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Consumption Values and E-Learning Adoption in Higher Education: Evidence from Ho Technical University, Ghana

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Abstract

This study investigated the drivers of e-learning adoption among students at Ho Technical University by integrating Consumption Values Theory and the Technology Acceptance Model. Adopting a quantitative research design, data were collected from 379 students through a Google Form survey and analysed using variance-based structural equation modelling. The results showed that conditional, epistemic, functional, and social values did not significantly influence students' adoption behaviour toward e-learning. In contrast, emotional value emerged as a significant predictor of adoption behaviour. The findings further revealed that perceived ease of use and perceived usefulness positively influenced students' intention to use e-learning platforms. In addition, intention to use partially mediated the relationship between perceived usefulness and adoption behaviour whereas intention to use fully mediates the relationship between perceived ease of use and adoption behaviour. Finally, gender did not moderate the relationship between intention to use and adoption behaviour. The study therefore underscores the importance of prioritizing emotional value, usability, usefulness, and behavioural intention in the design of e-learning systems. The study's novelty lies in its integration of Consumption Values Theory and the Technology Acceptance Model to explain e-learning adoption in higher education

Introduction

The rapid advancement of information and communication technologies has transformed the delivery of higher education and accelerated the institutionalization of e-learning across universities worldwide (Al-Kurdi et al., 2020; Rughoobur-Seetah & Hosanoo, 2021; Gunasinghe et al., 2020). In both developed and emerging economies, e-learning is increasingly regarded not merely as an auxiliary mode of instruction but as a strategic infrastructure for widening access, sustaining continuity, and enhancing pedagogical flexibility (Almaiah, Al-Khasawneh & Althunibat, 2020, Fauzi, 2022; Salloum et al., 2019**;** This shift became especially pronounced during and after the COVID-19 period, when educational systems, including those in Ghana, turned to digital platforms to sustain teaching and learning activities. Consequently, the growing policy emphasis on educational digitalization has intensified scholarly and managerial interest in the factors that shape students' willingness to adopt e-learning technologies.

Despite its widely acknowledged benefits, e-learning adoption remains uneven, particularly in developing-country contexts where infrastructural, behavioural, and value-related constraints often impede sustained use (Bossman & Agyei, 2022; Gunasinghe et al., 2020). Prior studies have shown that e-learning can improve flexibility, facilitate interaction beyond physical boundaries, and support independent knowledge acquisition (Choi & Lam, 2018; Mehta et al., 2019; Mashroofa et al., 2023). However, the availability of an e-learning platform does not necessarily guarantee its acceptance or continued use. Rather, adoption is shaped by how users evaluate the platform's utility, usability, and experiential worth within their educational environment.

Existing scholarship has explained e-learning adoption from multiple theoretical lens. Some studies have emphasized technological attributes, including system quality and usability, whereas others have focused on individual dispositions and behavioural antecedents (Baig, Shuib & Yadegaridehkordi, 2022; Saleh, Nat & Aqel, 2022; Şahin, Doğan, Okur & Şahin, 2022). Within this stream, the Technology Acceptance Model (TAM) has remained one of the most influential frameworks because it explains technology use through perceived usefulness, perceived ease of use, and behavioural intention (Davis, 1989; Salloum et al., 2019). Yet, although TAM captures important cognitive evaluations, it is less explicit about the broader value perceptions that may shape users' affective and social responses to digital learning systems.

Consumption Values Theory (CVT) offers a complementary perspective by arguing that individuals' choices are influenced by the functional, emotional, social, epistemic, and conditional values they attach to a product or service (Sheth, Newman & Gross, 1991). In the e-learning context, this perspective is especially relevant because students' decisions are unlikely to depend solely on instrumental beliefs; they may also reflect emotional engagement, contextual convenience, curiosity, and social meaning. Conceptually, integrating CVT with TAM is therefore compelling because consumption values can inform the evaluative beliefs that subsequently shape intention and actual use (Amin &Tarun, 2021; Dewi &Annas, 2022). Although earlier studies have examined consumption value in relation to e-learning adoption (Mehta et al., 2019) and others have applied TAM-based models in Ghanaian higher education (Bossman & Agyei, 2022), research that integrates CVT and TAM to explain students' e-learning adoption remains limited in this context.

This limitation reveals a clear gap in the literature. First, prior studies have tended to examine either value-based determinants or technology-acceptance beliefs in isolation, thereby offering only a partial account of e-learning adoption. Second, although the Ghanaian context has received some attention, evidence remains sparse on how consumption values interact with perceived usefulness, perceived ease of use, and intention to influence actual adoption behaviour among university students. Third, the potential conditioning role of gender in the intention–adoption link remains insufficiently settled. As your draft already indicates, the literature highlights the relevance of both value perceptions and technology-acceptance beliefs; however, integrated evidence remains scarce, particularly in Ghanaian higher education. Addressing this gap is theoretically important because it enables a more holistic explanation of adoption behaviour, and it is practically significant because it can guide institutions in designing e-learning systems that are not only useful and easy to use, but also meaningful and engaging for students.

Accordingly, this study integrates Consumption Values Theory and the Technology Acceptance Model to examine how consumption values, perceived usefulness, perceived ease of use, and intention to use shape students' adoption behaviour toward e-learning at Ho Technical University. It further considers whether gender functions as a boundary condition in the intention–adoption relationship. By doing so, the study extends the e-learning literature in two important ways: it advances an integrative explanatory framework for student adoption behaviour, and it provides context-specific evidence from a Ghanaian higher education institution, where such theoretically combined investigations remain limited.

Literature Review

Theory of consumption values (TCV)

The Theory of Consumption Values (TCV) (Sheth, Newman, & Gross, 1991) provides a compelling lens for explaining why individuals adopt one product or service over another. The theory posits that choice is fundamentally value-driven, with individuals evaluating alternatives according to the benefits they perceive them to offer. Rather than reducing decision-making to purely economic rationality, TCV conceptualizes consumer behaviour as a multidimensional process shaped by five distinct value dimensions: functional, social, emotional, epistemic, and conditional value. Whilst functional value explains how a product or service can provide its core purpose (Dewi & Annas, 2022). Social value measures social recognition and status attached to the use of the product (Amin &Tarun, 2021; Kim & Jan, 2024). Further, emotional value defines self-satisfaction through feelings and state of mind associated with a product or service (Şahin, Doğan, Okur & Şahin, 2022). In addition, individuals expect epistemic value which involves perceived novelty or newness of a product which gives uniqueness to the consumer (Kim & Jan, 2024; Lee, 2021). finally, conditional value involves situational benefits associated with a product (Kim & Jan, 2024; Lee, 2021).

In the context of e-learning, these dimensions suggest that adoption is influenced not only by the platform's utility and performance, but also by its social legitimacy, affective appeal, novelty, and situational relevance. Thus, TCV explains e-learning adoption as a holistic evaluative process in which students assess whether digital learning systems are useful, meaningful, engaging, and contextually appropriate. However, while the theory is effective in capturing the value bases of student choice, it is less able to explain the technology-specific cognitive mechanisms through which such value perceptions translate into intention and actual use. This limitation justifies the inclusion of the Technology Acceptance Model (TAM), which more directly accounts for how perceived usefulness and perceived ease of use shape intention to use and, ultimately, adoption.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis (1989), remains one of the most influential frameworks for explaining users' acceptance of technology. The model posits that individuals' intention to use a technology, and ultimately their actual usage behaviour, are principally shaped by two cognitive beliefs: perceived usefulness and perceived ease of use. In the context of higher education, these constructs are especially salient for understanding students' adoption of e-learning. Perceived usefulness reflects the extent to which students believe that using e-learning will enhance their learning effectiveness, academic performance, and overall educational outcomes, whereas perceived ease of use denotes the degree to which they perceive the system as effortless, comprehensible, and free from undue complexity (Saleh et al., 2022). As such, students' decisions to embrace e-learning are likely to depend on whether they view it as offering clear pedagogical advantages over conventional instructional approaches and whether those benefits can be accessed without excessive difficulty or frustration (Fauzi, 2022). TAM is therefore particularly valuable in this study because it provides a parsimonious yet analytically powerful explanation of how beliefs about usefulness and usability shape intention to use and, in turn, actual adoption of e-learning (Ansong et al., 2017).

Notwithstanding its wide applicability, empirical evidence on TAM's explanatory power in e-learning remains mixed. Prior studies have reported both significant and inconsistent effects of perceived usefulness and perceived ease of use on technology adoption outcomes (Abdullah, Ward, & Ahmed, 2016; Mulyani, Najib, & Guteres, 2021; Saleh et al., 2022; Harrigan et al., 2021; Ventre & Kolbe, 2020). These divergent findings suggest that the relationship between TAM constructs and user behavior may be contingent on contextual, institutional, and learner-specific factors. Rather than undermining the relevance of TAM, such inconsistency underscores the continuing need to re-examine the model in distinct educational settings. In the present study, TAM provides an essential theoretical basis for explaining how students' perceptions of usefulness and ease of use shape their intention to engage with e-learning and their eventual decision to adopt it. Its inclusion is therefore justified not only by its theoretical clarity, but also by the unresolved empirical debate surrounding the mechanisms through which students accept digital learning technologies.

Adoption behaviour

Adoption behaviour, often conceptualised as actual use or realised purchase, represents the outcome of the consumer decision process (Mehta et al., 2019). Within the Technology Acceptance Model, actual use is preceded by behavioural intention, such that intention functions as the most immediate determinant of technology adoption (Davis, 1989). However, intention alone does not invariably culminate in use, as actual adoption may be constrained by users' resources, competencies, and opportunities to engage with the innovation. More broadly, diffusion research suggests that adoption is shaped by perceptions of relative advantage, complexity, risk, communicability, and trialability, all of which influence whether an innovation is ultimately accepted or rejected (Rogers, 1995). In the present study, adoption behaviour refers to students' actual decision to use e-learning as a mode of instruction in preference to, or alongside, traditional face-to-face learning. It therefore captures the concrete realisation of prior evaluative and intentional processes.

