000). When students perceive the system as engaging and enjoyable, it enhances their intrinsic motivation, positively influencing their intention to use e-learning (Al-Aulamie, 2013).

H6 - *Perceived playfulness has a positive impact on learners' behavioural intention to use e-learning.*

System characteristics

System quality (SQ)

"System quality" (SQ) is a measure of how elements like usability, reliability, availability, and flexibility in an e learning system impact user expectation (Iia, 2016). It plays a crucial role in determining the acceptance and utilisation of e-learning systems, as supported by various studies (Shah et al., 2013), (Calisir et al., 2014). Research has shown that an increase in SQ leads to an enhancement in the perceived usefulness of e-learning (Govender & Grange, 2015). Moreover, students' perceptions of the efficacy of e-learning also improve when SQ is utilised. Thus, the following hypothesis was developed:

H7: *System quality has a positive impact on learners' behavioural intention to use e-learning.*

Information quality (IQ)

Information quality (IQ) refers to the relevance, accuracy, and timeliness of learning materials provided through e-learning platforms (Cho et al., 2009). High-quality information enhances users' trust in the system and contributes to overall satisfaction (McKinney et al., 2002; Jaber, 2016). Previous research indicates that learners' perceptions of platform usability and effectiveness are strongly influenced by IQ, and higher intelligence levels further enhance users' appreciation of the system (Jaber, 2016; Damnjanovic et al., 2015).

H8 – *Information quality has a positive impact on learners' behavioural intention to use e-learning.*

Service quality (SEQ)

Service quality (SEQ) refers to the level of support and responsiveness provided to users when interacting with an information system (DeLone & McLean, 2003). High-quality service fosters trust, satisfaction, and positive user experiences, which are critical for the adoption of e-learning platforms (Sharma, 2015, 2016). Earlier studies indicate that students are more likely to engage with online learning when they perceive the service as reliable and supportive (Milosevic et al., 2015).

H9 – *Service quality has a positive impact on learners' behavioural intention to use e-learning*.

The above discussion integrates insights from TAM and UTAUT, contextualised to Indigenous medical education. However, empirical evidence in Sri Lanka's Indigenous medical universities remains limited, highlighting the need for this study to test these relationships in a novel cultural and educational setting.

The adoption of e-learning in higher education has been widely studied using technology acceptance frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These models explain why individuals choose to adopt or reject technologies, emphasising constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003; Venkatesh et al., 2012). Recent studies confirm their continued relevance in the context of online learning (Al-Emran et al., 2021; Bozkurt, 2022). However, most existing research focuses on general higher education or corporate e-learning environments, with limited attention to Indigenous medical education, where pedagogical practices, cultural knowledge transmission, and access disparities differ significantly.

A growing body of evidence from developing countries shows that learners' technical readiness, system quality, and service accessibility strongly affect e-learning adoption (Dhawan, 2020; Al-Fraihat et al., 2020). In Sri Lanka, studies by Perera and Hewagamage (2021) and Jayasinghe et al. (2022) identified challenges such as low digital literacy, limited infrastructure, and inadequate training as barriers to effective e-learning use. While these findings provide valuable insights, they do not address the unique characteristics of Indigenous medical education, where students rely heavily on experiential and community-based learning. Consequently, models like TAM and UTAUT must be extended with additional constructs such as system quality, information quality, service quality, enjoyment, and accessibility to better explain technology acceptance in this context (Al-Emran & Granić, 2023).

Critically, prior studies often treat e-learning adoption as a uniform phenomenon, overlooking cultural and contextual nuances. For example, studies from South Asia highlight that while performance expectancy and ease of use are significant, social and environmental factors, including peer influence, institutional support, and cultural attitudes toward technology, play stronger roles in traditional disciplines (Rahman et al., 2022). Furthermore, most empirical research in Sri Lanka's higher education sector uses generalised student samples, rarely distinguishing between programs in traditional or Indigenous medicine (Gunawardhana & Hewagamage, 2020). This leaves a clear empirical and theoretical gap regarding how technology acceptance theories apply to Indigenous medical undergraduates, whose learning combines theoretical knowledge with traditional practices.

Therefore, this study addresses that gap by integrating constructs from TAM and UTAUT with quality-related and affective dimensions (system quality, information quality, service quality, accessibility, playfulness, and enjoyment) to develop an extended model explaining students' intention to use e-learning in Indigenous medical education. By contextualising established theories within Sri Lanka's higher education framework, the study provides a focused, critical, and problem-aligned contribution that extends existing knowledge in e-learning adoption research.

