Magister
Journal of Educational Research
ISSN 2984 - 6641 (Online) ISSN 2545 - 9902 (Print)
Website: www.errc.ctu.edu.ph/ojs/magister
EDUCATIONAL RESEARCH AND RESOURCE CENTER

Examining Behavioral Intentions for E-learning: The Role of Perceived Enjoyment, Interactivity, Flexibility, and Quality

[a,b]Retchelyn Talisic, [b]Ayessa Mae Gonzales, [b]Lowella Lawas, [b]Arlene Monte, [b]Angel Marie Ruiz, [c,*]Gesselle Batucan

[a]Shechaniah Christian Learning Center, Poblacion, Liloan, Cebu, 6002 Philippines
[b]College of Education at Danao Campus, Cebu Technological University, Sabang, Danao City, Cebu, 6004 Philippines
[c]Department of Education, Division of Danao City, Danao City, Cebu 6004 Philippines

[*]Corresponding author: gesselle.batucan@deped.gov.ph

Article citation details: Talisic et al., (2024). Examining Behavioral Intentions for E-Learning: The Role of Perceived Enjoyment, Interactivity, Flexibility, and Quality. *Magister – Journal of Educational Research*, *3*(1), 83-104.

Abstract

This study investigates the factors influencing e-learning acceptance among college students using the unified theory of acceptance and use of technology (UTAUT) model. The UTAUT model is modified by exploring the inclusions of perceived flexibility, enjoyment, interactivity, and perceived quality. Employing structural equation modeling (SEM), data from 976 college students from the Visayas, Philippines, were analyzed. SEM analysis revealed an acceptable model based on model fit measures. Results indicate that effort and performance expectancy significantly influence perceived flexibility, enjoyment, interactivity, and quality. Notably, perceived enjoyment and perceived interactivity significantly affect behavioral intention. These findings suggest the importance of user-friendliness, engagement, and interactive features in shaping students' intentions to adopt e-learning. The findings highlight the need for educational institutions to develop policy directions for effective management of e-learning adoption. The nonsignificant paths from system quality and flexibility to intention may be attributed to the developing economy context of the case study, where internet infrastructure remains a challenge. Therefore, further research is recommended.

Keywords: *E-learning, UTAUT, higher education, SEM*

1. Introduction

E-learning is aided and enhanced by information and communication technologies (ICT). This rapidly evolving domain within education encompasses diverse activities, including the support of learning and teaching through ICTs, the incorporation of blended learning methods, and the complete acquisition of skills and knowledge via the Internet. Additionally, e-learning is facilitated and delivered through ICTs (Jenkins & Hanson, 2003; Sambrook, 2003). This highlights the integration of telecommunication technology tools in enhancing, supporting, and providing educational content.

Successful e-learning adoption relies on how users perceive the use of the technology (Ashraf et al., 2016) and its impact on various aspects of educational applications and learning (Al Mulhem, 2020). This is especially pertinent in developed countries. Data revealed that over 80% of global youth in 104 countries use online learning, with 94% in the age bracket of 15–24 entirely using the Internet among developed nations, while only 67% in less developed countries (Sanou, 2017). This indicates that while developing regions can significantly benefit from Internet resources, they have received relatively less attention in research and innovations (Al-Adwan et al., 2018). Nonetheless, developing economies like Jordan and Indonesia are adopting e-learning courses to enhance education quality (Kim & Park, 2018). However, these countries face more obstacles than developed ones due to the challenges in infrastructure and human resources (Costan et al., 2021), low technology acceptance (Bingtan et al., 2022), and lack of institutional support and access to information (Heagney & Benson, 2017). Despite investments in education and technological advancements, e-learning systems are not yet fully in place in developing nations. Recent studies have examined various factors affecting online learning in the Philippines. These include teachers' behavioral intentions to use GeoGebra (Mangubat & Batucan, 2023), the influence of self-regulated learning (SRL) strategies on student satisfaction and engagement (Buot, 2023), and the acceptance of flexible online learning (Bingtan et al., 2022).

The emerging literature on e-learning system utilization in the Philippines lacks an investigation to examine behavioral intentions to use these systems with various constructs on system characteristics. While several studies have addressed the broader aspects of e-learning system implementation and associated challenges within the Philippine education system (Abbad, 2021; Arinto, 2016; Casillano, 2019; Gracia, 2017), there is a notable lack of focus on evaluating the factors influencing behavioral intentions to adopt e-learning systems. For instance, Batucan et al. (2022) investigated the factors affecting online learning during the COVID-19 pandemic, conducting empirical research to validate the expanded UTAUT model concerning students' attitudes and behaviors towards online learning platforms. Building on the basic constructs of UTAUT, we introduce a novel inclusion of perceived enjoyment, interactivity, flexibility, and quality as factors influencing behavioral intention. The gap identified in the literature highlights the potential reversibility of the associations between external factors and the core UTAUT factors, given that most studies explore external factors to explain UTAUT elements (e.g., Abbad, 2021; Abdekhoda, 2022). Therefore, this paper proposes reversible associations, building on the work of Batucan et al. (2022), by positioning effort expectancy and performance expectancy as antecedents of enjoyment, interactivity, flexibility, and quality, with intention as the ultimate endogenous factor. The investigation utilized archival data and adhered to all relevant protocols. We further build these associations in the hypothesis development section.

Understanding the inclination toward e-learning behaviors is crucial for designing effective educational interventions and platforms in this domain. This research investigates these behaviors using the UTAUT model, which incorporates factors like effort expectancy, performance expectancy, and behavioral intention. The UTAUT model has undergone extensive validation and is essential in predicting technology acceptance and usage across different settings. This study explores how perceived enjoyment, perceived interactivity, perceived flexibility, and perceived quality influence the relationship between the core constructs of the UTAUT model and behavioral intention toward online learning. Specifically, it examines how these factors affect the adoption of e-learning systems among college students, assessing the antecedents of behavioral intentions and their impact on usage patterns.