Research model and hypothesis development.

Functional value represents the utilitarian benefits consumers derive from a product or service and is widely regarded as a central driver of adoption behaviour (Sheth et al., 1991; Tanrikulu, 2021). In the e-learning context, it captures the extent to which the platform reduces learners' effort, lowers costs, enhances reliability, and improves the overall learning experience. Empirical evidence largely supports the salience of functional value in shaping adoption-related outcomes. Studies by Kim and Jan (2024), Mason et al. (2023), and Mehta et al. (2019) found a positive association between functional value and purchase or adoption decisions, while Karjaluoto et al. (2021) similarly found that functional value positively predicts mobile banking adoption, suggesting that its explanatory power extends across digital service settings. However, the evidence is not entirely uniform. Kwaku Nimsaah et al. (2025) found no significant effect in the context of sustainable e-government services, indicating that contextual contingencies may moderate this relationship. Overall, the preponderance of evidence suggests that functional value is likely to positively influence students' adoption of e-learning. We therefore hypothesised that:

H1a: Functional value significantly and positively influences adoption behaviour of e-learning among Ho Technical University students.

Social value and adoption behaviour

Social value, as conceptualised by Sheth et al. (1991), refers to the utility derived from a product's ability to enhance social approval, recognition, and a sense of belonging within relevant reference groups. In consumer research, this dimension is often linked to peer influence, social norms, and symbolic status, all of which can shape adoption behaviour (Shoukat et al., 2021; Tanrikulu, 2021). Empirical evidence generally supports its explanatory relevance. For instance, Ramayah et al. (2018) showed that social status positively influences the adoption of technological products, while Misra (2025) similarly reported that social value exerts a significant positive effect on product and service adoption. These findings suggest that individuals are more likely to embrace an innovation when its use confers social legitimacy or aligns with the expectations of valued groups. However, the evidence is equivocal. Chakraborty et al. (2022), for example, found no significant effect of social value on food purchase intention implying that its influence may be contingent on context, product type, and user characteristics. We therefore hypothesized that:

H1b: Social value significantly and positively influences adoption behaviour of e-learning among Ho Technical University students.

Emotional value and adoption behaviour

Emotional value, according to Sheth et al. (1991) is measured based on a product or service ability to evoke desirable emotions and feelings. Emotional value drives perceived feelings that enhances consumer's inner satisfaction. In the context of e-learning, emotional value comprises of the extent to which e-learning offers learners a greater relief, convenience and satisfaction (Tanrikulu, 2021). Zolkepli et al. (2021) found that consumers are driven by emotions when buying a product or service whereas Kwaku Nimsaah (2025) found no significant effect of emotional value on sustainable e-government service adoption. Besides, Al-Kurdi et al. (2020) found that consumer feeling of easy use of digital services positively influence their decision to adopt and continue to use. Hence, the study hypothesised that:

H1c: Emotional value significantly and positively influences adoption behaviour of e-learning among Ho Technical University students.

Epistemic value and adoption behaviour

Epistemic value denotes the utility derived from a product or service's ability to stimulate curiosity, provide novelty, and enrich users' knowledge or experience (Sheth et al., 1991). In the e-learning context, this value is expressed through students' attraction to innovative learning platforms and their familiarity with the technological tools required for meaningful participation. Accordingly, adoption is more likely when e-learning is perceived as intellectually engaging, technologically novel, and capable of offering learning experiences beyond those available in conventional classrooms. Empirical evidence largely supports this view. Chakraborty et al. (2022) found that epistemic value significantly influences digital service usage, while Karjaluoto et al. (2020) reported a positive effect on consumers' electronic product purchase decisions. However, Ramayah et al. (2018) found no significant relationship between epistemic value and purchase intention, suggesting that its effect may depend on context, user readiness, and perceived risk. Generally, epistemic value appears to be a credible, albeit context-sensitive, predictor of e-learning adoption. Therefore, we hypothesised that:

H1d: Epistemic value significantly and positively influences adoption behaviour of e-learning among Ho Technical University students.

Conditional value and adoption behaviour

Conditional value is the perceived utility associated with a product or service with respect to a particular situation faced by the purchaser or consumer (Sheth et al., 2011). E-learning, even though an old learning method in advanced countries, however, became common in the era of covid -19. Therefore covid-19 became a condition for adoption of e-learning in majority of the under-developed countries like Ghana (Sarpong, Dwomoh, Boakye & Ofosua-Adjei, 2021). Conditional value relates with individual's circumstances that motivates them to make a particular decision. Chu et al (2018) found that financial incentives for green vehicles from the Switzerland government increases adoption of green vehicles. Empirically, Mason et al. (2023) found that conditional value significantly influences purchase decision. Similarly, Kwaku Nimsaah et al. (2025) revealed that conditional value influence adoption behaviour. This implies that conditional factors could influence the purchase decision of product or service. From the above arguments, this study hypothesised that:

H1e: *Conditional value significantly and positively influences adoption behaviour of e-learning among Ho Technical University students.*

Perceived Usefulness and Adoption Behaviour

Empirical studies suggest that perceived usefulness is a central explanatory factor in adoption behaviour, particularly when users believe that a technology meaningfully improves task performance, learning effectiveness, and overall productivity (Ventre & Kolbe, 2020; Baig et al., 2022. In the e-learning context, Al-Kurdi et al. (2020) and Almaiah et al. (2020) show that students are more inclined to adopt digital platforms when they perceive them as beneficial to achieving desired outcomes, while Harrigan et al. (2021) and Mulyani et al. (2021) likewise report that the instrumental value attached to a system strengthens favourable usage decisions. Comparable evidence from more recent educational technology research further indicates that perceived usefulness enhances students' readiness to engage with e-learning systems because it reduces doubts about the practical relevance of the platform and reinforces the expectation of academic gain (Baig et al., 2022; Saleh et al., 2022). As suggested by Baig, students are more willing to embrace e-learning platforms when its value is visible in their daily academic experience. Although, perceived usefulness consistently exerts a positive influence on adoption-related outcomes, its effect is not always purely direct, as some studies suggest that it operates more strongly through behavioural intention and related enabling conditions. Generally, the empirical findings remain that perceived usefulness is a robust predictor of adoption behaviour across digital learning platforms. This study therefore hypothesised that:

H2: Perceived usefulness positively and significantly influences adoption behaviour of e-learning among Ho Technical University students.

Perceived Ease of Use and Adoption Behaviour

Perceived ease of use remained an important predictor of adoption behaviour in the e-learning literature. For example, Davis(1989) posits that technology is highly acceptable when its functions are clear, accessible, and require minimal effort to use. Recent empirical studies generally converge on this position. For example, Tahar et al. (2020) found that when users perceive a technology to be simple and manageable, their willingness to engage with it increases while Al-Kurdi et al. (2020) similarly showed that ease of use strengthens favourable evaluations of e-learning systems and encourages acceptance. Comparable, Ventre and Kolbe (2020), Harrigan et al. (2021), and Mulyani et al. (2021), all of whom suggest that platforms perceived as less complex are more readily adopted because they reduce cognitive burden and uncertainty during use. Recent studies (Baig et al., 2022; Saleh et al., 2022) also affirm that intuitive design, clear guidance, and seamless interaction enhance students' readiness to adopt digital learning platforms. However, the literature is not entirely uniform in its interpretation of this relationship. While most studies report a positive association, some indicate that perceived ease of use may not always exert a strong direct effect on adoption behaviour but rather operates indirectly by strengthening behavioural intention and reinforcing perceptions of usefulness. However, prior literature suggests that perceived ease of use is an important driver of adoption behaviour. Based, on the evidence above, the study therefore hypothesised that:

H3: Perceived ease of use positively and significantly influences adoption behaviour of e-learning among Ho Technical University students.

Mediating role of intention to use

Prior empirical studies suggest that intention to use is a key mechanism through which perceived usefulness translates into actual adoption behaviour. When students perceive an e-learning platform as beneficial to their academic performance, learning efficiency, and task accomplishment, they are more likely to develop a strong intention to use it, which subsequently drives actual adoption. Evidence from Al-Emran et al. (2020) suggest that perceived usefulness of a technology drives users' intention to use. Similarly, Saeed Al-Maroof et al. (2020) found significant relationship between perceived usefulness and adoption behaviour of e-learning platform. On the other hand, Al-Kurdi et al. (2020) and Ventre and Kolbe (2020) posit that users' intentions about a technology drives their willingness to adopt.

