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Determinants of online learning application effectiveness: Evidence from Vietnam

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A B S T R A C T

This study investigates the determinants of online learning application effectiveness in Vietnam using a structural equation modeling (SEM) approach. Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and extended with psychological constructs, the proposed model integrates performance expectancy, effort expectancy, social influence, facilitating conditions, learning habits, intrinsic motivation, technostress, and feeling of isolation. Data were collected from 501 online learners and analyzed using SPSS and AMOS. The results reveal that performance expectancy, effort expectancy, learning habits, intrinsic motivation, and technostress significantly influence behavioral intention, while social influence and facilitating conditions are not significant. Behavioral intention strongly predicts actual usage behavior. Notably, technostress emerges as the most influential factor, suggesting that technological pressure may act as both a barrier and a driver of engagement depending on user adaptation. The study contributes to the literature by integrating enabling and inhibiting factors into a unified framework and offers practical implications for improving online learning systems in developing countries.

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1. Introduction

In the context of global digital transformation, online learning (e-learning) has become a crucial training method in modern education. The rapid development of information technology, especially learning management systems (LMS), online conferencing platforms, and digital interaction tools, has facilitated learners' flexible access to knowledge in terms of space and time. Globally, the application of these tools has become widespread in most higher education institutions, particularly after the impact of the COVID-19 pandemic, when online learning became an essential alternative to traditional learning. In Vietnam, the transition to online teaching and learning has also been strong, contributing to maintaining training activities and gradually promoting innovation in teaching methods in the context of educational digitalization ((Alvedi Sabani et al., 2025; Pham, 2022). Along with this development, the effectiveness of online learning has become a central research topic in the field of education. Numerous studies have identified that online learning effectiveness is influenced by various groups of factors, including technological factors (system quality, accessibility), personal factors (learning motivation, technological competence, self-efficacy), pedagogical factors (course design, teaching methods), and organizational factors (support from the school and instructors) (Roy & Al-Absy, 2022). Furthermore, the level of interaction between learners and instructors, the ease of use of the system, and learner satisfaction have been shown to be important factors determining learning outcomes in the online environment (Vu et al., 2024; Nguyen, 2022). These studies show that the effectiveness of online learning is a multidimensional construct, simultaneously influenced by many factors related to technology, people, and the learning environment. However, applying international research findings to the Vietnamese context remains limited due to differences in infrastructure, digital skills, and learner characteristics. Vietnam is a developing country with disparities in access to technology between regions, as well as differences in students' online learning experiences. Some domestic studies have initially identified factors affecting online learning effectiveness such as technology quality, teaching methods, and level of

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interaction (Pham, 2022; Nguyen et al., 2023); however, these results are fragmented and have not yet formed a systematic research model.

This underscores the necessity for a comprehensive and context-specific investigation into the determinants of online learning effectiveness in Vietnam. Addressing this gap, this study aims to advance the theoretical and empirical understanding of online learning by developing and validating a research model tailored to a developing country context. In addition to its theoretical contributions, the study offers practical implications for educational institutions and policymakers in designing, implementing, and optimizing online learning systems that are aligned with the technological, institutional, and behavioral realities of Vietnam.

2. Research Model

2.1 Performance Expectation

Performance expectation refers to the extent to which users consider that utilizing a specific technology enhances their ability to accomplish tasks efficiently (Venkatesh et al., 2003). Within the context of online learning, this construct is conceptually aligned with perceived usefulness in the Technology Acceptance Model (TAM) and motivational factors emphasized in prior behavioral models. It reflects learners' beliefs that adopting digital learning platforms can improve academic outcomes, efficiency, and overall learning effectiveness. Previous studies have consistently identified performance expectation as a critical determinant of technology adoption in educational settings. For instance, it has been shown to significantly influence students' willingness to engage with e-learning systems, particularly in environments characterized by rapid technological change (Sugandini & Istanto, 2022). Similarly, Samsudeen and Mohamed (2019) found that students who perceive clear academic benefits from online learning are more likely to adopt and continuously use such platforms. Furthermore, the application of the UTAUT framework in mobile learning contexts has demonstrated that performance-related beliefs play a central role in shaping students' behavioral intentions (Thomas et al., 2013; Yadav & Pathak, 2016). Taken together, these findings suggest that when learners perceive online learning applications as useful and capable of enhancing their academic performance, they are more likely to develop a stronger intention to use these technologies. Therefore, the following hypothesis is proposed:

H_1: *Performance expectation (PE) positively influences the intention to use online learning applications.*

2.2 Effort Expectancy

Effort expectancy refers to the degree of ease associated with the use of a technological system (Venkatesh et al., 2003, 2012). In the context of online learning, it reflects learners' perceptions of how simple, clear, and effortless it is to interact with digital learning platforms. This construct is conceptually related to perceived ease of use in the Technology Acceptance Model (TAM) and plays a crucial role in shaping users' acceptance of new technologies. Given that online learning systems are continuously evolving and may involve complex interfaces or functionalities, users' perceptions of effort required to use such systems become particularly important. When learners perceive online learning applications as easy to use, they are more likely to adopt and continue using them. Prior empirical studies have consistently demonstrated that effort expectancy significantly influences behavioral intention in technology adoption contexts. For example, Sharma et al. (2016) and Zuiderwijk et al. (2015) reported that perceived ease of use positively affects users' intention to adopt digital systems. Similarly, in e-learning environments, effort expectancy has been identified as a key determinant of students' intention to use online learning platforms (Mtebe & Raisamo, 2014; Tarhini et al., 2017). Based on these arguments, when learners perceive that online learning applications require minimal effort to use, their intention to adopt such systems is likely to increase. Therefore, the following hypothesis is proposed:

H_2: *Effort expectancy (EE) positively influences the intention to use online learning applications.*

2.3 Social Influence

Social influence describes the impact of perceived expectations from relevant others on an individual's decision to use a specific technological system (Venkatesh et al., 2003). This construct encompasses subjective norms, social pressure, and the influence of peers, instructors, and reference groups on an individual's decision-making process. In the context of online learning, social influence reflects how recommendations, expectations, and support from others shape learners' willingness to adopt digital learning platforms. Previous research has highlighted the significant role of social factors in technology acceptance. Individuals are more likely to adopt a system when they receive encouragement or endorsement from people they trust or consider important (Bagozzi & Lee, 2002; Zhou, 2011). The UTAUT model further emphasizes that social influence captures the combined effects of subjective norms, social image, and interpersonal expectations (Venkatesh et al., 2003). Empirical studies in e-learning contexts have confirmed that social influence positively affects users' behavioral intention to adopt online learning systems (Ali et al., 2018; Tarhini et al., 2017). Moreover, the impact of social influence tends to be stronger in environments where technology use is encouraged or required, such as formal educational settings (Venkatesh & Davis, 2000). Accordingly, when learners perceive that significant others support or expect them to use online

learning applications, their intention to adopt such systems is likely to increase. Therefore, the following hypothesis is proposed:

H_3: *Social influence (SI) positively influences the intention to use online learning applications.*

2.4 Facilitating Conditions

Facilitating conditions refer to individuals' perceptions of the availability of resources and support necessary to use a technological system effectively (Venkatesh et al., 2003). In the context of online learning, this construct encompasses the extent to which learners believe that adequate technical infrastructure, institutional support, and access to learning resources are available to facilitate their use of digital learning platforms. When users perceive that sufficient support mechanisms are in place, such as reliable internet access, technical assistance, and guidance, they are more likely to adopt and engage with online learning systems. Prior studies have highlighted the importance of facilitating conditions in shaping technology adoption behavior. For instance, Teo (2010) demonstrated that access to supporting infrastructure significantly influences users' willingness to use educational technologies. Similarly, empirical evidence from e-learning contexts suggests that facilitating conditions positively affect students' behavioral intention to use online learning systems (Sharma et al., 2016; Tarhini et al., 2017; Raza et al., 2021). These findings indicate that when learners perceive the presence of adequate resources and institutional support, they are more confident in using online learning applications, which in turn strengthens their intention to adopt such systems. Therefore, the following hypothesis is proposed:

H_4: *Facilitating conditions (FC) positively influence the intention to use online learning applications.*

2.5 Learning Habits

Habit refers to the extent to which individuals perform behaviors automatically as a result of prior learning and repeated experience (Limayem et al., 2007). Within the UTAUT2 framework, habit reflects the degree to which technology use becomes routine and is carried out with minimal conscious effort, thereby influencing both behavioral intention and actual usage (Venkatesh et al., 2012). Extant literature has identified habit as a significant predictor of technology adoption and continued usage. Studies by Kim et al. (2005) and Limayem et al. (2007) demonstrate that habitual behavior plays a crucial role in shaping individuals' interaction with information systems. In the context of online learning, students who have prior experience with digital learning platforms are more likely to develop habitual usage patterns, which can reinforce their intention to continue using such systems. Furthermore, the inclusion of habit in extended technology acceptance models has been shown to improve the explanatory power of user behavior in digital environments (Pahnila et al., 2011). Accordingly, when students develop habitual engagement with online learning platforms, their intention to use these systems is expected to increase. Therefore, the following hypothesis is proposed:

H_5: *Learning habits (LH) positively influence the intention to use online learning applications.*

2.6 Intrinsic Motivation

Intrinsic motivation refers to engaging in an activity for its inherent satisfaction rather than for external rewards or outcomes (Berlyne, 1966; de Charms, 2013). In educational contexts, intrinsic motivation plays a vital role in fostering deep learning, creativity, and sustained engagement. It represents learners' internal drive to explore, understand, and master new knowledge without external pressure. Extant research has highlighted the importance of intrinsic motivation in shaping learning behaviors and technology adoption. Ryan et al. (1994) emphasized that intrinsic motivation serves as a natural source of learning and achievement, which can be enhanced or hindered by instructional practices. Studies have also shown that autonomy-supportive teaching environments significantly increase students' intrinsic motivation, curiosity, and willingness to engage in challenging learning tasks (Deci et al., 1981; Ryan & Grolnick, 1986). In the context of online learning, intrinsically motivated students are more likely to actively participate, explore digital resources, and maintain long-term engagement with learning platforms. Given these arguments, intrinsic motivation is expected to positively influence learners' intention to adopt online learning applications. Therefore, the following hypothesis is proposed:

H_6: *Learner intrinsic motivation (IM) positively influences the intention to use online learning applications.*

2.7 Technostress

Technostress refers to the psychological strain and negative emotional responses associated with the use of information and communication technologies (Tarafdar et al., 2015). In online learning environments, technostress may arise from factors such as information overload, system complexity, and insufficient technical skills, which can adversely affect learners' cognitive and emotional states. Prior research has demonstrated that technostress can significantly impair users' ability to process information, concentrate, and retain knowledge, thereby negatively influencing learning outcomes. Conrad et al. (2022) found that information overload and perceived technological challenges contribute to increased difficulty and reduced satisfaction in online learning contexts. Similarly, Zia et al. (2023) reported that students often experience dissatisfaction with virtual learning environments, particularly in courses requiring practical or hands-on skills. Moreover, technostress has

been associated with heightened levels of anxiety, depression, and reduced academic performance among students (Torales et al., 2022). As a result, excessive technological pressure can diminish learners' engagement, reduce their perceived effectiveness of online learning, and weaken their intention to use such systems. Therefore, the following hypothesis is proposed:

H_7: *Technostress (TS) negatively influences the intention to use online learning applications.*