2. Literature Review and Hypothesis Development

E-learning platforms are specialized software systems for open education and interactive learning environments, providing convenient online access to educational materials and support. They offer students flexible and engaging learning opportunities that cater to their schedules and locations. The adoption of e-learning hinges on users' decisions to engage with the technology, a behavioral aspect (Al-Emran et al., 2020b;

Davis, 1989). The technology acceptance model (TAM) explains behavioral intentions as influenced by perceived usefulness and ease of use (Al-Emran et al., 2020a; Davis, 1989). Building on TAM, Venkatesh et al. (2003) developed the UTAUT model, enhancing the original TAM's explanatory power. The UTAUT model evaluates the effectiveness of theoretical frameworks across various information technology sectors (Venkatesh et al., 2003). It provides a robust theoretical foundation and detailed insights (Al-Emran et al., 2021).

UTAUT synthesizes components from other pre-existing models, such as the theory of reasoned action (TRA) (Fishbein & Ajzen, 1977), TAM (Davis, 1985), and the theory of planned behavior (TPB) (Ajzen, 1991). It identifies four elements. These are the performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). This study expands the UTAUT model by incorporating additional factors like perceived flexibility, perceived enjoyment, perceived interactivity, and perceived quality. Figure 1 illustrates the proposed model.

2.1 Effort Expectancy

Effort expectancy (EE) refers to how easy it is perceived to use a system (Al-Emran et al., 2022c; Venkatesh et al., 2003). It reflects academics' belief that e-learning tools are straightforward and user-friendly (Gunasinghe et al., 2020). In the early stages of e-learning, the perceived effort required is crucial in influencing intentions towards its adoption (Salloum & Shaalan, 2019). It is hypothesized that individuals' acceptance of e-learning significantly hinges on the system's ease of use and accessibility, highlighting EE's impact on behavioral intention.

Empirical studies consistently demonstrate that EE positively influences the behavioral intention to use e-learning among academics in Indonesian higher education contexts (Jameel et al., 2022). Similarly, research by Abbad et al. (2021) and Mehta et al. (2019) affirms EE's significant impact on BI related to e-learning usage. However, contrasting results are found in studies reporting insignificant effects of EE on BI concerning e-learning adoption among academics (Jameel et al., 2022; Wu et al., 2022), which aligns with earlier research findings (Batucan et al., 2021; Salloum & Shaalan, 2019).

Therefore, the authors propose the following hypotheses:

H1: Effort Expectancy directly impacts perceived flexibility.
H2: Effort Expectancy directly impacts perceived enjoyment.
H3: Effort Expectancy directly impacts perceived interactivity.

H4: Effort Expectancy directly impacts perceived quality.

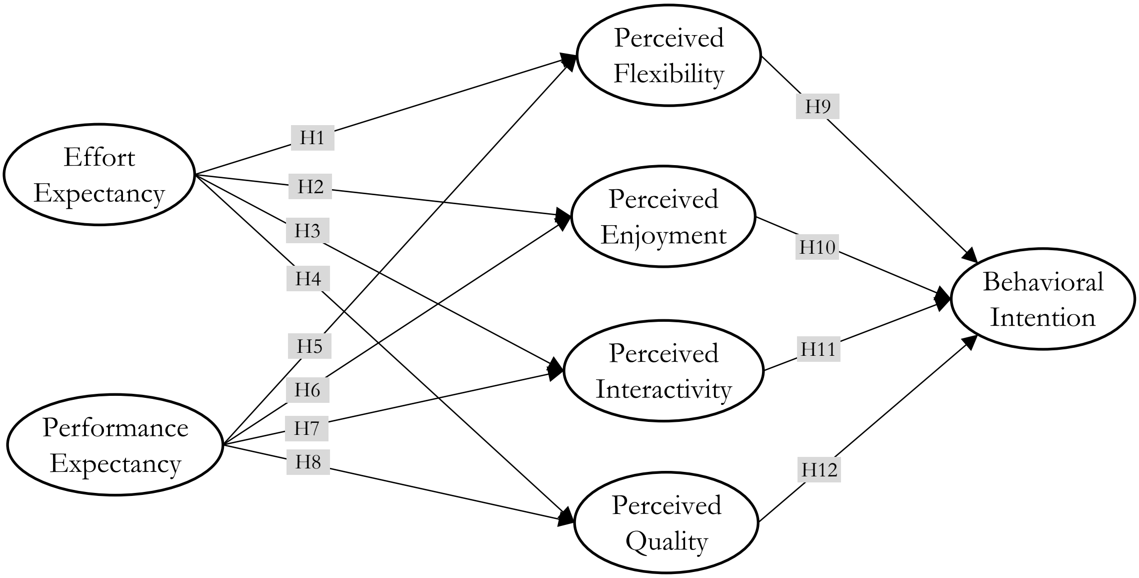

Figure 1: The proposed model

2.2 Performance Expectancy

Users will likely be convinced that applied technology boosts their efficiency when it leads to work gains (Venkatesh et al., 2012). Likewise, for e-learning to be perceived as beneficial in university settings, students must have strong confidence in its ability to yield significant outcomes for their academic endeavors. The extent to which individuals believe that using the system will enhance their productivity is often the primary predictor of their intention to adopt it (Mehta et al., 2019). In an educational context, performance expectancy (PE) emerges when students perceive that e-learning can assist them in completing tasks more efficiently and effectively (Gunasinghe et al., 2020). Increased efficiency, in terms of time and effort savings, encourages the uptake of e-learning (Gunasinghe et al., 2020). This study incorporates PE to investigate students' perceptions regarding the potential advantages of utilizing e-learning. Studies underscore the significance of PE in influencing the behavioral intention (BI) to adopt e-learning, confirming its positive impact on higher education (Gurban & Almogren, 2022;

Qashou, 2021; Raza et al., 2022). Consequently, the following hypotheses are proposed:

H5: Performance expectancy directly impacts perceived flexibility.
H6: Performance expectancy directly impacts perceived enjoyment.
H7: Performance expectancy directly impacts perceived interactivity.
H8: Performance expectancy directly impacts perceived quality.