Similarly, the literature indicates that intention to use mediates the relationship between perceived ease of use and adoption behaviour. A system that is simple, clear, and easy to navigate tends to reduce users' effort expectations and increase their willingness to engage with it. Studies such as (Tahar et al., 2020; Rattanaburi &Vongurai, 2021) show that ease of use strengthens users' intention to use digital platforms. On the other hand, some scholars (Ansong et al., 2017; Al-Kurdi et al., 2020) argued that intention to use is a requirement for actual usage or adoption. This evidence suggests that perceived ease of use could influence e-learning adoption through favourable behavioural intention. Based on the existing literature, we hypothesised that:

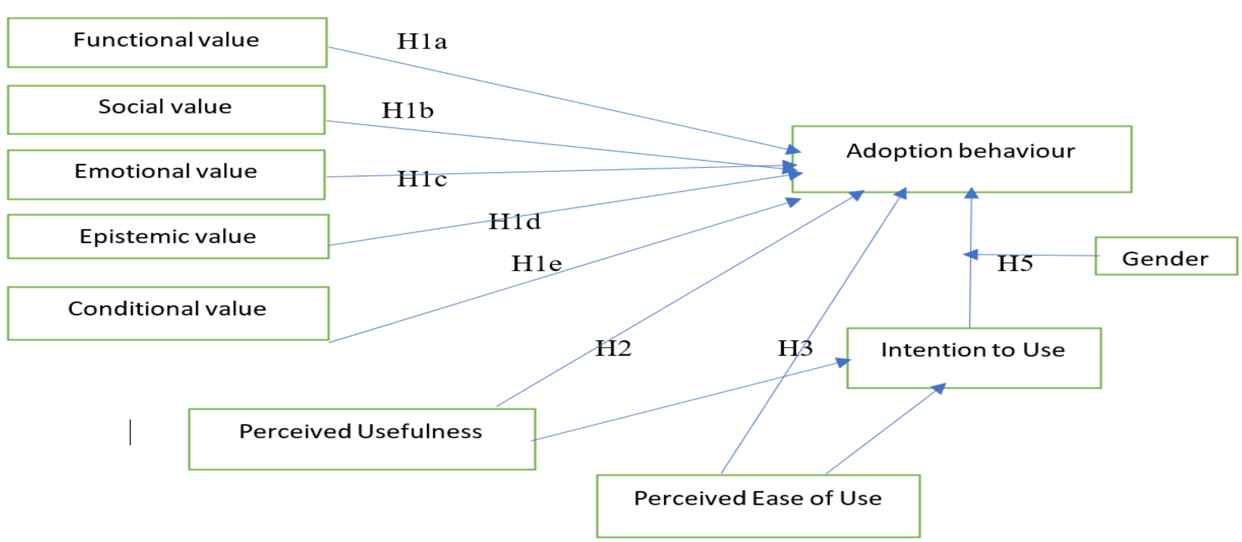
H4a: Intention to use positively and significantly mediates the relationship between perceived usefulness and adoption behaviour of e-learning among Ho Technical University students.

H4b: Intention to use positively and significantly mediates the relationship between perceived ease of use and adoption behaviour of e-learning among Ho Technical University students.

Moderating role of gender

This study examines how intention to use and actual adoption behaviour could be conditioned by gender. This is because females and males respond differently on the variables. For example, Friedl, Pondorfer & Schmidt (2020) pointed that female and male differ in terms of their risk aversion, whilst males are more likely to take risk, females are less willing. Besides, Abou-El-Sood (2021) found that risk taking decisions negatively influenced by females. Further, females' adolescent students were found to have higher psychological effects when dissatisfied than males. Therefore, as suggested by Yurdagül, Kircaburun, Emirtekin, Wang & Griffiths (2021) gender differences could alter the relationship between intention to use and adoption behaviour. Based on the evidence, the study hypothesised that:

H5: There is a significant and positive moderating effect of gender in the relationship between intention to use and adoption behaviour.



H4a: Perceived usefulness->Intention to use->Adoption behaviour.
H4b: Perceived ease of use->Intention to use->Adoption behaviour.

Figure 1: Conceptual Framework
Source: Authors Own Construct

Research Methods

Research design and approach

This study was grounded in the post-positivist paradigm, which assumes that reality exists independently of the researcher, although its apprehension may be imperfect because individuals interpret social phenomena through differing beliefs, experiences, and value systems (Kivunja & Kuyini, 2017). In line with this philosophical stance, the study adopted an explanatory research design and a quantitative approach. The explanatory design was considered appropriate because the study sought to examine the directional relationships among the study constructs and to evaluate theoretically derived hypotheses. Similarly, the quantitative approach was justified by the need for systematic measurement of variables, statistical estimation of effects, and empirical validation of the proposed relationships (Shiau et al., 2019). This design-approach combination was therefore suitable for generating objective, replicable, and theory-driven evidence, while also minimizing undue researcher subjectivity in the interpretation of findings (Kivunja & Kuyini, 2017).

Sample and data collection

The target population comprised all registered students of Ho Technical University as of October 2024 (N = 6,360), spanning Higher National Diploma, Diploma, Bachelor's, and Postgraduate programmes across the HTU Business School, the Faculty of Engineering, the Faculty of Art and Design, the Faculty of Built and Natural Environment, and the Faculty of Applied Science and Technology. The sampling frame was obtained from the Planning and Quality Assurance Directorate, from which respondents were recruited through an online questionnaire administered via Google Forms. Given the online mode of administration and the voluntary nature of participation, the study relied on a non-probability self-selection sampling approach, albeit anchored in an institutional population frame. To determine the minimum sample required for adequate population representation, Yamane's (1967) formula for finite populations, $n = N/1 + N(e2)$, was applied at a 95% confidence level and 5% margin of error, yielding a minimum sample size of 376. The final dataset comprised 379 valid responses, thereby exceeding the minimum threshold.

Although PLS-SEM sample planning is often strengthened through effect-size, statistical-power, and model-complexity considerations, the use of Yamane's formula in this study was justified as a pragmatic and defensible starting point because the population size was known and the primary objective at the data collection stage was to secure a sufficiently large and broadly representative sample for multivariate analysis. In this sense, Yamane's approach provided a conservative population-based benchmark, while the achieved sample size also satisfied widely accepted minimum expectations for PLS-SEM estimation. Nevertheless, the use of a voluntary online survey introduces the possibility of self-selection bias, as students with stronger digital access or greater interest in e-learning may have been more likely to participate. This risk was mitigated by drawing respondents from the full institutional student population, distributing the survey across multiple faculties and programme levels, and retaining only complete and eligible responses for analysis.

To facilitate access to potential respondents and enhance the quality of participation, the researcher first engaged class leaders across the selected cohorts and scheduled brief sessions to explain the purpose of the study and the content of the instrument to students in their respective classrooms. These interactions also provided an opportunity to clarify unfamiliar terms and improve respondents' understanding of the questionnaire items before participation. Following these engagements, permission was obtained to join the relevant class WhatsApp groups, through which the survey link was distributed directly to students. This procedure enabled the researcher to maintain control over the circulation of the instrument and helped ensure that the questionnaire reached the intended respondents across the available classes. To improve response rates, periodic reminders were issued throughout the data collection period. The survey was administered between 1 November and 30 November 2024, and, at the close of the fieldwork, 379 valid responses had been received, thereby exceeding the minimum required sample size of 376.

Measurement of constructs

All the nine constructs in the study were adapted from previously validated scales which were measured on five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). In all, there were 55 indicators measuring all the nine constructs (Appendix A). Specifically, Functional Value (Items=7, α = .897), Social Value (Items=6, α = .863), Emotional Value (Items=6, α = .849), Epistemic Value (Items=7, α = .902), Conditional Value (Items=7, α = .905) were adapted from (Amin &Tarun, 2021; Kim &Jan, 2024; Sheth et al., 1991). Additionally, Perceived Usefulness (Items = 5, α = .861), Perceived Ease of Use (Items = 7, α = .900) and Intention to Use (Items = 6, α = .916) were adapted from (Cheon et al., 2012; Davis, 1989). Finally, Adoption Behaviour (Items=4, α = .892) was adapted from Mohammadi (2015). After measurement evaluation, some of the items failed to measure their respective constructs sufficiently. This means that those indicators loaded below the recommended threshold of 0.708. However, they were maintained because they created no issues with validity and reliability to necessitate their deletion. Among the items that were loaded below 0.708 but maintained in the model include FV6, EV2, EPV7 and IOU6. Following measurement evaluation, all the 55 items were retained as the measurement of the study constructs as presented in Table 1.

Common Method Variance/Bias

Common method variance (CMV) arises when observed variation in responses is attributable to the measurement method rather than to the constructs the measures are intended to capture (MacKenzie & Podsakoff, 2012). To reduce the potential influence of CMV, the study implemented both ex ante and ex post procedural and statistical remedies. At the design stage, the questionnaire was masked, the order of items was varied to minimise contextual and consistency effects, and respondents were assured of confidentiality to reduce evaluation apprehension and response bias. At the post hoc stage, Harman's single-factor test was performed by loading all measurement items into an exploratory factor analysis to assess whether a single latent factor accounted for most of the covariance among the indicators (Harman, 1976). The results showed that the first factor explained 40.179% of the total variance (Appendix B), which is below the 50% threshold commonly used to indicate serious common method bias; thus, CMV was unlikely to pose a substantial threat to the validity of the findings. In addition, collinearity diagnostics within the PLS-SEM model were examined using variance inflation factor (VIF) values. As all inner-model VIF values fell below the recommended threshold of 5 (Table 1), the results further suggest that common method bias and problematic collinearity were not significant concerns in this study (Hair et al., 2019).

Results

Measurement model assessment

In consistent with Hair et al. (2019) structural model estimation ought to be premised on evidence of validity and reliability of the measurement items. Internal consistency of the observable variables was measured with Cronbach alpha (CA) and composite reliability (CR). Average Variance Extracted (AVE) and Heterotrait-monotrait ratio of correlations were employed to measure convergent validity and discriminant validity, respectively. From Table 1 and 2, internal consistency and validity of the constructs were obtained (CA>0.7; CR > 0.708; AVE ≥ 0.50; HTMT<0.90) (Hair et al., 2019). HTMT threshold <0.90 was considered satisfactory because the constructs under the study are theoretically related. Even though some of the items loaded below the recommended threshold, they were maintained because there were no issues with reliability and validity of the constructs.

Table 1: Measurement Model Assessment				
Constructs	**Loadings**	**CA**	**CR**	**AVE**
Functional Value		**.897**	**.901**	**.621**
FV1	0.826			
FV2	0.794			
FV3	0.807			
FV4	0.831			
FV5	0.808			
FV6	**0.658**			
FV7	0.779			
Social Value		**.863**	**.869**	**.598**
SV1	0.750			
SV2	0.805			
SV3	0.627			
SV4	0.824			
SV5	0.802			
SV6	0.812			
Emotional Value		**.849**	**.872**	**.576**
EV1	0.822			
EV2	**0.518**			
EV3	0.810			
EV4	0.790			
EV5	0.736			
EV6	0.831			
Epistemic Value		**.900**	**.904**	**.631**
EPV1	0.787			
EPV2	0.724			
EPV3	0.840			
EPV4	0.847			
EPV5	0.829			
EPV6	0.820			
EPV7	**0.699**			
Conditional Value		**.905**	**.913**	**.637**
CV1	0.782			
CV2	0.832			
CV3	0.807			
CV4	0.786			
CV5	0.728			
CV6	0.839			
CV7	0.805			
Perceived Usefulness		**.899**	**.900**	**.714**
PU1	0.828			
PU2	0.811			
PU3	0.879			
PU4	0.875			
PU5	0.829			

Table 1 Contd.

