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Original Research Article

Factors Influencing University Students' Behavioral Intention and Use of eLearning in Kathmandu Valley

Sudip Pokhrel[1*], Pitambar Acharya[2]

[1]Centre for Postgraduate Studies, Nepal Engineering College, Pokhara University, Nepal
[2]Central Department of Education, Tribhuvan University, Nepal

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***Corresponding author:** Sudip Pokhrel
Centre for Postgraduate Studies, Nepal Engineering College, Pokhara University, Nepal

Abstract

This study aims to investigate the factors influencing university students' intention and behavior toward eLearning in Kathmandu Valley, Nepal. The research framework used in this study was the Unified Theory of Acceptance and Usage of Technology (UTAUT). The most common factors associated with UTAUT are social influence, facilitating conditions, habit, performance expectancy, effort expectancy, behavioral intention, and use behavior. Data were collected from 385 university students through a closed-ended questionnaire through social media platforms. The demographic information of respondents was summarized using SPSS version 25 software, while structural equation modeling was performed using SmartPls version 3 to identify the factors that influence behavioral intention and use behavior of eLearning. The data analyses revealed that performance expectancy, effort expectancy, facilitating conditions, social influence, and habit all significantly influence the behavioral intention of eLearning, with facilitating conditions being the most significant factor. Similarly, habit, facilitating conditions, and behavioral intention also significantly influence the use behavior of eLearning, with facilitating conditions as the most significant factor. It suggests that students are more likely to utilize eLearning tools when they have access to various technical devices and receive sufficient support from educational institutions. Therefore, universities should prioritize accessibility, feedback mechanisms, and seamless integration of eLearning into curricula. Peer support, technical assistance, and promotion of the benefits of eLearning are also essential for fostering engagement. By focusing on these aspects, eLearning adoption can be optimized, leading to improved academic performance and learning outcomes among university students in Kathmandu Valley.

Keywords: eLearning, Behavioral Intention, Use behavior, University Students, Kathmandu Valley.

INTRODUCTION

There have been revolutionary changes in acquiring information through various time-efficient strategies as a result of the substantial advancements in the field of information and communication technology (Al-Emran & Salloum, 2017; Al-Ghurbani *et al.*, 2022; Skersys *et al.*, 2011). Many students are increasingly drawn to educational activities that use modern technology and electronic resources because of their remarkable growth and advances (Al-Emran & Salloum, 2017; Alenezi, 2023; Alkandari, 2015). The education sector must integrate information and communication technology (ICT) tools across all stages of the educational process and implement an innovative learning approach. Educational professionals are drawn to different innovations in the realm of ICT to incorporate them into teaching and learning practices (Henriksen *et al.*, 2016; Lawrence & Tar, 2018). The ELearning (e-learning, electronic learning) is a learning platform that is based on using internet. It is used in higher education to promote and enhance learning while also facilitating lifelong learning. Advancements in ICT, enhancements in internet infrastructure, and widespread usage of the World Wide Web have elevated e-learning to a more flexible, interactive, and well-designed level (Alhumaid *et al.*, 2020; Alkandari, 2015; MacKeogh & Fox, 2009).

Elearning, a form of distance learning, utilizes online and digital tools to facilitate education through platforms such as the web, personal computers, cell phones, and electronic gadgets. It enhances the speed at which instructors and students engage with one another, and promotes access to learning and connection through innovative approaches to online education (Baruah, 2018; Kumar Basak *et al.*, 2018; Mouli, 2023; Weller *et al.*, 2005). With the assistance of this teaching approach, students can participate and communicate their opinions to the group's other members. The method encourages optimistic and productive communication among participants for a more enjoyable learning atmosphere (Sayaf, 2023). As a result, universities today are on the verge of adopting new learning systems. Although the e-learning system is prevalent in universities in developed countries, it can be called a new experience in terms of practical usage, especially in the higher education sector in developing countries (Oye *et al*., 2011; Shahmoradi *et al*., 2018). One of COVID-19's biggest losses has been in the education sector, regardless of the state of the economy. However, to continue their academic programs after the COVID-19 outbreak, several universities have shifted to eLearning. As a result, traditional teaching methods have been changed (Maatuk *et al*., 2022; Sayaf, 2023; Turnbull *et al*., 2021).