2.3 Perceived Flexibility

System flexibility within the e-learning context refers to the freedom students feel e-learning provides regarding time and location (Hsia & Tseng, 2008). This flexibility allows undergraduate students to pursue a degree without being constrained by physical location or time schedules. Numerous studies highlight the critical role of flexibility in the success and acceptance of e-learning systems (Alkhuwaylidee, 2019; Batucan et al., 2022). For instance, Batucan et al. (2022) investigated students' acceptance of online learning systems in the Philippines, underscoring the significance of flexibility in adopting e-learning. Hence, we propose the hypothesis:

H9: Perceived flexibility directly impacts behavioral intention.

2.4 Perceived Enjoyment

Perceived enjoyment is a crucial motivator determining how enjoyable an IT or IS can be. Park et al. (2012) describe perceived enjoyment as "the extent that, in addition to any performance effect caused by system use, the activity of utilizing a particular system is evaluated as pleasurable by itself." This study examines the effects of perceived enjoyment on e-learning. Numerous studies have shown that enjoyment significantly impacts behavioral intention in various technology adoption contexts, such as mobile payments (Sudono et al., 2020) and logistic services via online platforms (Septiani et al., 2017). These studies found that enjoyment greatly influences users' intention towards online platforms. Similarly, system enjoyment in the online modality of learning affects performance expectancy and effort expectancy (Chao, 2019). Therefore, we propose the hypothesis:

H10: Perceived enjoyment directly impacts behavioral intention.

2.5. Perceived Interactivity

Interactivity in e-learning systems involves collaborative tools that facilitate student interactions and interactions between students and instructors (Alshehri et al., 2020). Research indicates that effective interaction within a learning system greatly enhances the perceived usability of a computerized learning system (Compeau & Higgins, 1995). The learning process benefits greatly from these interactions, whether between instructors and learners, among learners themselves or with the organization (Abbad et al., 2009). Furthermore, multiple studies have demonstrated a direct correlation between system interactivity and the behavioral intention to use an e-learning system (Uğur & Turan, 2018; Wrycza & Kuciapski, 2018). This indicates that when students perceive higher levels of system interactivity, they develop a stronger belief in the system's usefulness, significantly impacting their intention to use the system to achieve educational objectives (Alshehri et al., 2020). Based on these insights, we propose the hypothesis:

H11: Perceived interactivity directly impacts behavioral intention.

2.6. Perceived Quality

System quality includes reliability, ease of access, system responsiveness in terms of time, and the flexibility of the learning platform (DeLone & McLean, 2003). Prior research has confirmed the hypothetical paths of system quality in various applications of online platforms, such as internet services (Wang & Chen, 2011), online shopping (Chen, 2013), and augmented/virtual reality environments (Jung et al., 2015). Using DeLone and McLean's IS model, the paper of Jung et al. (2015) reported the impact of system quality on customer responses, satisfaction, and loyalty when interacting with augmented reality technologies. System quality enhances students' experiences in online learning, increasing their engagement. For example, Batucan et al. (2022) found that system quality influences students' behavioral intentions in online education. This study proposes the following hypothesis:

H12: Perceived quality directly impacts behavioral intention.

2.7. Behavioral Intention

Behavioral intention assesses the strength of an individual's intent to engage in a specific behavior and willingness to use a system (Fishbein & Ajzen, 1977). It indicates the extent to which students consciously plan to undertake a particular future behavior and is regarded as a key dependent variable in the UTAUT model (Davis, 1989; Warshaw & Davis, 1985).

3. Method

This section describes the participants' selection, the survey instrumentation, and the Covariance-based Structural Equation Modeling (CB-SEM) procedural application.

3.1. Participants

The study involved college students from the Visayas, Philippines. Nine hundred seventy-six (976) valid were analyzed. The data used in this study is part of a larger survey derived from the work of Batucan et al. (2022). We adhered to established study protocols for handling and utilizing archival data.

Table 1: Descriptive Statistics of Respondents' Demographics

Category	Variable	f	%
Sex			
	Male	284	29.10
	Female	692	70.90
Age			
	≤ 20 yrs. old	568	58.20
	21 yrs. old	289	29.61
	21 yrs. old and above	119	12.19
Level			
	1st year	292	29.92
	2nd year	255	26.13
	3rd year	405	41.50
	4th year	23	2.36
	5th year	1	0.10

As presented in Table 1, the results show that the sample consisted of a majority of female students (70.90%) and a smaller proportion of male students (29.10%). In terms of age, the largest group was 20 years old or younger (58.20%), followed by those who were 21 years old (29.61%) and those 21 years old and above (12.19%). Regarding the academic level, the distribution was more varied: 1st-year students made up 29.92% of the sample, 2nd-year students accounted for 26.13%, 3rd-year students constituted the largest group at 41.50% and 4th- and 5th-year students represented a small fraction at 2.36% and 0.10%, respectively.