Methodology and Model Specifications

Target population and sampling technique

The study population consisted of all undergraduate students (N = 630) enrolled in the Faculty of Indigenous Medicine at Gampaha Wickramarachchi University of Indigenous Medicine, Sri Lanka. Using Krejcie and Morgan's (1970) sampling table, a sample size of 239 was determined as appropriate for this population.

A simple random sampling technique was employed, ensuring that every student had an equal probability of selection. Random sampling enhances the representativeness of the sample, reduces selection bias, and allows for generalisation of the findings to the broader student population (Etikan et al., 2016).

Data collection methodology and technique

This study adopted a positivist research philosophy, reflecting the focus on objective measurement and hypothesis testing. Following a deductive research logic, the study aimed to test theoretical propositions derived from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). A quantitative research approach was employed, and the study utilised a cross-sectional survey design to investigate factors influencing students' intention to use e-learning in Indigenous medical education.

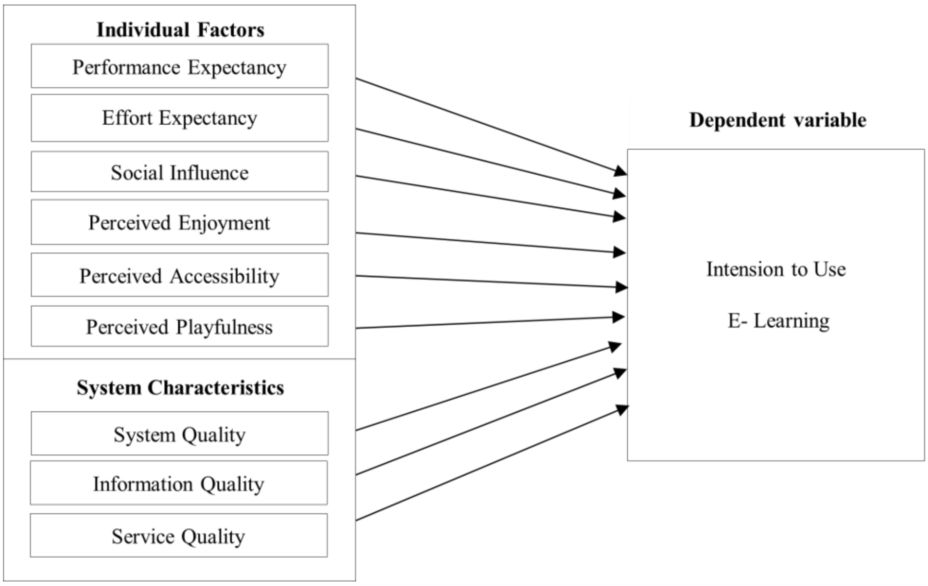
Initially, a review of secondary data was conducted, drawing on journal articles, books, and credible online sources. This review identified key factors affecting e-learning adoption, highlighted gaps in existing research, and informed the development of the conceptual framework. Grounding the study in empirical literature ensured that the variables included in the questionnaire were theoretically and contextually relevant.

For primary data collection, a structured questionnaire was developed and divided into two sections. Section A gathered demographic information, including age, gender, and year of study. Section B measured research variables using a five-point Likert scale. Independent variables included individual acceptance factors (e.g., performance expectancy, effort expectancy, social influence, perceived enjoyment, accessibility, playfulness) and system-related factors (system quality, information quality, service quality), while the dependent variable was students' intention to use e-learning.

The questionnaire was distributed electronically via Google Forms to undergraduate students at the Faculty of Indigenous Medicine. The survey method was chosen because it allows for systematic measurement of perceptions, attitudes, and behaviours across a population, facilitating objective analysis of relationships between variables. Data were analysed using descriptive statistics, correlation, and regression analyses to test the study hypotheses. This method aligns with the deductive, quantitative nature of research, enabling rigorous testing of theoretical constructs within a specific educational context.

Conceptual framework

Figure 1
Conceptual framework



(Source: Authors' work)

Pilot Study

A pilot study was conducted with 30 learners to assess the clarity, reliability, and validity of the questionnaire. Feedback from the participants was used to refine the wording of the items and ensure that each question measured the intended construct.