Perceived ease of Use		**.861**	**.864**	**.714**
PEOU1	0.785			
PEOU2	0.847			
PEOU3	0.751			
PEOU4	0.781			
PEOU5	0.827			
PEOU6	0.815			
PEOU7	0.721			
Intention to Use		**.916**	**.927**	**.710**
IOU1	0.859			
IOU2	0.886			
IOU3	0.890			
IOU4	0.873			
IOU5	0.864			
IOU6	**0.662**			
Adoption Behaviour		**.892**	**.893**	**.755**
AB1	0.875			
AB2	0.855			
AB3	0.885			
AB4	0.860			

Source: Field Survey (2024)

Table 2: Discriminant Validity (HTMT)

Construct	AB	CV	EPV	EV	FV	IOU	PEOU	PU	SV
AB									
CV	0.519								
EPV	0.732	0.632							
EV	0.808	0.558	0.822						
FV	0.684	0.413	0.682	0.781					
IOU	0.885	0.534	0.734	0.771	0.690				
PEOU	0.819	0.544	0.806	0.825	0.714	0.858			
PU	0.843	0.569	0.802	0.863	0.629	0.818	0.879		
SV	0.711	0.567	0.734	0.884	0.761	0.751	0.720	0.736	

Source: Field Survey (2024)

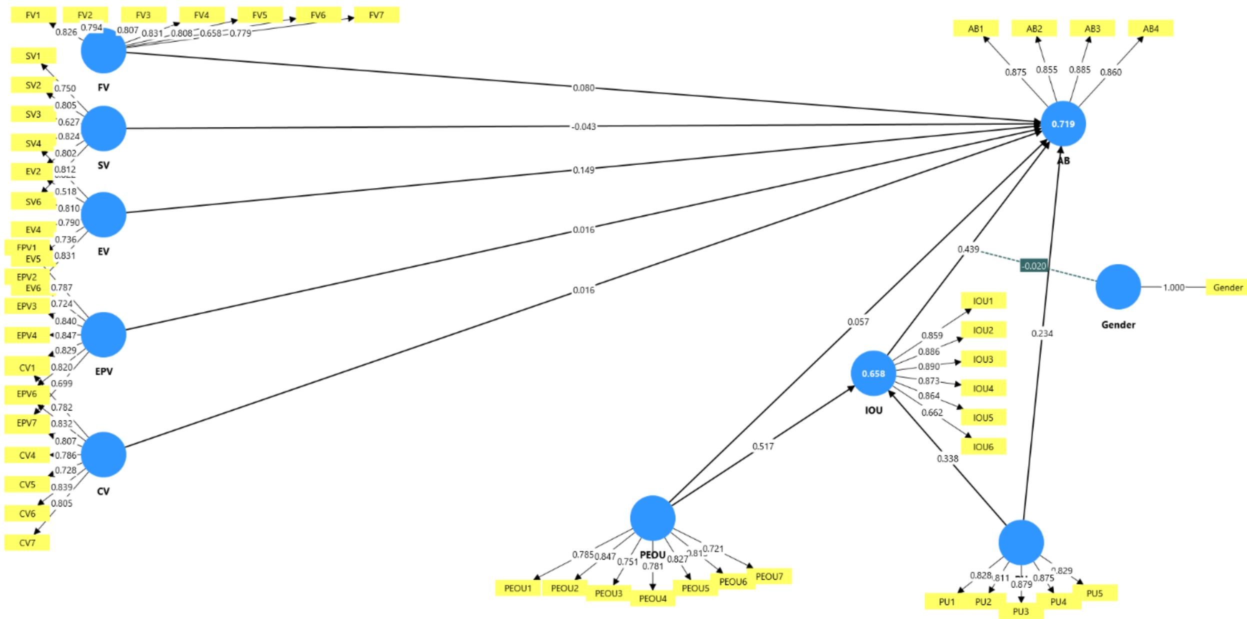


Figure 2: Measurement model

Structural Equation Modelling

The structural model results, presented in Table 3, reveal that emotional value exerts a positive and significant effect on adoption behaviour (β=0.150, p<0.005) Likewise, perceived usefulness (β=0.234, p<0.002) demonstrates positive and significant effects on adoption behaviour, underscoring the central role of perceptual value in shaping students' engagement with e-learning. In contrast, perceived ease of use (β=0.056, p>0.05), epistemic value (β=0.016, p>0.05), functional value (β=0.080, p>0.05), social value (β=-0.043, p>0.05), and conditional value (β=-0.016, p>0.05) do not exhibit significant effects, suggesting that these dimensions were less influential in explaining students' adoption behaviour in the present context. The mediation analysis further indicates that intention to use fully mediates the relationship between perceived ease of use and adoption behaviour (β=0.227, p<0.001), while, intention to use partially mediates the relationship between perceived usefulness and adoption behaviour (β=0.149, p<0.001), thereby confirming the intervening role of behavioural intention in the proposed model. Finally, gender does not significantly moderate the relationship between intention to use and adoption behaviour (β = -0.020, p > 0.05), implying that the effect of intention to use on adoption behaviour is consistent across male and female students. The results are shown in Table 3.

Table 3: Path Coefficients

Path (Hypothesis)		Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
FV -> AB	**(H1a)**	0.080	0.044	1.813	0.070
SV -> AB	**(H1b)**	-0.043	0.054	0.803	0.422
EV -> AB	**(H1c)**	0.150	0.065	2.305	0.021
EPV -> AB	**(H1d)**	0.016	0.060	0.263	0.792
CV -> AB	**(H1e)**	0.016	0.038	0.416	0.678
PU->AB	**(H2)**	0.234	0.071	3.305	0.001
PEOU->AB	**(H3)**	0.056	0.060	0.930	0.352

Table 3 Contd.				
PU->IOU->AB (H4a)	0.149	0.033	4.453	0.000
PEOU->IOU->AB (H4b)	0.227	0.038	6.047	0.000
Gender x IOU -> AB (H15)	-0.020	0.028	0.724	0.469

Source: Field Survey (2024)

Note: FV means Functional value, SV means social value, EV means Emotional value, EPV means Epistemic value, CV means Conditional value, PU means Perceived Usefulness, PEOU means Perceived Ease of Use, IOU means Intention to Use and AB means Adoption Behaviour

Table 4: The Mediation Effect of Intention to use between perceived usefulness and Adoption Behaviour

Total effect PU -> AB		Direct Effect PU -> AB		Indirect Effect					
B	p-value	β	p-value		β	SD	T value	P value	BI (2.5%-97.5%)
0.383	0.000	0.234	0.001	PU -> IoU-> AB	0.149	0.033	4.453	0.000	0.091-0.223

Variance accounted for (VAF)=Indirect/Total effect* 100

Source: Field survey (2024)

VAF No mediation (< 20%); Partial mediation (20% < mediation < 80%); Full mediation (mediation > 80%)

VAF= 0.149/0.383 * 100

VAF= 38.90% (Partial mediation)

The findings indicate that intention to use partially mediates the relationship between perceived usefulness and students' adoption of e-learning at Ho Technical University (Table 4), suggesting that perceived usefulness influences adoption through both direct and indirect pathways. Indirectly, students who perceive the e-learning system as beneficial for enhancing their academic performance and learning efficiency are more likely to develop a stronger intention to use it, which subsequently translates into actual adoption, consistent with the Technology Acceptance Model (TAM). However, the significant direct effect of perceived usefulness on adoption behaviour indicates that students may also adopt the system independently of their behavioural intentions because of its immediate practical and performance-enhancing benefits. In the higher education context, where e-learning platforms are often integral to course delivery, assessments, communication, and access to learning resources, students may use the system out of necessity or because of its perceived instrumental value.

The findings reveal that intention to use fully mediates the relationship between perceived ease of use and students' adoption of e-learning at Ho Technical University (Table 5), indicating that perceived ease of use does not directly influence adoption behaviour but operates entirely through behavioural intention. This suggests that although students who perceive the e-learning system as easy to learn, navigate, and operate are more likely to develop favourable intentions to use it, these perceptions alone are insufficient to translate into actual adoption. Rather, the ease of using the system first shapes students' willingness and motivation to engage with the platform, and it is this intention that subsequently drives actual usage.

Table 5: The Mediation Effect of intention to use between Perceived Ease of Use and Adoption Behaviour									
Total effect PEOU -> AB		Direct Effect PEOU -> AB		Indirect Effect					
β	p-value	β	p-value		β	SD	T value	P value	BI (2.5%-97.5%)
0.283	0.000	0.056	0.352	PEOU -> IoU-> AB	0.227	0.038	6.047	0.000	0.162-0.310
Variance accounted for (VAF)=Indirect/Total effect* 100									

Source: Field survey (2024)

VAF No mediation (< 20%); Partial mediation (20% < mediation < 80%); Full mediation (mediation > 80%)

VAF= 0.227/0.283 * 100

VAF= 80.21% (Full mediation)

Moderation Effect

The conditional effect estimates indicate that the direct influence of intention to use on adoption behaviour remains positive and substantively stable across all levels of gender (Table 6 &Figure 3). Specifically, the conditional direct effect varies only marginally, from 0.419 at +1 SD of gender to 0.460 at −1 SD, with the mean-level estimate of 0.439 suggesting a consistently positive association (Hair et al., 2019). A similar pattern is evident for the conditional indirect effects: the indirect effect of perceived usefulness on adoption behaviour through intention to use ranges from 0.142 to 0.156, while the indirect effect of perceived ease of use on adoption behaviour through intention to use ranges from 0.217 to 0.238. Although these coefficients are slightly stronger at lower levels of gender, the variation is trivial in magnitude.