3.2. Instruments

A questionnaire was designed and divided into two sections: (1) demographic information and (2) constructs related to the study. To measure perceived enjoyment, items from Simon et al. (1996), Venkatesh (2000), and Venkatesh et al. (2003) were used, including statements like "I find using the e-learning system to be enjoyable." Perceived interactivity was assessed with items from Barki et al. (2007), such as "I use the e-learning system to solve various problems." Perceived flexibility was evaluated using items from Nelson et al. (2005) and Saraf et al. (2007), including "The e-learning system can flexibly adjust to new demands or conditions." System quality was measured with items from Barki et al. (2001) and Kulkarni et al. (2006), such as "The e-learning system is user-friendly."

Effort expectancy, based on Venkatesh et al. (2003) and Brown et al. (2010), included statements like "Learning to operate the e-learning system is easy for me." Performance expectancy was assessed with items from Venkatesh et al. (2003), including "The e-learning system enables me to accomplish tasks more quickly." Behavioral intention was measured using items from Hong et al. (2002), such as "I intend to continue using the e-learning system in the future." All items were rated on a 5-point Likert scale, ranging from "strongly agree" (1) to "strongly disagree" (5).

3.3. Data Analysis

This study employed the statistical package for social sciences (SPSS) software to analyze item reliability and validity, and the AMOS 27 was used to assess the measurement model and perform path analysis. SPSS was used to calculate Cronbach's alpha for each construct to measure internal consistency. The coefficients of the indicators were analyzed to determine convergent validity. Confirmatory Factor Analysis (CFA) was conducted to evaluate the measurement model, following Fornell and Larcker's (1981) criteria, including standardized loadings (SL), composite reliabilities (CR), and average variance extracted (AVE), to confirm the constructs' validity and reliability.

Hypotheses were tested using path analysis within the structural equation modeling (SEM) framework. The structural model was assessed to determine how well the hypothesized relationships fit the data. Due to the sensitivity of chi-square tests to large sample sizes, the minimum discrepancy chi-square value (CMIN/DF) was used to evaluate model adequacy (Hair, 2009). Additional fit indices were included to facilitate robust model specification. These are the Tucker-Lewis index (TLI), standardized root mean square residual (SRMR), comparative fit index (CFI), and root mean square error of approximation (RMSEA). This approach captures model specificity, even though the chi-square test is sensitive to sample size.

4. Results and Discussions

4.1. Measurement Model Assessment

The measurement model assessment included the reliability of the constructs and indicators with an analysis of convergent validity tests (see Table 2). A composite reliability (CR) of 0.60 or higher indicates acceptable construct reliability (Bagozzi & Yi, 1988). The results presented in Table 2 indicate that the computed CR for all latent variables ranged from 0.686 to 0.878, exceeding the 0.60 threshold. This provides evidence that all latent variables are reliable. Cronbach's alpha was also measured to evaluate the items' reliability index. The current paper has Cronbach's alpha values ranging from 0.725 to 0.876.

Table 2: CFA results of the final measurement model

Items	Standardized loadings		CR	AVE	α
Performance expectancy (PE)	PE3	0.60	0.739	0.489	0.728
	PE2	0.772			
	PE1	0.714			
Effort expectancy (EE)	EE5	0.504	0.686	0.427	0.670
	EE2	0.746			
	EE1	0.686			
Behavioral Intention (BI)	BI5	0.788	0.861	0.555	0.857
	BI4	0.752			
	BI3	0.752			
	BI2	0.760			
	BI1	0.667			
Perceived Enjoyment (PEn)	PEn5	0.725	0.878	0.590	0.876
	PEn4	0.794			
	PEn3	0.81			
	PEn2	0.764			
	PEn1	0.744			
Perceived Flexibility (PF)	PF5	0.775	0.867	0.566	0.867
	PF4	0.752			
	PF3	0.776			

	PF2	0.732			
	PF1	0.725			
Perceived Interactivity (PI)	PI5	0.730	0.838	0.510	0.838
	PI4	0.736			
	PI3	0.696			
	PI2	0.738			
	PI1	0.667			
Perceived Quality (PQ)	PQ5	0.697	0.802	0.504	0.802
	PQ4	0.741			
	PQ2	0.654			
	PQ1	0.745			

Convergent validity was established in two ways: first, by ensuring that factor loadings were significant and exceeded 0.5 (Bagozzi & Yi, 1988), and second, by verifying that the average variance extracted (AVE) for each factor was greater than 0.5 (Fornell & Larcker, 1981). While the AVEs for Perceived Enjoyment (PE) and Effort Expectancy (EE) were below the 0.5 threshold, Fornell and Larcker (1981) noted that an AVE below 0.5 is acceptable if the Composite Reliability (CR) is above 0.6. The scale's reliability was confirmed since the CR values for each construct were above 0.6. The overall measurement model exhibited satisfactory fit indices, with RMSEA at 0.057, SRMR at 0.044, TLI at 0.913, and CFI at 0.923.

4.2. Relationships Between the Latent Variables

Pearson correlation coefficients were used to perform correlational analyses that supported the path analysis in SEM. Following the correlation strength guidelines proposed by Schober et al. (2018), correlation strengths were classified as: negligible (0.00–0.09), weak (0.10–0.39), moderate (0.40–0.69), strong (0.70–0.89), and very strong (0.90–1.00).

Table 3: Correlation results among the constructs in CFA.