The reliability of the questionnaire was assessed using Cronbach's alpha for each variable separately, and all constructs exceeded the acceptable threshold of 0.7, indicating a high level of internal consistency. This process helped ensure that the survey instrument was suitable for the main study.

Empirical Results

Convergent validity

To determine whether the hypothesis that the correlation components of the data matrix form an identity matrix is valid, the sphericity test developed by Bartlett is applied.

KMO (Kaiser-Meyer-Olkin) Test

Data from 239 undergraduate students were analysed using SPSS. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.838, indicating a moderate to high level of adequacy and suggesting that the sample was suitable for factor analysis. Bartlett's test of sphericity was significant ($\chi^2 = 3618.595$, df = 45, $p < 0.001$), confirming that the correlations among variables were sufficient to justify factor analysis. These results demonstrate that the dataset is appropriate for exploring underlying factor structures. Table 1 summarises the KMO and Bartlett's test results, supporting the validity of proceeding with further analyses, including correlation and regression tests.

Table 1
Kmo And Bartlett's Test Results

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.838
Bartlett's Test of Sphericity	Approx. Chi-Square	3618.595
	df	45
	Sig.	.000

(Source: Authors' work)

Correlation test

Pearson correlation coefficients revealed positive associations between students' intention to use e-learning and the independent variables: performance expectancy ($r = 0.645$, $p < 0.001$), effort expectancy ($r = 0.639$, $p < 0.001$), social influence ($r = 0.781$, $p < 0.001$), perceived enjoyment ($r = 0.007$, $p = 0.019$), accessibility ($r = 0.606$, $p < 0.001$), computer playfulness ($r = 0.554$, $p < 0.001$), system quality ($r = 0.780$, $p < 0.001$), information quality ($r = 0.734$, $p < 0.001$), and service quality ($r = 0.623$, $p < 0.001$). These results suggest that all proposed factors are positively related to learners' intention to adopt e-learning, consistent with prior studies highlighting the importance of perceived usefulness, ease of use, and system quality in technology acceptance (Venkatesh et al., 2012; Al-Fraihat et al., 2020).

Table 2
Correlation test results

Variable	Pearson's Correlation	Sig. (2tailed)	N
Performance Expectancy	.645**	.000	239
Effort Expectancy	.639**	.000	239
Social Influence	.781**	.000	239
Enjoyment	.007**	.019	239
Accessibility	.606**	.000	239
Computer Playfulness	.554**	.000	239
System Quality	.780**	.000	239
Information Quality	.734**	.000	239
Service Quality	.623**	.000	239

(Source: Authors' work)

Multicollinearity

Multicollinearity among the independent variables was assessed using the Variance Inflation Factor (VIF), which quantifies how much the variance of a regression coefficient is inflated due to correlation with other predictors (Hair et al., 2019). As shown in Table 3, the VIF values for all variables ranged from 1.034 to 2.802, well below the commonly used threshold of 5, indicating that multicollinearity is not a major concern.

This suggests that the independent variables performance expectancy, effort expectancy, social influence, accessibility, computer playfulness, enjoyment, system quality, information quality, and service quality are sufficiently independent, allowing for reliable estimation of regression coefficients in subsequent analyses.

Table 3
VIF Values

Model	Unstandardized Coefficients		Standardized Coefficients	Collinearity Statistics	
	β	Std. Error	*β*	Tolerance	VIF
(Constant)	-.410	.053			
PE	.075	.020	.064	.397	1.987
EF	.024	.020	-.020	.568	2.032
SI	.151	.026	.102	.247	1.034
PE	.014	.006	-.015	.508	1.128
PA	.029	.013	-.027	.325	1.077
PP	.737	.011	.760	.398	2.024
SQ	.311	.012	.319	.534	1.114
IQ	.167	.019	-.147	.465	1.941
SEQ	.052	.024	.046	.708	2.802

(Source: Authors' work)