2.8 Feeling of Isolation

Feeling of isolation refers to the perceived lack or insufficiency of meaningful social relationships, which leads to a sense of social disconnection (De Jong Gierveld & Van Tilburg, 2010). In recent years, social isolation and loneliness have become increasingly prominent concerns, particularly in digitally mediated environments (Luhmann et al., 2022). Within higher education, the rapid transition to online learning and the reduction of face-to-face interactions have intensified concerns regarding students' sense of isolation (Lyons et al., 2020; Vakoufari et al., 2014). Although digital technologies have enabled the continuity of education, they may also limit opportunities for social engagement, thereby increasing students' feelings of loneliness. Empirical evidence suggests that young adults, especially those aged 18–22, are particularly vulnerable to experiencing social isolation (Muramatsu et al., 2019). Furthermore, a substantial proportion of university students report experiencing loneliness during their academic journey, with recent studies indicating an upward trend in such experiences (Diehl et al., 2018; Hysing et al., 2020). In online learning contexts, a heightened sense of isolation may reduce learners' engagement, satisfaction, and perceived value of digital learning platforms, thereby weakening their intention to use such systems. Accordingly, the following hypothesis is proposed:

H_8: *Feeling of isolation (SoI) negatively influences the intention to use online learning applications.*

2.9 Behavioral Intention and Usage Behavior of Online Learning Applications

Behavioral intention is widely recognized as a key determinant of actual system usage in technology acceptance models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). It reflects an individual's readiness and willingness to perform a particular behavior, which in turn drives actual usage (Venkatesh et al., 2003). In the context of online learning, intention to use represents learners' commitment to adopting and engaging with digital learning platforms. When individuals demonstrate a strong intention to use online learning applications, they are more likely to access these systems frequently, sustain their usage over time, and integrate them into their learning routines. Prior research has consistently confirmed that behavioral intention is a strong predictor of actual usage behavior across various technology contexts. Therefore, it is expected that a higher level of intention to use online learning applications will lead to increased actual usage. The following hypothesis is proposed:

H_9: *Intention to use online learning applications positively influences actual usage behavior.*

From the above hypotheses, the research model is proposed as shown in Fig. 1.