Study variable	PE	EE	BI	PEn	PF	PI	PQ
PE	1						
EE	0.654**	1					
BI	0.492**	0.529**	1				
PEn	0.607**	0.619**	0.616**	1			
PF	0.526**	0.548**	0.580**	0.721**	1		

PI	0.433**	0.443**	0.577**	.483**	0.564**	1	
PQ	0.543**	0.599**	0.610**	0.721**	0.741**	0.595**	1

Table 3 reveals that the strongest correlation observed was between PF and PQ, with a coefficient of 0.741, indicating a strong relationship. On the other hand, the lowest correlation between PE and PI was found at 0.433, which is classified as a moderate correlation. Other notable coefficients include a strong correlation between PEn, PF, and PQ, each at 0.721. BI also showed moderate correlations with PE and EE, at 0.492 and 0.529, respectively. All other coefficients, ranging from 0.483 to 0.654, indicate moderate relationships across the various constructs.

4.3. Structural Model and Hypothesis Testing

Path analysis was employed to test the research hypotheses with the results figuratively depicted in Figure 1 outlined in Table 4. A total of 12 hypotheses were examined. All hypotheses were supported except for H9 and H10, which were rejected. Figure 2 depicts the final model, while a detailed presentation of the coefficients and significance is presented in Table 4.

Table 4: Path Analysis and Significance

Hypothesis	Path	β	SE	CR	Label
H1	EE → PF	0.884***	0.137	11.009	Yes
H2	EE →PEn	0.791***	0.139	10.975	Yes
H3	EE→ PI	0.684***	0.103	9.872	Yes
H4	EE→PQ	0.957***	0.125	10.991	Yes
H5	PE → PF	0.265***	0.06	6.28	Yes
H6	PE →PEn	0.431***	0.075	9.201	Yes
H7	PE→ PI	0.221***	0.053	5.165	Yes
H8	PE→PQ	-0.174***	0.052	6.573	Yes
H9	PF→ BI	-0.174	0.175	-1.3	No
H10	PEn→ BI	0.311**	0.116	3.101	Yes
H11	PI→ BI	0.34***	0.091	5.565	Yes
H12	PQ→ BI	0.367	0.334	1.705	No

The results indicate a significant impact of EE on PE, PEn, PI, and PQ for e-learning adoption ($\beta = 0.884, 0.791, 0.684, 0.957, p < 0.001$), affirming hypotheses H1, H2, H3, and H4. This aligns with the notion that academics perceive e-learning tools as user-friendly (Gunasinghe et al., 2020), emphasizing the critical role of effort expectancy in early e-learning adoption phases (Salloum & Shaalan, 2019). Additionally, the significance of an e-learning system's ease of use and user-friendliness in creating a positive learning experience is another takeaway from this study. PE substantially impacts the perceived system flexibility, enjoyment, interactivity, and quality of e-learning platforms (β = 0.265, 0.431, 0.221, -0.174, $p < 0.001$), thereby validating hypotheses H5, H6, H7, and H8.

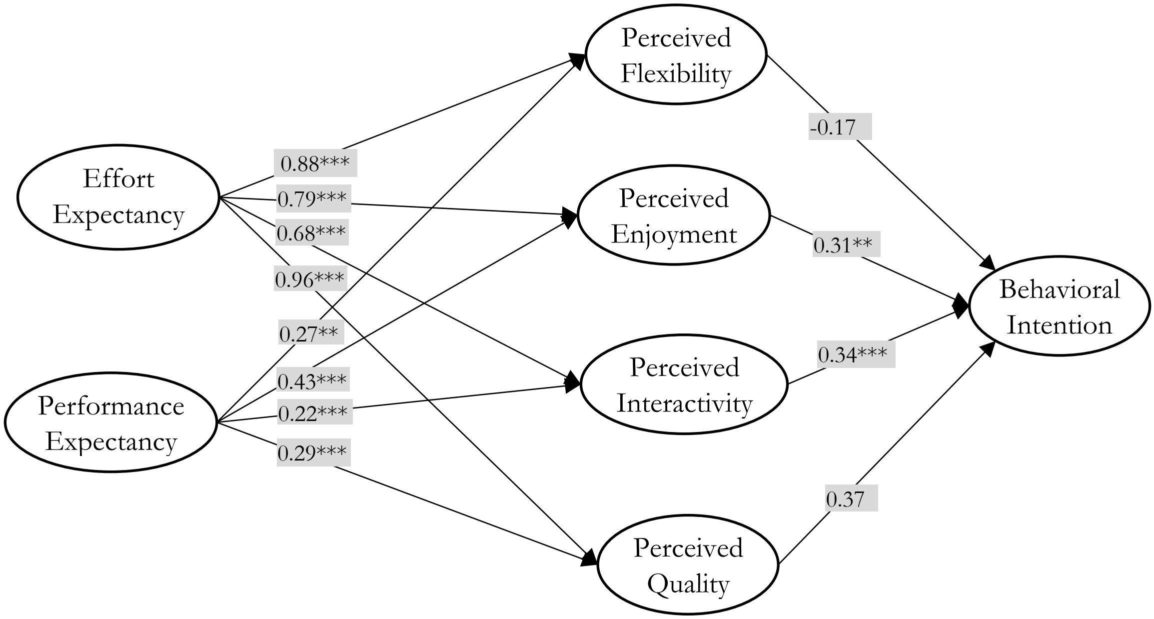

Figure 2. The final study

Students' performance expectations in e-learning play a crucial role in enhancing efficiency and effectiveness, promoting the adoption of e-learning systems. When students anticipate that e-learning platforms will improve their academic performance and facilitate better learning outcomes, they are more likely to embrace these systems (Gunasinghe et al., 2020). High-performance expectations lead students to believe that the e-learning tools will provide them with the necessary resources and support to achieve their educational goals more efficiently. Consequently, students' performance expectations are integral in driving the successful integration and widespread use of e-learning platforms (Wu et al., 2022). Students' performance expectations in e-learning enhance efficiency and effectiveness, promoting system adoption (Gunasinghe et al., 2020). This positive outlook motivates students to use the technology and helps overcome initial resistance or skepticism toward adopting new learning methods.