Regression analysis

Multiple linear regression was conducted to examine the impact of the independent variables on students' intention to use e-learning. The model was significant ($R^2 = 0.888$, Adjusted $R^2 = 0.886$, $p < 0.001$), indicating that 88.8% of the variance in intention could be explained by the predictors. Performance expectancy ($\beta = 0.075$, $p < 0.001$), effort expectancy ($\beta = 0.024$, $p = 0.014$), social influence ($\beta = 0.151$, $p < 0.001$), perceived enjoyment ($\beta = 0.014$, $p = 0.018$), accessibility ($\beta = 0.029$, $p = 0.029$), computer playfulness ($\beta = 0.737$, $p < 0.001$), system quality ($\beta = 0.311$, $p < 0.001$), information quality ($\beta = 0.167$, $p < 0.001$), and service quality ($\beta = 0.052$, $p = 0.028$) were significant predictors of intention. The intercept was -0.410, representing the expected intention score when all predictors are zero. While most factors showed positive effects, the small coefficient for perceived enjoyment may indicate that although students find e-learning enjoyable, its influence on behavioural intention is weaker compared to functional and social factors. This is in line with prior studies suggesting that affective factors may have a secondary influence in professional or practice-oriented education contexts (Ramírez-Correa et al., 2015; Elkaseh et al., 2020).

Table 4.
Regression Analysis

	Coefficients				
	Unstandardized Coefficients	Standardized Coefficient			
Model	*β*	Std. Error	*β*	t	Sig.
Constant	-.410	.053		-7.710	.000
PE	.075	.020	.064	3.778	.0001
EF	.024	.020	-.020	-1.245	.014
SI	.151	.026	.102	5.736	.0001
PE	.014	.006	-.015	-2.387	.018
PA	.029	.013	-.027	-2.191	.029
PP	.737	.011	.760	68.379	.0001
SQ	.311	.012	.319	25.923	.0001
IQ	.167	.019	-.147	-8.683	.0001
SEQ	.052	.024	.046	2.207	.028

(Source: Authors' work)

Accuracy of the model

The overall fit and predictive power of the regression model were evaluated using the model summary statistics (Table 5). The R value of 0.942 indicates a strong correlation between the observed and predicted values of students' intention to use e-learning. The R^2 value of 0.888 shows that approximately 89% of the variance in the dependent variable is explained by the independent variables included in the model. The adjusted R^2 of 0.886 accounts for the number of predictors and confirms the model's robustness.

These results suggest that the selected individual and system-related factors, performance expectancy, effort expectancy, social influence, accessibility, computer playfulness, enjoyment, system quality, information quality, and service quality, collectively have a substantial impact on students' intention to adopt e-learning, while also leaving room for future research to explore additional variables that may influence this behaviour.

Table 5
Model Summary

R	R Square	Adjusted R Square	Std. The error of the Estimate
.942[a]	.888	.886	.1870

(*Source: Authors' work)*

Conclusion

This study demonstrates that the Extended Technology Acceptance Model (TAM), integrated with contextual factors, effectively explains students' intention to use e-learning in Indigenous medical education in Sri Lanka. The findings indicate that key factors such as performance expectancy, effort expectancy, social influence, accessibility, computer playfulness, system quality, information quality, and service quality significantly influence students' behavioural intentions. Interestingly, Perceived Enjoyment showed only a weak effect, suggesting that students' engagement is more strongly driven by perceived usefulness, ease of use, and system reliability rather than intrinsic enjoyment.

These results align with prior studies in higher education e-learning adoption, where usefulness and ease of use often outweigh hedonic factors in influencing student intentions (Al-Fraihat et al., 2020; Venkatesh et al., 2012). The weak effect of enjoyment implies that current e-learning platforms in Indigenous medical education may lack engaging, interactive, and practical components, limiting students' motivation to explore the system voluntarily. Enhancing the platform with practical simulations, visual demonstrations, interactive exercises, and gamified learning could increase engagement and learning effectiveness.

From a practical and policy perspective, the study emphasises the importance of user-friendly system design, high-quality content, prompt support services, and reliable infrastructure. University administrators and policymakers should ensure that e-learning systems are accessible, responsive, and aligned with the practical and experiential needs of Indigenous medical students. This approach will not only improve learning outcomes but also encourage broader adoption of digital learning solutions in culturally specific educational contexts.

The study was conducted at a single faculty and relied on self-reported data, which may limit generalizability and introduce response bias. Future research could include multiple institutions, longitudinal designs, and objective usage measures to strengthen and extend these findings.

Finally, the study contributes theoretically by extending TAM with context-specific factors such as system quality, information quality, service quality, accessibility, and playfulness. Future research could explore additional motivational and cultural factors, longitudinal adoption patterns, and the integration of blended learning approaches to further enhance e-learning acceptance in Indigenous medical education. Overall, these findings provide actionable insights for educators, developers, and decision-makers aiming to improve e-learning systems in Sri Lanka and similar developing country contexts.

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