In the past, the Nepalese teaching method had no other alternatives except to employ chalk, duster, blackboard, textbook, and teaching materials using 'chalk and talk method' (Muttappallymyalil *et al*., 2016; Pangeni, 2016). Recognizing the importance of ICT in education, the Ministry of Education Nepal introduced the "ICT in Education Master Plan 2013-2017" to promote digital literacy and the integration of technology in education (MoE, 2013). In line with this, the Government of Nepal implemented an official ICT policy in 2015, which aims to incorporate technology into education across the whole Nepalese educational system by improving its accessibility (Lim *et al*., 2020; Rana *et al*., 2020). The subsequent School Sector Development Plan (SSDP) 2016-2023 emphasizes the use of ICT as a key instrument to improve educational content delivery, facilitate access to teaching-learning materials, and improve the effectiveness and efficiency of educational activities (Bhattarai & Maharjan, 2020). Research in many developing countries, including Nepal, has shown that technology integration in academics and infrastructure fails to meet the requirements (Dhungel, 2020; Karki, 2019). However, various implementation problems hinder the successful functioning of the e-learning system in Nepal (Bhattarai, 2020; Gharti, 2023; Rijal, 2022). Yet, only a small number of educational institutions have developed the necessary infrastructure and are prepared to provide the necessary amenities (Muttappallymyalil *et al.*, 2016; Pangeni, 2016). According to Bhattacharya *et al.*, (2020), only 13% of schools can provide online lessons, while 35% of schools have internet connectivity. However, the current state of technology does not ensure the effective implementation of ICT in eLearning (Bhattarai & Maharjan, 2020; Reader *et al.*, 2020; Tamang, 2022).

Due to the worldwide COVID-19 pandemic, all organizations and educational institutions in Nepal were temporarily closed beginning in the week of March 2020 (Bhattarai, 2020; Dawadi *et al*., 2020). After two months, some institutions started using an online system to continue with their educational activities. This period of mandated class suspension has led to significant changes in the education system. One notable development is the introduction of eLearning, which involves conducting instruction remotely through digital platforms. In the Kathmandu Valley, most schools and colleges have started offering online classes using video conferencing applications such as Zoom, Microsoft Teams, Skype, and others (Bhattarai, 2020; Dawadi *et al*., 2020). Additionally, Google apps like Google Docs, Google Meets, Google Forms, Google Slides, etc. are also used for evaluating and conveying assignments (Andrew, 2019).

In the early stages of introducing digital platforms, faculty members and students often hesitate to use new technologies due to a negative perception of ICT in education. However, over time, these technologies not only transform teaching and learning activities, but also equip students to thrive in today's and tomorrow's technological world (Mhlongo *et al*., 2023). The current generation of students seeks access to quality education anytime and anywhere, regardless of their location. They can enroll in courses and study remotely. Given the rapid pace of innovation and technological development, it is essential to ensure that students and institutions are adequately prepared to effectively utilize digital tools for educational purposes (Bhattarai & Maharjan, 2020).

Numerous theories and models provide valuable insights into the factors that shape students' acceptance and usage of eLearning technologies, deepening our understanding of their behaviors in eLearning environments. This study aims to address a research gap in comprehending the factors that influence university students' behavioral intentions and use behaviors of eLearning in Kathmandu Valley. To achieve this, we used the Unified Theory of Acceptance and Usage of Technology (UTAUT) model (Venkatesh *et al*., 2003). By applying the UTAUT model, we identified the factors that influence eLearning behavioral intention and use behavior, including variables such as effort expectancy, habit, social influence, performance expectancy, and facilitating conditions. The timing of this study is significant as it was conducted immediately after successive lockdowns due to COVID-19, highlighting the crucial role of student acceptance in online learning success. Therefore, it is important to comprehensively examine these factors within the specific geographical context, viz, Kathmandu Valley in Nepal, to inform strategies that can enhance eLearning platform adoption and utilization among university students. This, in turn, will help the policy recommendation towards improving the quality and effectiveness of online education delivery in the higher education system of Nepal.

MATERIALS AND METHODS

Research Approach

The research approach for this study was a quantitative descriptive design used to determine the factors that influence university students' behavioral intention and use behavior toward eLearning. The main technique for data collection was distributing questionnaires to university students, followed by in-depth data analysis.

Research Framework

The variables in this study were examined using the UTAUT framework. Figure 1 illustrates the relationship between the assessment factors of eLearning as per the UTAUT model. The study framework was constructed based on a literature review, which lays out the following research hypotheses:

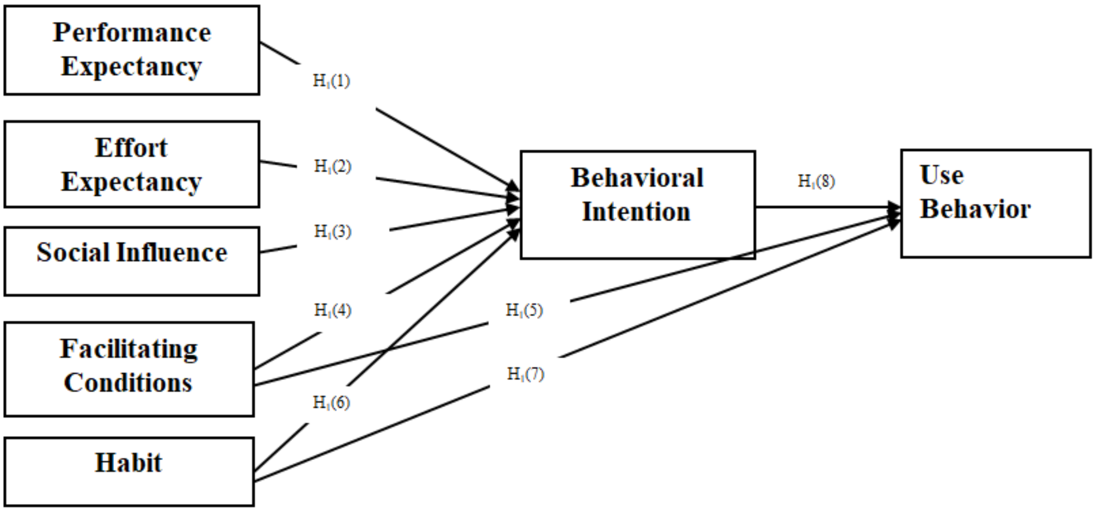

Figure 1. Conceptual framework

This study has formulated eight hypotheses based on seven variables taken from different studies and empirically examined the students' behavioral intention (BI) and use behavior (UB) from the viewpoint of eLearning.

Performance Expectancy (PE):

Performance Expectation (PE) describes the belief that the adoption of new technology will enhance user performance or work efficiency (Venkatesh *et al.*, 2012). Studies reveal that a user's inclination to stick with new technology is strongly influenced by PE (Wu & Ho, 2022). For example, if students believe that eLearning will assist them in finishing their assignments and accomplishing their goals more quickly, they are more likely to continue with it (Alam, 2022). It is hypothesized that;

> H_1(1): University students' behavioral intention of eLearning is significantly influenced by Performance expectancy.

Effort Expectancy (EE):

According to Onaolapo and Oyewole (2018), effort expectancy refers to how easily users can utilize a technology from their perspective. It is defined as the ease of application of a system. On the other hand, effort expectation explains the potential for technology application, highlighting the ease of use and simplicity of all technological products and services (Tamrin *et al.*, 2022). The degree of naturalness required by students while using a system or technology is known as effort expectation (Mahande & Malago, 2019). It is hypothesized that;

> H_1(2): University students' behavioral intention of eLearning is significantly influenced by effort expectancy.

Social Influence (SI):

Social Influence (SI) shows how people's intentions are influenced by the views of others (Venkatesh *et al.*, 2003; Venkatesh *et al*., 2012). Raza *et al.*, (2021) stated that participants' behavior was predicted by social cognitive characteristics (e.g., considering the beliefs of important individuals). This study examines the use of eLearning platforms by university students for their academic studies and their perceptions of the opinions of significant individuals, such as classmates and university instructors. It is hypothesized that;

> H_1(3): University students' behavioral intention of eLearning is significantly influenced by social influence.

Facilitating Conditions (FC):

According to Venkatesh *et al.*, (2012), "facilitating conditions" refers to how users' perception of institutional support and the availability of the necessary infrastructure to support the use of desired technology. Traditionally, resources, support, and technical assistance that make it easier to use technological systems are categorized under enabling conditions. Facilitating situations, as suggested by

(Venkatesh *et al.*, 2012), have an impact on users' intentions and actual usage. It is hypothesized that;

H_1(4): University students' behavioral intention of eLearning is significantly influenced by facilitating conditions.

H_1(5): University students' use behavior of eLearning is significantly influenced by facilitating conditions.

Habit (HB):

Habit refers to individuals' automatic or habitual adoption of new technology. This behavioral pattern is developed instinctively and automatically based on experience accumulated from a series of past activities (Venkatesh *et al.*, 2012). Furthermore, this repetitive behavior adds to the establishment of cognitive commitment to particular conduct, which is gradually established but not easy to modify (Murray & Häubl, 2007). Over time, the automated behavior will reach a generally stable and continuous state (Venkatesh *et al.*, 2012). This implies that a person's habitual use of technology will become a consistent and regular practice that is difficult to change. It is hypothesized that;

H_1(6): University students' behavioral intention of eLearning is significantly influenced by habit.

H_1(7): University students' use behavior of eLearning is significantly influenced by habit.