The influence of perceived flexibility (PF) and perceived quality (PQ) on behavioral intention (BI) were not significant; hence, H9 and H12 were rejected. While flexibility is deemed crucial in e-learning success (Alkhuwaylidee, 2019; Batucan et al., 2022), its direct impact on students' usage intentions appears limited. This suggests that the flexibility of the e-learning system does not directly impact students' intentions to use it. Contrasting to recent literature (e.g., Turan et al., 2022), this means that even though PF is essential for the success of e-learning, simply having a flexible system doesn't directly influence whether students will choose to use it. On the insignificant path from PQ to BI, this might seem counterintuitive and in contrast to emerging studies at first (e.g., Al-Fraihat et al., 2020; Alkhawaja et al., 2022), as quality is often seen as a crucial factor in user satisfaction. However, this finding suggests that students' decision to engage with e-learning platforms is driven more by their personal experience and enjoyment than their assessment of the system's quality. Moreover, in environments with limited internet infrastructure or technology access, students might focus more on the system's practical aspects rather than its overall quality. Both constructs, PF and PQ, require further investigation, particularly since internet infrastructure and human resources have been identified as barriers to implementing digital systems in the Philippines, the case country of the current study (Costan et al., 2021).

The levels of enjoyment in e-learning systems significantly affect students' intentions to continue using them. When students find the e-learning system enjoyable, they are more likely to be motivated to use it regularly. Enjoyment leads to greater engagement and a more substantial commitment to using the system (Goh & Yang, 2021). Thus, the enjoyment and pleasure students derive from the system strongly impact their intention to use it. Chao (2019) emphasized the importance of system enjoyment in online learning, noting its influence on performance and effort expectancies. This implies that student engagement with the e-learning system positively influences their intention to continue using it. Creating a fun and engaging learning environment is critical to encouraging students to adopt and persist with e-learning platforms.

Lastly, a higher perception of system interactivity enhances students' intention to use e-learning platforms, confirming H11. When students perceive an e-learning system as highly interactive, they are more likely to view it as a valuable educational tool (Alshehri et al., 2020). Interactive features like discussion forums, live chats, and collaborative projects facilitate active participation and engagement. These features create a dynamic learning environment where students can communicate with peers and instructors, ask real-time questions, and collaborate on assignments. The interactive experience makes learning more engaging and reinforces the perception that the e-learning system is an effective and beneficial educational tool (Wu et al., 2022). Interactivity in e-learning platforms can mimic the traditional classroom experience, making students feel more connected and less isolated (Ren, 2023). This sense of connection can lead to higher satisfaction with the learning process, motivating students to use the platform more frequently and consistently. The ability to interact and collaborate also helps students develop critical thinking and problem-solving skills, as they are often required to discuss concepts, share ideas, and work together to find solutions.

5. Conclusion

This study investigates the factors influencing the acceptance and use of e-learning in higher education using structural equation modeling grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT). Analyzing empirical data from 976 college students in the Visayas region of the Philippines, the results highlight three key findings:

1. Effort and performance expectancy significantly impact the perceived flexibility, enjoyment, interactivity, and quality of e-learning systems.
2. Perceived enjoyment and perceived interactivity significantly affect students' behavioral intention to use e-learning systems.
3. The study also notes that the nonsignificant paths from system quality and flexibility to behavioral intention warrant further investigation especially in developing economies.

The findings support the gap we wish to explain on the possible reversibility of associations from the paper of Batucan et al. (2022). These results highlight several key aspects: a user-friendly e-learning platform enables students to easily customize their learning experiences, access various features, and adapt the platform to their individual needs and schedules. When a system is easy to use, it allows students to manage their time more effectively, which enhances their perception of flexibility in how and when they engage with the material. Improved academic performance from effective system use can lead to a more positive attitude towards the platform, thereby increasing students' enjoyment. Furthermore, if users believe that the system enhances their productivity and meets their needs, they are more likely to perceive it as having high quality.

Designing e-learning platforms that are user-friendly, engaging, and flexible is crucial for increasing students' intentions to use them. Developers should create intuitive interfaces, incorporate interactive features, and ensure the system effectively supports students' learning needs. Regular user feedback can also help refine the platform to better align with students' expectations and enhance their overall experience. Educational leaders should prioritize these elements to foster a more effective learning environment. Additionally, the nonsignificant paths from system quality and flexibility to intention might be influenced by the developing economy context of the case study, where internet infrastructure poses a challenge. Therefore, further research is recommended to explore the impact of these factors in different contexts and investigate how various interactive features, system flexibility, and feedback mechanisms affect e-learning adoption and effectiveness.

References

Abbad, M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. *Education and information technologies*, *26*(6), 7205-7224.

Abbad, M. M., Morris, D., & De Nahlik, C. (2009). Looking under the bonnet: Factors affecting student adoption of e-learning systems in Jordan. *International Review of Research in Open and Distributed Learning*, *10*(2).

Abdekhoda, M., Dehnad, A., & Zarei, J. (2022). Factors influencing adoption of e-learning in healthcare: integration of UTAUT and TTF model. *BMC Medical Informatics and Decision Making*, *22*(1), 327.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

Al Mulhem, A. (2020). Exploring the key factors in the use of an e-learning system among students at King Faisal University, Saudi Arabia.

Al-Adwan, A. S., Al-Madadha, A., & Zvirzdinaite, Z. (2018). Modeling students' readiness to adopt mobile learning in higher education: An empirical study. *International Review of Research in Open and Distributed Learning*, *19*(1).