Table 6: Moderation effect			
	Conditional Direct Effect	Conditional Indirect Effect	
	IOU-> AB	PU-> IOU->AB	PEOU-> IOU-> AB
Gender at +1SD	0.419	0.142	0.217
Gender at -1SD	0.460	0.156	0.238
Gender at Mean	0.439	0.149	0.227

Source: Field survey (2024)

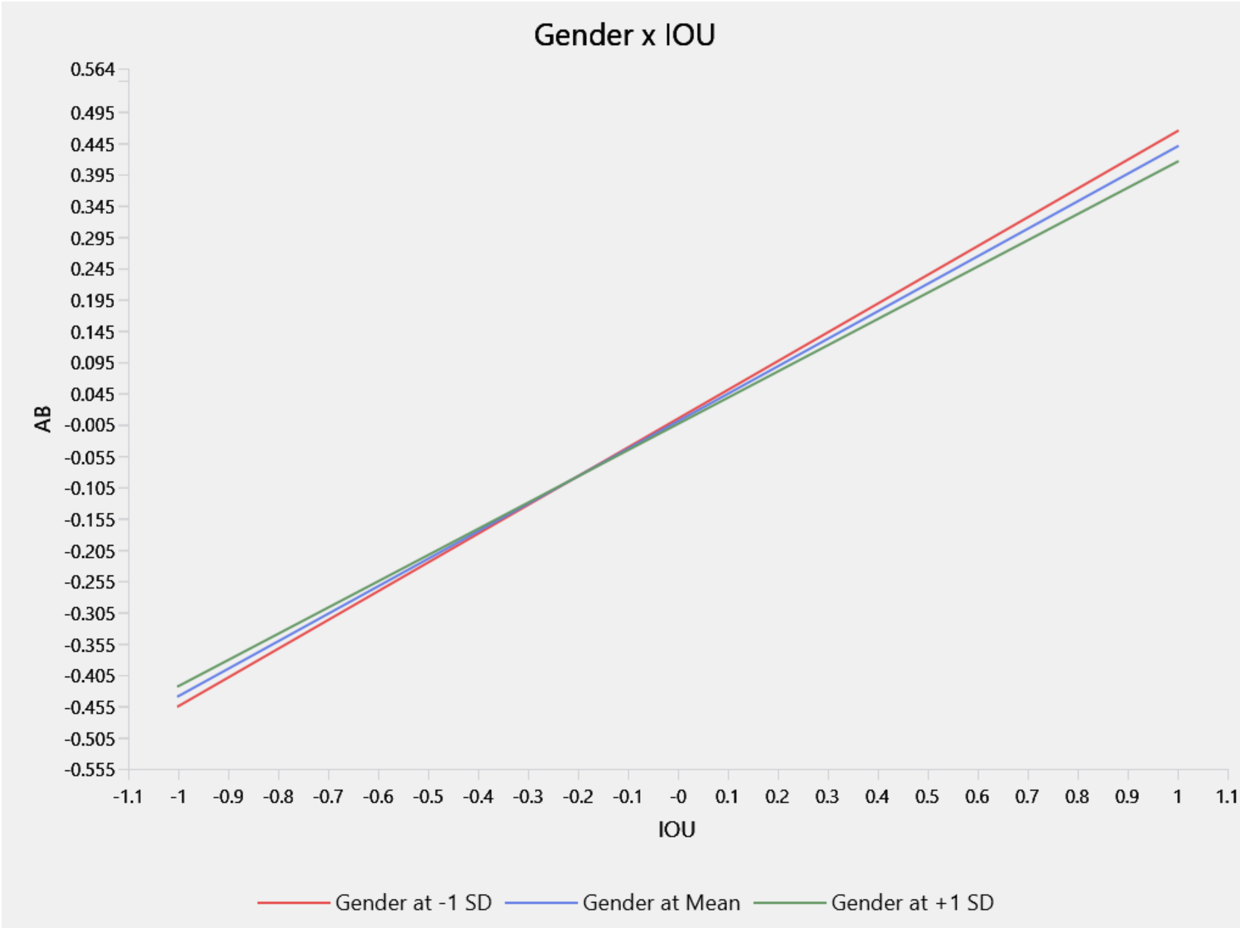


Figure 3: Moderation slope

Since the moderating effect of gender on the relationship between intention to use and adoption behaviour is non-significant, these conditional differences should not be construed as meaningful evidence of heterogeneity across gender. Rather, the findings suggest that gender does not materially alter the strength of the direct relationship between intention to use and adoption behaviour, nor meaningfully differentiate the indirect paths linking perceived usefulness and perceived ease of use towards adoption behaviour through intention to use. This implies that the relationship between intention to use and adoption of e-learning among students at Ho Technical University is generic in the context of gender. Thus, gender of students, either male or female is not an important determinant to their adoption of e-learning.

Predictive Relevance Assessment

The study employed the R-squared(R^2) and PLS predict to assess the explanatory power of the structural model. It was revealed that adoption behaviour has an R^2 value of 0.719, indicating 71.9 % of the variance in adoption behaviour is explained by functional value, social value, emotional value, epistemic value, perceived usefulness, perceived ease of use and intention to use. Intention to use obtained R^2 value of 0.658 indicating that 65.8 % of its variance were explained by perceived usefulness and perceived ease of use. Besides, the predictive values for adoption behaviour ($Q^2 = 0.634$) and intention to use ($Q^2 = 0.652$) were above zero, indicating that the model met predictive relevant criteria (Chin, 1998). Further, the Q^2 values of the endogenous variable (adoption behaviour=0.634; intention to use=0.652) suggest large predictive relevance of the model (Hair et al., 2019). The results are shown in Table 7.

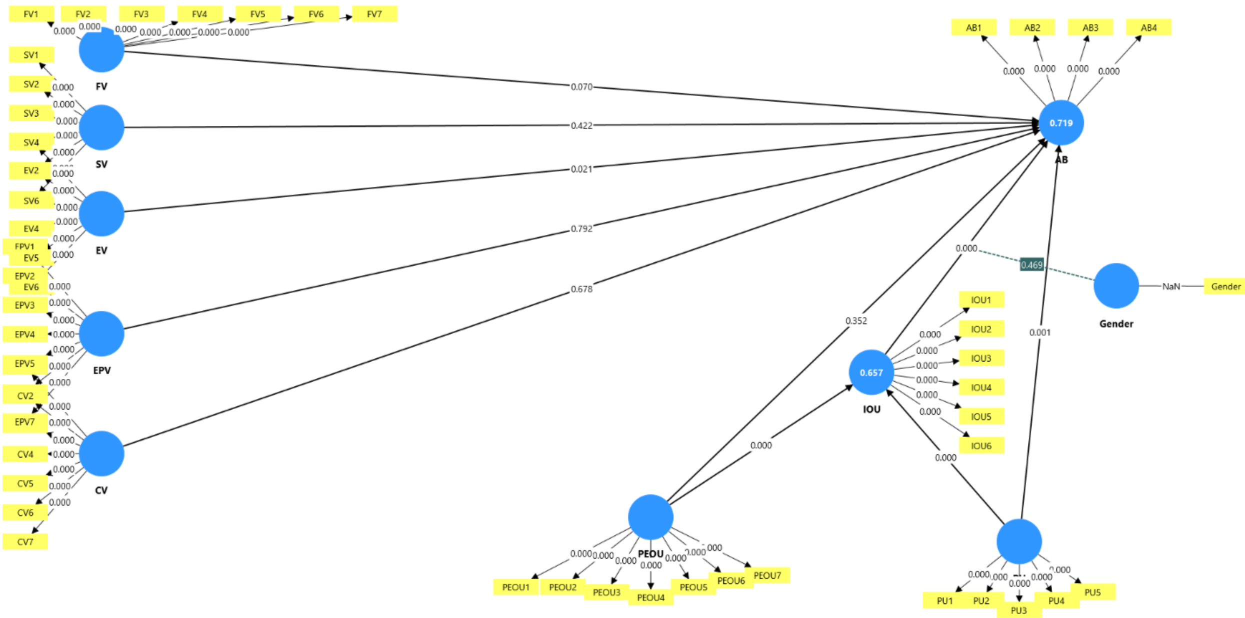


Figure 4: Structural Equation model

Table 7: R-Squared and PLS Predict			
Endogenous variables	**R-square**	**R-square adjusted**	
AB	0.719	0.712	
IOU	0.658	0.656	
PLS Predict	**Q^2 Predict**	**RMSE**	**MAE**
Adoption Behaviour	0.634	0.609	0.452
Intention to Use	0.652	0.593	0.447

Source: Field Survey (2024)

Effect sizes and Multicollinearity Assessment

The assessment of the effect size(f2) measures how removal of a predictor variable changes R^2 value of an endogenous construct. The study evaluated for effect size(f2) and multicollinearity statistics (VIF). Effect sizes values of 0.02, 0-15 and 0.35 connotes small, medium and large effects, respectively. From Table 5, except CV -> AB; EPV -> AB; FV -> AB and SV -> AB that suggest predictor variable to be of no relevant, the remaining relationship demonstrated medium to strong predictor variable. Even though, path with f^2 below 0.02 suggest the predictor variable not statistically significant, however, practically and theoretically they are, hence, maintaining them in the model is not erroneous (Hair et al., 2019). Again, it suggests that such predictor variables are not fully understood, hence further research into them is required to fully identify their effects (Hair et al., 2019). Besides, all the VIF values in the table were less than 5, indication of no multicollinearity issues in the model (Hair et al, 2019). The results are shown in Table 8.