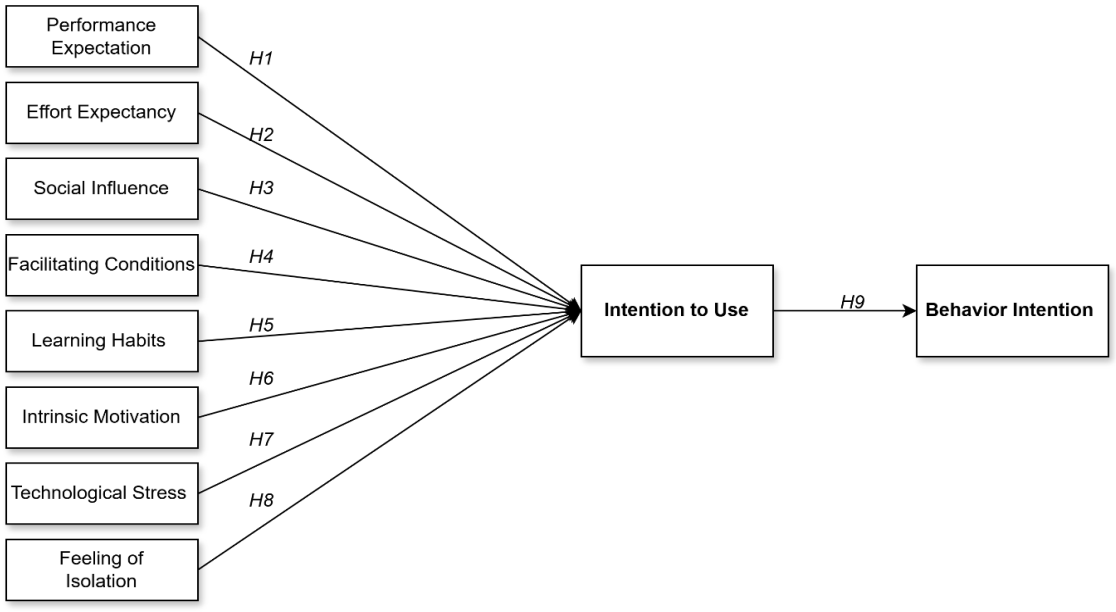

Fig. 1. Hypothetical Model

3. Material and Methods

3.1 Research Design and Data Collection

This study adopts a quantitative research approach to examine the factors influencing the intention to use online learning applications and actual usage behavior. A structured questionnaire was developed based on validated measurement scales from prior studies, with necessary adaptations to fit the context of online learning in Vietnam. Data were collected from learners who have experience using online learning platforms. A convenience sampling method was employed, targeting university students and young learners. A total of 501 valid responses were obtained and used for subsequent analysis. All measurement items were assessed using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Ten percent of valid answers are cross-checked by interviewers via phone. Finally, the sample size of valid questionnaires was 501.

3.2 Measurement Scale

The constructs in this study were measured using established scales adapted from previous literature. Specifically, performance expectancy, effort expectancy, social influence, and facilitating conditions were adapted from Venkatesh et al. (2003, 2012). Learning habits were measured based on Limayem et al. (2007), while intrinsic motivation items were adapted from Ryan et al. (1994). Technostress and feeling of isolation were measured using scales adapted from Tarafdar et al. (2015) and De Jong Gierveld and Van Tilburg (2010), respectively. Behavioral intention and usage behavior were measured based on prior technology adoption studies.

3.3 Data Analysis Method

The data were analyzed using Structural Equation Modeling (SEM) with SPSS and AMOS. The analysis results are shown as in the next part.

4. Results

4.1. Results of Cronbach's Alpha

The reliability of the scales was assessed using Cronbach's Alpha in SPSS, with the results presented in Table 1 for each construct:

Table 1
Summary of Cronbach's Alpha Test Results

Factor	Short word	observed variable	Cronbach's Alpha
1. Performance Expectations	PE	5	0.880
2. Effort Expectations	EE	4	0.822
3. Social Influences	SI	4	0.810
4. Favorable Conditions	FC	4	0.843
5. Learning Habits	LH	3	0.861
6. Learner Intrinsic Motivation	IM	3	0.874
7. Technological Stress	TS	4	0.890
8. Feelings of Isolation	Sol	3	0.845
9. Intention to Use	BI	3	0.804
10. Usage Behavior	UB	3	0.751

(Source: Results of SPSS data analysis)

The variables PE, EE, SI, FC, LH, IM, TS, Sol, BI, and UB were tested for reliability using Cronbach's Alpha coefficient. TS had the highest Cronbach's Alpha coefficient at 0.890. Performance Expectations (PE), Effort Expectations (EE), Social Influence (SI), Facilitating Conditions (FC), Learning Habits (LH), Intrinsic Motivation (IM), Technological Stress (TS), Feeling of Isolation (Sol), and Intention to Use (BI) all had Cronbach's Alpha coefficients of 0.8 or higher, indicating high reliability. Usage Behavior (UB) had a Cronbach's Alpha of 0.751, reaching an acceptable level of reliability. All scales had Cronbach's Alpha coefficients greater than 0.7, indicating that the observed variables were well-designed and had high internal consistency.

4.2 Result of Confirmatory Factor Analysis (CFA)

According to the data analysis results presented in Table 2, the CMIN/DF ($\chi 2/df$) value of 1.702 falls within the range of 1 to 3, indicating that the model is excellent (Hair et al., 2010). The analysis also evaluated other indicators as follows: CFI = 0.953 ≥ 0.95; RMSEA = 0.041 ≤ 0.06, indicating a good model fit; and PCLOSE = 0.999 ≥ 0.05, excellent result (Hu & Bentler, 1999); GFI = 0.892, indicating an acceptable fit (Baumgartner & Homburg, 1996; Doll et al., 1994). Therefore, the model is appropriate.