Al-Emran, M., Al-Maroof, R., Al-Sharafi, M. A., & Arpaci, I. (2022c). What impacts learning with wearables? An integrated theoretical model. *Interactive learning environments*, *30*(10), 1897-1917.

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

Al-Emran, M., Granić, A., Al-Sharafi, M. A., Ameen, N., & Sarrab, M. (2021). Examining the roles of students' beliefs and security concerns for using smartwatches in higher education. *Journal of Enterprise Information Management*, *34*(4), 1229-1251.

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2020b). Towards a conceptual model for examining the impact of knowledge management factors on mobile learning acceptance. *Technology in Society*, *61*, 101247.

Al-Fraihat, D., Joy, M., & Sinclair, J. (2020). Evaluating E-learning systems success: An empirical study. *Computers in human behavior*, *102*, 67-86.

Alkhawaja, M. I., Halim, M. S. A., Abumandil, M. S., & Al-Adwan, A. S. (2022). System Quality and Student's Acceptance of the E-Learning System: The Serial Mediation of Perceived

Alkhuwaylidee, A. R. (2019). Extended unified theory acceptance and use technology (utaut) for e-learning. *Journal of Computational and Theoretical Nanoscience*, *16*(3), 845-852.

Alshehri, A., J Rutter, M., & Smith, S. (2020). The effects of UTAUT and usability qualities on students' use of learning management systems in Saudi tertiary education. *Journal of Information Technology Education: Research*, *19*.

Arinto, P. B. (2016). Issues and challenges in open and distance e-learning: Perspectives from the Philippines. *International Review of Research in Open and Distributed Learning*, *17*(2), 162-180.

Ashraf, S., Khan, T. A., & ur Rehman, I. (2016). E-learning for secondary and higher education sectors: A survey. *International Journal of Advanced Computer Science and Applications*, *7*(9).

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the academy of marketing science*, *16*, 74-94.

Barki, H., Titah, R., & Boffo, C. (2007). Information system use–related activity: an expanded behavioral conceptualization of individual-level information system use. *Information Systems Research*, *18*(2), 173-192.

Batucan, G. B., Gonzales, G. G., Balbuena, M. G., Pasaol, K. R. B., Seno, D. N., & Gonzales, R. R. (2022). An extended UTAUT model to explain factors affecting online learning system amidst COVID-19 pandemic: The case of a developing economy. *Frontiers in Artificial Intelligence*, *5*, 768831.

Bingtan, W., Dalaguit, J., Perez, J. P., Seño, N., & Batucan, G. (2022). Evaluating the Acceptance of Flexible Online Learning via Extended TAM: The Case of a Developing Economy. *Magister-Journal of Educational Research*, *1*(1), 17-41.

Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010). Predicting collaboration technology use: Integrating technology adoption and collaboration research. *Journal of management information systems*, *27*(2), 9-54.

Buot, J. (2023). Exploring the Influence of Self-Regulated Learning Strategies on Learning Motivation in a Blended Learning Environment. *Magister-Journal of Educational Research*, *2*(2), 1-17.

Casillano, N. F. B. (2019). Challenges of implementing an e-learning platform in an internet struggling province in the Philippines. *Indian Journal of Science and Technology*, *12*(10), 1-4.

Chao, C. M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in psychology*, *10*, 446627.

Chen, L. Y. (2013). The quality of mobile shopping system and its impact on purchase intention and performance. *International Journal of Managing Information Technology (IJMIT) Vol*, *5*.

Compeau, D. R., & Higgins, C. A. (1995). Application of social cognitive theory to training for computer skills. *Information systems research*, *6*(2), 118-143.

Costan, E., Gonzales, G., Gonzales, R., Enriquez, L., Costan, F., Suladay, D., ... & Ocampo, L. (2021). Education 4.0 in developing economies: a systematic literature review of implementation barriers and future research agenda. *Sustainability*, *13*(22), 12763.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation, Massachusetts Institute of Technology).

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: a ten-year update. *Journal of management information systems*, *19*(4), 9-30.

Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

Garcia, M. B. (2017). E-learning technology adoption in the Philippines: An investigation of factors affecting Filipino college students' acceptance of learning management systems. *The International Journal of E-Learning and Educational Technologies in the Digital Media (IJEETDM)*.

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.

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.

Gurban, M. A., & Almogren, A. S. (2022). Students' actual use of E-learning in higher education during the COVID-19 pandemic. *SAGE Open*, *12*(2), 21582440221091250.

Hair, J. F. (2009). Multivariate data analysis.

Heagney, M., & Benson, R. (2017). How mature-age students succeed in higher education: Implications for institutional support. *Journal of Higher Education Policy and Management*, *39*(3), 216-234.

Hong, W., Thong, J. Y., Wong, W. M., & Tam, K. Y. (2002). Determinants of user acceptance of digital libraries: an empirical examination of individual differences and system characteristics. *Journal of management information systems*, *18*(3), 97-124.

Hsia, J. W., & Tseng, A. H. (2008, September). An enhanced technology acceptance model for e-learning systems in high-tech companies in Taiwan: analyzed by structural equation modeling. In *2008 International Conference on Cyberworlds* (pp. 39-44). IEEE.

Hsiao-Hui Wang, E., & Chen, C. Y. (2011). System quality, user satisfaction, and perceived net benefits of mobile broadband services.

Jameel, A. S., Karem, M. A., & Ahmad, A. R. (2022). Behavioral intention to use e-learning among academic staff during COVID-19 pandemic based on UTAUT model. In *Proceedings of International Conference on Emerging Technologies and Intelligent Systems: ICETIS 2021 (Volume 1)* (pp. 187-196). Springer International Publishing.