Table 8: F-squared and Multicollinearity Statistics		
Paths	f-square	VIF
FV -> AB	0.010	2.360
SV -> AB	0.002	2.914
EV -> AB	0.020	3.918
EPV -> AB	0.003	3.050
CV -> AB	0.001	1.622
PU->AB	0.052	3.734
PEOU->AB	0.030	3.922
Gender x IOU -> AB	0.040	1.025
IOU->AB	0.210	3.263
PU->IOU	0.126	2.656
PEOU-> IOU	0.294	2.656

Source: Field Survey (2024)

Model Fit Assessment

The fitness of the model measures the extent to which the model accurately explains the underlying relationship between the constructs under investigation. In assessing the model fit, Standard Root Mean Squared Residual (SRMR) as well as other fit indicators explicated in the Table 9. The minimum threshold of SRMR value for a model fitness is 0.08. specifically, SRMR for saturated model (0.050) and the Estimated model (0.054) are all below the minimum threshold. The results are shown in Table 9.

Table 9: Model Fit		
Criteria	Saturated model	Estimated model
SRMR	0.050	0.054
d_ULS	4.018	4.619
d_G	1.607	1.625
Chi-square	3323.403	3338.277
NFI	0.800	0.799

Source: Field Survey (2024)

Importance Performance Map Analysis (IPMA)

The study further assessed the relative contribution of each construct in explaining adoption behaviour. This was necessary to identify the constructs that merit greater managerial emphasis, particularly in relation to strategic resource allocation. Figure 5 illustrates the relative importance and performance of the exogenous constructs in shaping the adoption behaviour of students at Ho Technical University.

The results provide a clear order of strategic priorities. Intention to use stands out as the most influential determinant of adoption behaviour, exhibiting the highest importance despite only moderate performance, with perceived usefulness and perceived ease of use following closely behind. This result is practically significant, as it indicates that the constructs with the greatest explanatory leverage are not yet performing at commensurate levels, thereby revealing substantial scope for managerial intervention. Contrary, conditional value and epistemic value demonstrate comparatively strong performance but limited importance, suggesting that further enhancement in these values is unlikely to produce meaningful incremental gains in adoption of e-learning. emotional value and functional value occupy an intermediate position, reflecting modest relevance and therefore representing less priority for improvement. Meanwhile, gender and social value show negligible explanatory salience and thus offer little strategic value confirming their non-significant effect on adoption behaviour of e-learning among students.

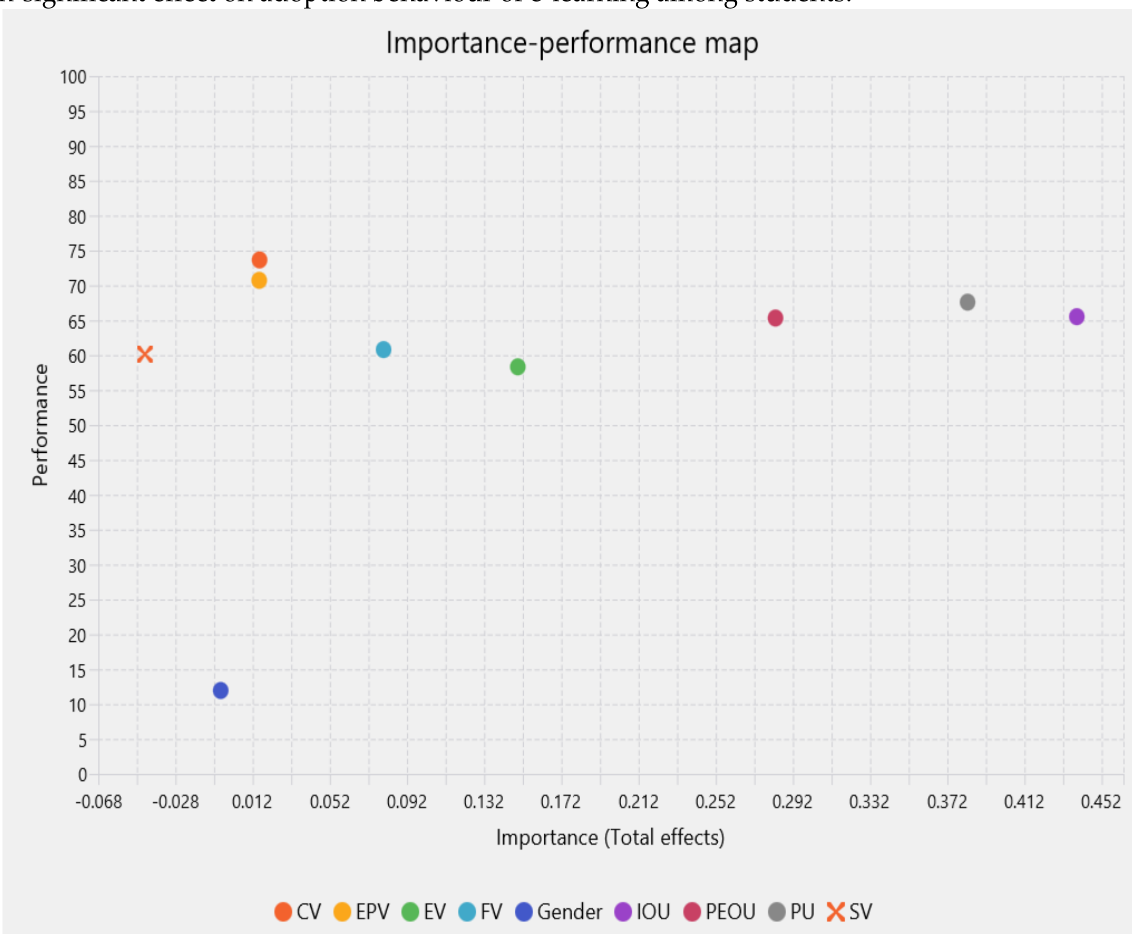


Figure 5: Performance-Importance Map Analysis

Discussion

The study's findings reveal that emotional value had a significant positive effect on adoption behaviour, suggesting that students at Ho Technical University are more likely to adopt e-learning when it evokes positive feelings and meaningful experiences. This aligns with Tanrikulu (2021), who found that emotional value enhances adoption behaviour. In contrast, epistemic value showed a positive but non-significant relationship with adoption behaviour, indicating that novelty, curiosity, or knowledge-seeking may not be strong motivations for students' e-learning adoption in this context. This result contradicts prior studies (e.g., Chakraborty et al., 2022; Karjaluoto et al., 2020), which reported that epistemic value can strengthen students' inclination toward e-learning.

Similarly, functional value had a positive but non-significant effect on adoption behaviour, implying that students do not primarily base their adoption decisions on the utilitarian or performance-related benefits of e-learning. This finding contrasts with Kim and Jan (2024), who argued that functional value significantly shapes consumers' adoption decisions. Social value also exhibited a negative and non-significant effect, suggesting that peer approval or social image does not meaningfully influence students' adoption of e-learning, contrary to Misra (2025). In the same vein, conditional value was found to be non-significant, indicating that situational factors or specific conditions do not substantially drive students' e-learning behaviour. This diverges from the findings of Mason et al. (2023) and Kwaku Nimsaah et al. (2025), who reported a significant effect of conditional value on adoption behaviour.

Regarding the Technology Acceptance Model constructs, perceived usefulness had a positive and significant influence on intention to use, indicating that students are more inclined to use e-learning when they perceive it as beneficial to their academic performance, consistent with Al-Kurdi et al. (2020). Perceived ease of use does not significantly influenced intention to use, suggesting that students' willingness to engage with e-learning does not depend on the platform easiness to operate. The mediation analysis further showed that intention to use partially mediated the relationship between perceived usefulness and adoption behaviour (Table 4), while it fully mediated the relationship between perceived ease of use and adoption behaviour (Table 5). These findings underscore the central role of behavioural intention in translating students' perceptions of e-learning into actual adoption.

Gender did not significantly moderate the relationship between intention to use and adoption behaviour ($B = 0.027$, $p = 0.685$), implying that gender does not strengthen or weaken students' e-learning adoption in this context. This contradicts earlier studies (Chawla & Joshi, 2020; Kebede, 2022; Tufa et al., 2022) and may reflect the specific institutional context of Ho Technical University. Finally, the IPMA results identify intention to use as the most strategic predictor of adoption behaviour, followed by perceived usefulness and perceived ease of use. Although these factors are incredibly important, their moderate performance indicates substantial room for managerial improvement. By contrast, conditional and epistemic value showed relatively strong performance but low importance, suggesting that further investment in these areas may yield limited gains.

Theoretical implication

This study advances the e-learning literature by demonstrating that the explanatory strength of the Theory of Consumption Values and the Technology Acceptance Model is not symmetrical in the higher education context. The findings provide weak support for consumption value theory, as among the five value dimensions, only emotional value significantly influenced adoption behaviour. This suggests that students' acceptance of e-learning is shaped less by a broad integration of consumption utilities and more by the affective meanings attached to the learning experience, such as enjoyment, confidence, and reduced anxiety. The non-significant effects of functional, social, epistemic, and conditional value indicate that these dimensions may lose predictive force when e-learning is institutionalised and experienced as a compulsory academic infrastructure rather than a discretionary service. By contrast, the strong effects of perceived usefulness, perceived ease of use, and intention to use offer substantial support for TAM and reaffirm its core assumption that technology adoption is fundamentally driven by instrumental beliefs and behavioural intention. The mediating role of intention further strengthens this interpretation. Overall, the study suggests that while consumption value theory enriches understanding of affective value formation, TAM remains the more robust framework for explaining e-learning adoption in higher educational institutions.