Table 2
Results of model fit measurement indicators

Measurement	Estimate	Threshold	Explanation
CMIN/DF	1.702	1 – 3	Good
CFI	0.953	≥ 0.95	Good
GFI	0.892	≥ 0.8	Acceptable
RMSEA	0.041	≤ 0.06	Good
PCLOSE	0.999	≥ 0.05	Good

(Source: Results of SPSS and Amos data analysis)

Table 3 shows that the CR values of the constructs are all higher than the threshold of 0.7, the AVE values are greater than 0.5, and MSV < AVE (Hair et al., 2010, 2016). However, according to the results obtained in Table 2, the MSV of BI and UB are greater than their AVE. But in studies of consumer behavior or psychology, many concepts can naturally be closely related, especially in this topic concerning factors influencing students' decisions to use online learning applications. The highly correlated concepts are intention to use and behavior to use. This does not mean that the two concepts are indistinguishable, but rather indicates a strong causal relationship between them, so the AVE < MSV value is acceptable in this case. Therefore, the reliability and validity of the model are established.

Table 3
Results of reliability, convergence, and discrimination tests

	CR	AVE	MSV	MaxR(H)	LH	TS	PE	FC	EE	SoI	IM	BI	UB
LH	0.911	0.775	0.212	1.006	0.880								
TS	0.900	0.564	0.297	0.912	0.092	0.751							
PE	0.882	0.601	0.511	0.888	0.403	0.046	0.775						
FC	0.817	0.529	0.511	0.826	0.447	0.069	0.715	0.728					
EE	0.824	0.540	0.030	0.833	0.172	-0.089	0.093	0.125	0.735				
SoI	0.817	0.528	0.039	0.822	0.118	0.018	0.141	0.197	0.075	0.727			
IM	0.876	0.702	0.465	0.881	0.460	0.094	0.586	0.682	0.102	0.150	0.838		
BI	0.806	0.581	0.650	0.811	0.435	0.545	0.594	0.514	0.156	0.150	0.520	0.763	
UB	0.753	0.504	0.650	0.754	0.300	0.344	0.332	0.321	0.070	0.148	0.344	0.806	0.710

(Source: Results of SPSS and Amos data analysis)

4.3 Results of the linear structural equation modeling (SEM)

Based on results obtained using AMOS 20 software, Table 4 presents the values used to test the hypothetical model: critical rate (C.R.), standard error (S.E.), and significance level (P-value). Six of the eight pathways were significant when the critical rate (C.R.) exceeded 1.96 and the P-value was less than 0.05.

Table 4
Results of SEM model analysis

Hypothesis	Relationship			Estimate	S.E.	C.R.	P value	Result
H_1	BI	←	PE	0.382	0.048	5.309	***	Support
H_2	BI	←	EE	0.112	0.031	2.547	0.011	Support
H_3	BI	←	SoI	0.044	0.027	1.012	0.312	Do not Support
H_4	BI	←	FC	0.001	0.057	0.013	0.99	Do not Support
H_5	BI	←	LH	0.127	0.024	2.928	0.003	Support
H_6	BI	←	IM	0.157	0.046	2.396	0.017	Support
H_7	BI	←	TS	0.491	0.027	9.91	***	Support
H_8	UB	←	BI	0.757	0.099	10.378	***	Support

Note: Estimate = Standardized regression coefficient, *** = P < 0.001

(Source: Results of SPSS and Amos data analysis)

The SEM results show that the structural model is suitable, $\chi^2/df = 1.722$, CFI = 0.951, RMSEA = 0.042, GFI = 0.890 (Hair et al., 2017; Hu & Bentler, 1999). Table 3 presents the coefficients of the structural model. Specifically, the structural model results reported in Table 4 provide strong empirical support for the proposed relationships among the constructs. Performance expectancy (PE) has a significant positive effect on behavioral intention (BI) ($\beta = 0.382$, $p < 0.001$), confirming its role as a primary driver of online learning adoption. Effort expectancy (EE) also positively influences behavioral intention (BI) ($\beta = 0.112$, $p = 0.011$), although the effect size is relatively modest, suggesting that perceived ease of use is less influential than perceived usefulness.