Behavioral Intention (BI):

A person's behavioral intention is their readiness to learn and use a particular technology. As described by Davis (1989), behavioral intention refers to an individual's likelihood of using technology. It implies a clear understanding of how behavior is employed. Venkatesh *et al.*, (2012) claim that BI determines the actual adoption and use of technology. In this study, BI represents the extent to which students intend to use eLearning tools for their academic pursuits, both presently and in the future. Students' behavioral intentions influence their use of eLearning platforms for their education. It is hypothesized that;

H_1(8): University students' use behavior of eLearning is significantly influenced by behavioral intention.

Use Behavior (UB):

User behavior refers to the consumption of eLearning technology, which is indicated by its frequency and purpose of its use. It is defined as the self-reported iterative use of eLearning and represents the extent to which the system is utilized (Venkatesh *et al.*, 2003). When accessing the information stored in the student's available knowledge base, both physical and mental operations are performed iteratively (Mouli, 2023). Different activities use specific sources, such as knowledge acquisition and learning activities related to eLearning approaches (Raith, 2019). This study acknowledges user behavior as an ongoing practice of eLearning among university students, both in their current situation and for future endeavors. The objective of this research is to examine how university students engage with eLearning over time and how this behavior can impact their academic performance and future career prospects.

Study Area

The study was conducted in three districts within Nepal's Kathmandu Valley, which consists of three districts: Kathmandu, Lalitpur, and Bhaktapur.

Population and Sample Size and Sampling Technique

The study population consisted of all university-level students enrolled at various institutions (universities) in the Kathmandu Valley. Since exact number of university-level students in Kathmandu Valley was unknown, so a representative sample of 385 students was taken. This sample size was determined using statistical parameters such as a population proportion of success of 0.50, a margin of error of 5%, and a Z^2 value of 3.841, which represents the standard error associated with a 95% confidence level. The sample size was calculated using the formula provided by Israel (1992). Data was collected from the sample size of 385 using a non-random sampling approach. Specifically, a convenience sampling technique was employed, targeting participants who were readily available and willing to participate in the study (Etikan *et al.*, 2016).

Study Instrument and Data Collection

A survey instrument presented in this research was used for hypothesis testing. The survey consisted of 36 items that measured the seven constructs outlined in the questionnaire. Table 1 provides the sources of these constructs. The questions from the previous studies were adopted and modified to enhance their relevance to the research.

Table 1: Source of variables and measurement indicator

Variables	Number of items	Source of Questionnaire (Measurement Indicator)
Performance Expectancy (PE)	**5**	(Venkatesh *et al.*, 2003)
Effort Expectancy (EE)	**5**	(Venkatesh *et al.*, 2003)
Social Influence (SI)	**5**	(Venkatesh *et al.*, 2003)
Facilitating Conditions (FC)	**5**	(Venkatesh *et al.*, 2003)
Habit (HB)	**3**	(Limayem *et al.*, 2007)
Behavioral Intentions (BI)	**7**	(Venkatesh *et al.*, 2012)
Use Behavior (UB)	**6**	(Venkatesh *et al.*, 2012)

The survey tool was divided into two sections. The first section focused on gathering personal data from the participants, such as age, gender, educational background, and university degree. In the second section, there were 36 items designed to assess various constructs related to use behavior, behavioral intentions, performance expectancy, effort expectancy, facilitating conditions, social influence, and habit. Each item was measured using a five-point Likert Scale, where respondents indicated their level of agreement or disagreement, ranging from strongly agree (5) to strongly disagree (1). The purpose of this section was to capture participants' perceptions and attitudes regarding eLearning behavioral intention and use behavior. To collect the data, self-reported questionnaires were distributed via digital platforms, including social networks, e-mail, and messaging applications to the university students in Kathmandu Valley.

Data Analysis

In this study, a combination of IBM SPSS version 25 and Smart PLS version 3 was used for data analysis and modeling. Initially, IBM SPSS version 25 was used to analyze the demographic data of respondents using descriptive statistics, providing valuable insights into the characteristics of the sample. Subsequently, Smart PLS version 3.3 was used for Partial Least Squares Structural Equation Modeling (PLS-SEM), a robust statistical technique suitable for analyzing complex relationships within a model. The methodology included two main components: the measurement model and the structural model.

The measurement model established the relationships between latent variables and their corresponding indicators, evaluating the reliability, discriminant validity, and convergent validity of the indicators to ensure the quality of measurement for formative constructs. On the other hand, the structural model examined the relationships between independent and dependent variables. It focused on path coefficients, hypothesis testing, and addressed concerns related to multicollinearity.