Managerial implication

The findings offer clear strategic guidance for university administrators seeking to improve students' adoption of e-learning platforms. Since intention to use emerged as the most critical predictor, followed by perceived usefulness and perceived ease of use, managerial efforts should focus on strengthening these core behavioural drivers. Institutions should ensure that e-learning systems visibly enhance academic performance through efficient access to course materials, assessments, feedback, and communication. The platform must also be designed and managed for simplicity, with intuitive navigation, orientation support, and responsive technical assistance, because ease of use contributes to adoption primarily by reinforcing students' willingness to engage. The significant role of emotional value further implies that implementation should move beyond technical functionality to include the cultivation of positive user experiences. Engaging interfaces, supportive lecturer interaction, timely assistance, and low-friction learning journeys can increase students' emotional attachment to the platform and, in turn, their adoption behaviour. Conversely, the weak influence of social, epistemic, functional, and conditional value suggests that managers should avoid overemphasising novelty, peer pressure, or situational incentives as primary levers of adoption. In this context, effective e-learning strategy depends on making the system useful, simple, and emotionally reassuring rather than merely feature-rich.

Conclusion

This study provides a comprehensive understanding of the determinants of e-learning adoption by integrating consumption value theory and the Technology Acceptance Model. The findings reveal that while emotional value plays a significant role in shaping students' adoption behaviour, the broader set of consumption values does not uniformly influence adoption decisions in this context. Instead, students appear to engage with e-learning platforms primarily as institutional and goal-oriented systems rather than discretionary consumption experiences. In contrast, the strong and consistent effects of perceived usefulness, perceived ease of use, and intention to use reinforce the robustness of TAM in explaining technology adoption. The mediating role of intention further confirms that students' cognitive evaluations of system utility and usability are central mechanisms through which adoption behaviour is formed. Collectively, these findings highlight a shift from multidimensional value-based evaluation toward a more utilitarian and experience-driven adoption logic in higher education environments.

Practically, the study underscores the need for higher education institutions to prioritise strategies that enhance system usefulness, usability, and positive user experiences. Strengthening these core drivers can significantly improve students' intention to use and, ultimately, their actual adoption of e-learning platforms. The non-significant influence of functional value, social value, epistemic value and conditional value suggests that investments in them may yield no returns compared to efforts focused on emotional value and user experience. Importantly, the role of emotional value indicates that adoption is not purely rational but also shaped by affective engagement, reinforcing the need for supportive and user-friendly digital learning environments. Generally, the study challenges and reinforces the consumption value theory and technology acceptance theory respectfully, demonstrating that effective e-learning adoption depends on aligning technological efficiency with positive user experiences within higher educational institutions, specifically Ho Technical University without emphasise on student gender type.

Limitations and suggestions for future studies

Irrespective of the significant contributions of the study to theory and practice, the findings are subject to limitations. First, focusing the study on a single higher education could neutralizes the strength of generalization of the findings across several higher education institutions. Therefore, future studies can consider widening the scope of the study to enhance generalization. Further, collection of data on both dependent and independent variables at same time could create common method bias issue. Therefore, future studies should consider collecting data on dependent and independent variables at different times. Besides, the use of only structured questionnaire disallowed respondents to freely express their opinion on the issue under investigation in a broader sense. Therefore, future studies should consider mixed method so that varied opinions on the issue of investigation can be obtained. Finally, reliance on a cross-sectional research design, which restricts the ability to capture changes in students' perceptions and adoption behaviour over time. Hence, future research is encouraged to adopt longitudinal designs that track participants across multiple time intervals.

Availability of Data and Materials

The datasets used for the study are available from the corresponding author upon request.

Competing Interests

The authors reported no potential conflict of interest.

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Consent to Participate

We confirm that participant consents were sought before participation and they have provided consent for the publication of their data. However, measures have been taken to ensure anonymity and confidentiality of their individual responses.

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References

Abdullah, F., Ward, R., & Ahmed, E. (2016). Investigating the influence of the most commonly used external variables of TAM on students' Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of e-portfolios. *Computers in human behaviour*, *63*, 75-90.

Abou-El-Sood, H. (2021). Board gender diversity, power, and bank risk-taking. *International Review of Financial Analysis*, *75*, 101733.

Al Kurdi, B., Alshurideh, M., Salloum, S., Obeidat, Z., & Al-dweeri, R. (2020). An empirical investigation into examination of factors influencing university students' behavior towards elearning acceptance using SEM approach, *International Journal of Interactive Mobile Technologies,* 14(2), 19-41.

Al-Emran, M., Arpaci, I., & Salloum, S. A. (2020). An empirical examination of continuous intention to use m-learning: An integrated model. *Education and information technologies*, *25*, 2899-2918.

Almaiah, M. A., Al-Khasawneh, A., & Althunibat, A. (2020). Exploring the critical challenges and factors influencing the E-learning system usage during COVID-19 pandemic. *Education and information technologies*, *25*(6), 5261-5280.

Amin, S., & Tarun, M. T. (2021). Effect of consumption values on customers' green purchase intention: a mediating role of green trust. *Social Responsibility Journal*, *17*(8), 1320-1336.

Ansong, E., Lovia Boateng, S., & Boateng, R. (2017). Determinants of e-learning adoption in universities: Evidence from a developing country. *Journal of Educational Technology Systems*, *46*(1), 30-60.

Baig, M. I., Shuib, L., & Yadegaridehkordi, E. (2022). E-learning adoption in higher education: A review. *Information Development*, *38*(4), 570-588.

Bossman, A., & Agyei, S. K. (2022). Technology and instructor dimensions, e-learning satisfaction, and academic performance of distance students in Ghana. *Heliyon*, *8*(4), 1-16

Chakraborty, D., Kayal, G., Mehta, P., Nunkoo, R., & Rana, N. P. (2022). Consumers' usage of food delivery app: a theory of consumption values. *Journal of Hospitality Marketing & Management*, *31*(5), 601-619.

Chawla, D., & Joshi, H. (2020). The moderating role of gender and age in the adoption of mobile wallet. *foresight*, *22*(4), 483-504.

Cheon, J., Lee, S., Crooks, S. M., & Song, J. (2012). An investigation of mobile learning readiness in higher education based on the theory of planned behavior. Computers & Education, 59(3), 1054–1064.

Chin, W.W. (1998). "The partial least squares approach to structural equation modelling," in Marcoulides, G.A. (Ed.), Modern Methods for Business Research, Erlbaum, Mahwah, 295-358

Choi, P. M. S., & Lam, S. S. (2018). A hierarchical model for developing e-textbook to transform teaching and learning. *Interactive Technology and Smart Education*, *15*(2), 92-103.

Chu, W., Baumann, C., Hamin, H., & Hoadley, S. (2018). Adoption of environment-friendly cars: direct vis-à-vis mediated effects of government incentives and consumers' environmental concern across global car markets. *Journal of Global Marketing*, *31*(4), 282-291.

Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13, 319 – 340

Dewi, C. S., & Annas, M. (2022). Consumption Value dimension of green purchase intention with green trust as mediating variable. *Dinasti International Journal of Economics, Finance & Accounting*, *3*(3), 315-325.

Fauzi, M. A. (2022). E-learning in higher education institutions during COVID-19 pandemic: current and future trends through bibliometric analysis. *Heliyon*, *8*(5).

Friedl, A., Pondorfer, A., & Schmidt, U. (2020). Gender differences in social risk taking. *Journal of Economic Psychology*, *77*, 102182.

Gunasinghe, A., Hamid, J. A., Khatibi, A., & Azam, S. F. (2020). The adequacy of UTAUT-3 in interpreting academician's adoption to e-Learning in higher education environments. *Interactive Technology and Smart Education*, *17*(1), 86-106.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review*, *31*(1), 2-24.

Harman, H. H. (1976). *Modern factor analysis* (3rd ed.). Chicago, IL: University of Chicago Press

Harrigan, M., Feddema, K., Wang, S., Harrigan, P., & Diot, E. (2021). How trust leads to online purchase intention founded in perceived usefulness and peer communication. *Journal of Consumer Behaviour*, *20*(5), 1297-1312.

Karjaluoto, H., Glavee-Geo, R., Ramdhony, D., Shaikh, A. A., & Hurpaul, A. (2021). Consumption values and mobile banking services: understanding the urban–rural dichotomy in a developing economy. *International Journal of Bank Marketing*, *39*(2), 272-293.

Kebede, H. A. (2022). Risk aversion and gender gaps in technology adoption by smallholder farmers: Evidence from Ethiopia. *The Journal of Development Studies*, *58*(9), 1668-1692.

Kim, H., & Jan, I. U. (2024). Consumption value factors as determinants of use intention and behavior of car-sharing services in the Republic of Korea. *Innovation: The European Journal of Social Science Research*, *37*(2), 462-480.

Kivunja, C., & Kuyini, A. B. (2017). Understanding and applying research paradigms in educational contexts. *International Journal of higher education*, *6*(5), 26-41.

Kwaku Nimsaah, W., Owusu-Mensah, S., Atakora, A., & Amofah, O. (2025). Consumption values and sustainable e-government services: retrospection of Ghana's digitalisation agenda and post-use trust in e-government. *Transforming Government: People, Process and Policy*, *19*(4), 795-813.

MacKenzie, S. B., & Podsakoff, P. M. (2012). Common Method Bias in Marketing: Causes, 731 Mechanisms, and Procedural Remedies. Journal of Retailing, 88(4), 542–555. 732 https://doi.org/10.1016/j.jretai.2012.08.001

Mashroofa, M. M., Haleem, A., Nawaz, N., & Saldeen, M. A. (2023). E-learning adoption for sustainable higher education. *Heliyon*, *9*(6).

Mason, M. C., Oduro, S., Umar, R. M., & Zamparo, G. (2023). Effect of consumption values on consumer behavior: a Meta-analysis. *Marketing Intelligence & Planning*, *41*(7), 923-944.

Mehta, A., Morris, N. P., Swinnerton, B., & Homer, M. (2019). The influence of values on E-learning adoption. *Computers & Education*, *141*, 1-16.

Misra, P. (2025). Purchase intention toward E-pharmacy: the consumption value perspective. *International Journal of Pharmaceutical and Healthcare Marketing*, *19*(2), 181-208.

Mohammadi, H. (2015). Social and individual antecedents of m-learning adoption in Iran. Computers in Human Behavior, 49, 191–207.