Learning habits (LH) ($\beta = 0.127$, $p = 0.003$) and intrinsic motivation (IM) ($\beta = 0.157$, $p = 0.017$) are both found to significantly enhance behavioral intention (BI), indicating that habitual behavior and internal motivation are important determinants of learners' intention to adopt online learning applications.

Notably, technostress (TS) exhibits the effect strongest on behavioral intention (BI) ($\beta = 0.491$, $p < 0.001$). Given the conceptual nature of this construct, this finding suggests that technological pressure plays a critical role in shaping users' perceptions and behavioral responses in digital learning environments. Although technostress is theoretically expected to

have a negative effect, the empirical results indicate a positive relationship. This may be explained by the adaptive behavior of learners in a mandatory digital learning environment, where technological pressure encourages engagement rather than avoidance.

In contrast, social influence (SI) ($\beta = 0.044$, $p = 0.312$) and facilitating conditions (FC) ($\beta = 0.001$, $p = 0.990$) do not have statistically significant effects on behavioral intention (BI), implying that external social pressure and institutional support are not decisive factors in this context. This highlights the dominance of individual-level determinants over environmental factors. Furthermore, behavioral intention (BI) strongly predicts actual usage behavior (UB) ($\beta = 0.757$, $p < 0.001$), confirming its central role as a mediator in the model. Overall, the findings presented in Table 4 support most of the proposed hypotheses and demonstrate the robustness and explanatory power of the structural model.

5. Discussion

The findings of this study provide several important theoretical and practical insights into online learning adoption in emerging economies. First, the significant impact of performance expectancy confirms its central role within the UTAUT framework, aligning with prior studies that emphasize perceived usefulness as a dominant driver of technology adoption (Venkatesh et al., 2003). In the Vietnamese context, this suggests that learners prioritize tangible academic outcomes when evaluating online learning systems. Effort expectancy, although significant, demonstrates a relatively weaker effect. This finding supports the argument that as users become increasingly familiar with digital technologies, ease of use becomes a baseline expectation rather than a decisive factor. This result is consistent with recent studies indicating that usability alone is insufficient to drive sustained engagement in digital learning environments. A particularly notable contribution of this study lies in the strong positive effect of technostress on behavioral intention. While prior literature predominantly conceptualizes technostress as a negative factor, this finding suggests a more nuanced interpretation. In contexts where digital learning is mandatory or highly prevalent, a certain level of technological pressure may actually motivate users to adapt, engage, and develop coping mechanisms. This aligns with the concept of "eustress," where moderate stress enhances performance and behavioral activation. Therefore, technostress in this study may reflect not only strain but also increased awareness and urgency to engage with online learning systems. Furthermore, learning habits and intrinsic motivation significantly influence behavioral intention, highlighting the importance of internal and behavioral drivers. Habit formation indicates repeated exposure and prior positive experiences, while intrinsic motivation reflects deeper cognitive engagement. These findings reinforce the need to integrate psychological constructs into technology acceptance models.

In contrast, social influence and facilitating conditions are found to be insignificant. This suggests a shift toward more autonomous decision-making among learners, where individual evaluation outweighs external pressures or institutional support. In the Vietnamese context, this may reflect the normalization of online learning, reducing reliance on social endorsement. Finally, the strong relationship between behavioral intention and actual usage behavior confirms the robustness of intention-based models and validates the mediating role of behavioral intention.

6. Conclusion

This study makes three key contributions to the literature. First, it extends the UTAUT framework by incorporating both enabling (e.g., performance expectancy) and inhibiting (e.g., technostress, isolation) factors into a unified model, thereby improving its explanatory power. Second, it introduces a nuanced perspective on technostress by demonstrating its potential dual role as both a barrier and a motivator in digital learning environments. Third, the study provides empirical evidence from a developing country context, contributing to the generalizability of technology adoption theories.

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