Jung, T., Chung, N., & Leue, M. C. (2015). The determinants of recommendations to use augmented reality technologies: The case of a Korean theme park. *Tourism management*, *49*, 75-86.

Kim, B., & Park, M. J. (2018). Effect of personal factors to use ICTs on e-learning adoption: comparison between learner and instructor in developing countries. *Information Technology for Development*, *24*(4), 706-732.

Kulkarni, U. R., Ravindran, S., & Freeze, R. (2006). A knowledge management success model: Theoretical development and empirical validation. *Journal of management information systems*, *23*(3), 309-347.

Mangubat, J., & Batucan, G. (2023). Teacher's Intentions to Use GeoGebra in Teaching Mathematics: An Empirical Study to Validate Technology Acceptance Model in the Philippines. *Magister-Journal of Educational Research*, *2*(2), 42-66.

Mehta, A., Morris, N. P., Swinnerton, B., & Homer, M. (2019). The influence of values on E-learning adoption. *Computers & Education*, *141*, 103617.

Mehta, A., Morris, N. P., Swinnerton, B., & Homer, M. (2019). The influence of values on E-learning adoption. *Computers & Education*, *141*, 103617.

Mikalef, P., Pappas, I. O., & Giannakos, M. (2016). An integrative adoption model of video-based learning. *The International Journal of Information and Learning Technology*, *33*(4), 219-235.

Nelson, R. R., Todd, P. A., & Wixom, B. H. (2005). Antecedents of information and system quality: an empirical examination within the context of data warehousing. *Journal of management information systems*, *21*(4), 199-235.

Park, Y., Son, H., & Kim, C. (2012). Investigating the determinants of construction professionals' acceptance of web-based training: An extension of the technology acceptance model. *Automation in construction*, *22*, 377-386.

Qashou, A. (2021). Influencing factors in M-learning adoption in higher education. *Education and information technologies*, *26*(2), 1755-1785.

Raza, S. A., Qazi, Z., Qazi, W., & Ahmed, M. (2022). E-learning in higher education during COVID-19: evidence from blackboard learning system. *Journal of Applied Research in Higher Education*, *14*(4), 1603-1622.

Ren, X. (2023). Investigating the experiences of online instructors while engaging and empowering non-traditional learners in eCampus. *Education and Information Technologies*, *28*(1), 237-253.

Salloum, S. A., & Shaalan, K. (2019). Factors affecting students' acceptance of e-learning system in higher education using UTAUT and structural equation modeling approaches. In *Proceedings of the International Conference* *on Advanced Intelligent Systems and Informatics 2018 4* (pp. 469-480). Springer International Publishing.

Sambrook, S. (2003). E-learning and small organisations. In *Human Resource Development in Small Organisations* (pp. 199-228). Routledge. Jenkins, M., & Hanson, J. (2003). *E-learning series No. 1: A guide for senior managers* (Vol. 1). Learning and Teaching Support Network Generic Centre.

Sanou, B. (2017). ICT Facts and Figures. *International Telecommunication*. https://www.itu.int/en/ITU-D/Statistics/Documents/facts/ICTFactsFigures2017.pdf

Saraf, N., Langdon, C. S., & Gosain, S. (2007). IS application capabilities and relational value in interfirm partnerships. *Information systems research*, *18*(3), 320-339.

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation coefficients: appropriate use and interpretation. *Anesthesia & analgesia*, *126*(5), 1763-1768.

Septiani, R., Handayani, P. W., & Azzahro, F. (2017). Factors that affecting behavioral intention in online transportation service: Case study of GO-JEK. *Procedia Computer Science*, *124*, 504-512.

Simon, S. J., Grover, V., Teng, J. T., & Whitcomb, K. (1996). The relationship of information system training methods and cognitive ability to end-user satisfaction, comprehension, and skill transfer: A longitudinal field study. *Information systems research*, *7*(4), 466-490.

Sudono, F. S., Adiwijaya, M., & Siagian, H. (2020). The influence of perceived security and perceived enjoyment on intention to use with attitude towards use as intervening variable on mobile payment customer in Surabaya. *Petra International Journal of Business Studies*, *3*(1), 37-46.

Tarhini, A., Masa'deh, R. E., Al-Busaidi, K. A., Mohammed, A. B., & Maqableh, M. (2017). Factors influencing students' adoption of e-learning: a structural equation modeling approach. *Journal of International Education in Business*, *10*(2), 164-182.

Turan, Z., Kucuk, S., & Cilligol Karabey, S. (2022). The university students' self-regulated effort, flexibility and satisfaction in distance education. *International Journal of Educational Technology in Higher Education*, *19*(1), 35.

Uğur, N. G., & Turan, A. H. (2018). Retracted article: E-learning adoption of academicians: a proposal for an extended model. *Behaviour & Information Technology*, *37*(4), 393-405.

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information systems research*, *11*(4), 342-365.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178.

Warshaw, P. R., & Davis, F. D. (1985). Disentangling behavioral intention and behavioral expectation. *Journal of experimental social psychology*, *21*(3), 213-228.

Wrycza, S., & Kuciapski, M. (2018). Determinants of academic e-learning systems acceptance. In *Information Systems: Research, Development, Applications, Education: 11th SIGSAND/PLAIS EuroSymposium 2018, Gdansk, Poland, September 20, 2018, Proceedings 11* (pp. 68-85). Springer International Publishing.

Wu, L., Hsieh, P. J., & Wu, S. M. (2022). Developing effective e-learning environments through e-learning use mediating technology affordance and constructivist learning aspects for performance impacts: Moderator of learner involvement. *The Internet and Higher Education*, *55*, 100871.