Mulyani, V. G., Najib, M. F., & Guteres, A. D. (2021). The effect of perceived usefulness, trust and visual information toward attitude and purchase intention. *Journal of Marketing Innovation (JMI)*, *1*(1).

Ramayah, T., Rahman, S. A., & Ling, N. C. (2018). How do consumption values influence online purchase intention among school leavers in Malaysia? *Revista Brasileira de Gestão de Negócios*, *20*, 638-654.

Rattanaburi, K., & Vongurai, R. (2021). Factors influencing actual usage of mobile shopping applications: Generation Y in Thailand. *The Journal of Asian Finance, Economics and Business*, *8*(1), 901-913.

Rogers, E.M. (1995). Diffusion of Innovations. fourth edition The Free Press, New York.

Rughoobur-Seetah, S., & Hosanoo, Z. A. (2021). An evaluation of the impact of confinement on the quality of e-learning in higher education institutions. *Quality Assurance in Education*, *29*(4), 422-444.

Saeed Al-Maroof, R., Alhumaid, K., & Salloum, S. (2020). The continuous intention to use e-learning, from two different perspectives. *Education Sciences*, *11*(1), 6.

Şahin, F., Doğan, E., Okur, M. R., & Şahin, Y. L. (2022). Emotional outcomes of e-learning adoption during compulsory online education. *Education and Information Technologies*, *27*(6), 7827-7849.

Saleh, S. S., Nat, M., & Aqel, M. (2022). Sustainable adoption of e-learning from the TAM perspective. *Sustainability*, *14*(6), 3690.

Salloum, S. A., Alhamad, A. Q. M., Al-Emran, M., Monem, A. A., & Shaalan, K. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE access*, *7*, 128445-128462.

Sarpong, S. A., Dwomoh, G., Boakye, E. K., & Ofosua-Adjei, I. (2021). Online teaching and learning under COVID-19 pandemic; perception of university students in Ghana. *European Journal of Interactive Multimedia and Education*, *3*(1),

Sheth, J. N., Newman, B. I., & Gross, B. L. (1991). Why we buy what we buy: A theory of consumption values. Journal of Business Research. 22, 159-170.

Sheth, J. N., Sethia, N. K., & Srinivas, S. (2011). Mindful consumption: A customer-centric approach to sustainability. Journal of the Academy of Marketing Science, 39, 21-39.

Shiau, W.L., Sarstedt, M. & Hair, J.F. (2019). "Internet research using partial least squares structural equation modeling (PLS-SEM)," Internet Research, 29(3), 398-406.

Shoukat, A., Baig, U., Batool Hussain, D., Rehman, N. A., & Shakir, D. K. (2021). An empirical study of consumption values on green purchase intention. *International Journal of Scientific and Technology Research*, *10*(3), 140-148.

Tahar, A., Riyadh, H. A., Sofyani, H., & Purnomo, W. E. (2020). Perceived ease of use, perceived usefulness, perceived security and intention to use e-filing: The role of technology readiness. *The Journal of Asian Finance, Economics and Business*, *7*(9), 537-547.

Tanrikulu, C. (2021). Theory of consumption values in consumer behaviour research: A review and future research agenda. *International Journal of Consumer Studies*, *45*(6), 1176-1197.

Tufa, A. H., Alene, A. D., Cole, S. M., Manda, J., Feleke, S., Abdoulaye, T., ... & Manyong, V. (2022). Gender differences in technology adoption and agricultural productivity: Evidence from Malawi. *World Development*, *159*, 106027.

Ventre, I., & Kolbe, D. (2020). The impact of perceived usefulness of online reviews, trust and perceived risk on online purchase intention in emerging markets: A Mexican perspective. *Journal of International Consumer Marketing*, *32*(4), 287-299.

Yamane, T. (1967). Statistics, An Introductory Analysis (2nd ed.). New York: Harper and Row.

Yurdagül, C., Kircaburun, K., Emirtekin, E., Wang, P., & Griffiths, M. D. (2021). Psychopathological consequences related to problematic Instagram use among adolescents: The mediating role of body image dissatisfaction and moderating role of gender. *International Journal of Mental Health and Addiction*, *19*, 1385-1397.

Zolkepli, I. A., Mukhiar, S. N. S., & Tan, C. (2021). Mobile consumer behaviour on apps usage: The effects of perceived values, rating, and cost. *Journal of marketing communications*, *27*(6), 571-593.

APPENDIX A: Measurement Instrument

The scale 1=Strongly disagree to 5=Strongly agree

Code	Statements	1	2	3	4	5
	Functional Value *(Adapted from Amin &Tarun, 2021; Sheth et al., 1991)*					
FV1	E-learning offers consistent quality					
FV2	E-learning is well-designed					
FV3	E-learning provides standard teaching and learning					
FV4	E-learning is beneficial					
FV5	E-learning addresses my learning needs					
FV6	E-learning involves minimal cost					
FV7	E-learning is suitable for my programme					
	Social Value *(Adapted from Kim &Jan, 2024; Sheth et al., 1991)*					
SV1	E-learning makes me feel a modern student					
SV2	E-learning improves the way others perceived me					
SV3	E-learning will make builds positive impression about me					
SV4	E-learning makes me feel part of academic society					
SV5	E-learning enhances my social status					
SV6	E-learning makes me feel part of the digital students					
	Emotional Value *(Adapted from Amin &Tarun, 2021; Sheth et al., 1991)*					
EV1	E-learning makes learning enjoyable					
EV2	E-learning makes me feel fearful of my privacy					
EV3	E-learning makes me feel as a better student					
EV4	E-learning makes me feel equal as other students in other universities					
EV5	E-learning provides easy support at any time					
EV6	E-learning makes me feel happy when learning					
	Epistemic Value *(Adapted from (Kim &Jan, 2024; Sheth et al., 1991)*					
EPV1	E-learning exposes me to new knowledge					
EPV2	E-learning makes me curious					
EPV3	E-learning makes me have new experiences					
EPV4	E-learning makes me explore new knowledge					
EPV5	E-learning makes me to seek for different knowledge					
EPV6	E-learning provides new method of learning					
EPV7	E-learning make me lazy to learn					
	Conditional Value *(Adapted from Kim &Jan, 2024; Sheth et al., 1991)*					
CV1	I will prefer e-learning if internet is easily accessible					
CV2	I will prefer e-learning if data will be free					
CV3	I will prefer e-learning if e-learning workshop is provided periodically					
CV4	1 will prefer e-learning if e-learning manual is provided					
CV5	1 will prefer e-learning if my fees will be reduced					

Appendix A Contd.

CV6	I will prefer e-learning if I have smartphone
CV7	I will prefer e-learning if I have computer
	Perceived Usefulness *(Adapted from Cheon et al., 2012; Davis, 1989).*
PU1	E-learning enhances my performance
PU2	E-learning saves time
PU3	E-learning gives me more control over learning
PU4	E-learning makes learning easier
PU5	E-learning enables me to complete learning tasks
	Perceived Ease of Use *(Adapted from Cheon et al., 2012; Davis, 1989).*
PEOU1	E-learning is convenient
PEOU2	E-learning involves less physical effort
PEOU3	E-learning limits learning challenges
PEOU4	E-learning makes learning easier
PEOU5	E-learning avoids frustration in learning
PEOU6	E-learning requires less mental effort
PEOU7	Learning Management System makes it easier to use e-learning
	Intention of Use *(Adapted from Cheon et al., 2012; Davis, 1989).*
IoU1	I intend to use e-learning regularly
IoU2	I expect to use e-learning regularly
IoU3	I plan to use e-learning regularly
IoU4	Assuming I had access to e-learning, I intend to use it
IoU5	Given that I had access to e-learning, I predict I would use it
	Adoption Behaviour (A*dapted from Mohammadi, 2015)*
AB1	I prefer to continue using e-learning
AB2	It took me less time to use e-learning
AB3	prefer using e-learning for all my courses
AB4	I prefer to use e-learning due to its convenient.

APPENDIX B: Herman Single Factor for Assessing Common Method Bias

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	22.098	40.179	40.179	22.098	40.179	40.179
2	4.478	8.141	48.320			
3	2.997	5.450	53.770			
4	2.240	4.072	57.842			
5	1.921	3.493	61.336			
6	1.583	2.878	64.214			
7	1.555	2.827	67.041			
8	1.376	2.502	69.543			
9	1.156	2.102	71.645			
10	1.084	1.971	73.616			

Appendix B Contd.			
11	1.000	1.818	75.434
12	.970	1.764	77.198
13	.884	1.608	78.806
14	.857	1.557	80.363
15	.746	1.356	81.719
16	.712	1.295	83.014
17	.693	1.260	84.274
18	.601	1.092	85.366
19	.579	1.052	86.418
20	.543	.987	87.405
21	.493	.896	88.301
22	.485	.882	89.183
23	.429	.779	89.963
24	.422	.767	90.729
25	.409	.744	91.473
26	.369	.671	92.144
27	.345	.626	92.771
28	.320	.581	93.352
29	.315	.573	93.925
30	.277	.504	94.429
31	.264	.479	94.908
32	.245	.445	95.353
33	.226	.411	95.764
34	.216	.394	96.158
35	.206	.374	96.531
36	.196	.355	96.887
37	.178	.324	97.210
38	.164	.298	97.508
39	.150	.272	97.780
40	.144	.261	98.041
41	.129	.235	98.276
42	.125	.228	98.504
43	.117	.213	98.717
44	.103	.187	98.904
45	.099	.180	99.083
46	.085	.154	99.238
47	.075	.137	99.374
48	.066	.120	99.494
49	.062	.113	99.607
50	.057	.103	99.710
51	.043	.078	99.788
52	.041	.074	99.862

Appendix B Contd.

53	.033	.060	99.922
54	.029	.053	99.975
55	.014	.025	100.000

Extraction Method: Principal Component Analysis

Source: Field Survey (2024)