RESULTS AND DISCUSSION

Demographic Information of Respondents

The participant demographics revealed that male students accounted for 55% of the participants, while female students accounted for 45%. The majority of respondents (70%) were between 18 to 30 years old, with the remaining 30% being over 30 years old. In terms of educational backgrounds, the largest portion (33%) was from the management stream, followed by engineering (26%), arts (19%), science and technology (12%), and education (10%). Notably, 73% of the respondents were pursuing bachelor's degrees, while the remaining 27% were enrolled in master's programs.

Confirmatory Factor Analysis

This research aims to apply Confirmatory Factor Analysis (CFA). All scale items in each variable showed significance and represented the factor loading to identify and test discriminant validity. The factor loading represents the goodness of fit for each item (Hair *et al.*, 2006). The first step in conducting a partial least squares (PLS) analysis involves assessing the reliability and validity of the measurement model. This evaluation included estimating the indicator's outer loading, Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha (CA) (Hair Jr *et al.*, 2020). The values of AVE, CR, and CA are presented in Table 2. An indicator outer loading value exceeding 0.7 for a specific construct indicates its reliability (Götz *et al.*, 2009). Likewise, all constructs in the model demonstrated Composite Reliability and Cronbach's Alpha values exceeding 0.7, indicating strong internal consistency reliability. Each of the constructs demonstrates an Average Variance Extracted value (AVE) surpassing the threshold of 0.5, indicating strong convergent validity (Roldán & Sánchez-Franco, 2012).

Table 2: Result of Indicator and Convergent Validity

Factors	Indicators	Outer loadings	AVE	CR	CA
Behavioral Intentions (BI)	**BI1**	0.781	0.633	0.923	0.908
	BI2	0.779			
	BI3	0.840			
	BI4	0.744			
	BI5	0.881			
	BI6	0.778			
	BI7	0.757			
Effort Expectancy (EE)	**EE1**	0.885	0.758	0.940	0.919
	EE2	0.885			
	EE3	0.760			
	EE4	0.911			
	EE5	0.903			
Facilitating Conditions (FC)	**FC1**	0.940	0.862	0.969	0.960
	FC2	0.917			
	FC3	0.919			

Factors	Indicators	Outer loadings	AVE	CR	CA
	FC4	0.920			
	FC5	0.947			
Habit (HB)	**HB1**	0.887	0.786	0.917	0.865
	HB2	0.884			
	HB3	0.889			
Performance Expectancy (PE)	**PE1**	0.892	0.948	0.785	0.931
	PE2	0.913			
	PE3	0.868			
	PE4	0.868			
	PE5	0.887			
Social Influence (SI)	**SI1**	0.904	0.802	0.953	0.940
	SI2	0.910			
	SI3	0.902			
	SI4	0.878			
	SI5	0.884			
Use Behavior (UB)	**UB1**	0.893	0.797	0.959	0.949
	UB2	0.884			
	UB3	0.879			
	UB4	0.935			
	UB5	0.881			
	UB6	0.883			

Discriminant validity was assessed through the application of Fornell and Larker criteria, Heterotrait Monotrait Ratio (HTMT), and cross-loading analyses.

Table 3: Discriminant Validity using Fornell-Larcker Criterion

	BI	EE	FC	HB	PE	SI	WB
BI	**0.796**						
EE	0.330	**0.871**					
FC	0.694	0.282	**0.898**				
HB	0.242	0.211	0.192	**0.887**			
PE	0.357	0.186	0.224	0.133	**0.886**		
SI	0.171	0.092	0.162	0.030	-0.119	**0.896**	
UB	0.564	0.185	0.670	0.168	0.138	0.120	**0.893**

The Fornell-Larcker criterion is a method used to assess the discriminant validity of constructs in a structural equation model. In Table 3, the diagonal elements represent the square root of the AVE for each construct, while the off-diagonal elements represent the correlations between constructs. Discriminant validity is supported if the AVE for each construct is greater than its correlations with other constructs (M. Ab Hamid *et al.*, 2017). In Table 3, it was observed that the diagonal elements (bolded) are higher than the corresponding off-diagonal elements in each row, indicating that each construct's AVE is greater than its correlations with other constructs.

Table 4: Analysis and Validity of Structural Model: Heterotrait-Monotrait Ratio (HTMT)

Factors	BI	EE	FC	HB	PE	SI	UB
BI							
EE	0.362						
FC	0.574	0.299					
HB	0.272	0.238	0.209				
PE	0.392	0.203	0.235	0.147			
SI	0.173	0.092	0.162	0.046	0.138		
UB	0.534	0.195	0.498	0.186	0.146	0.119	

The HTMT analysis provides evidence of adequate discriminant validity, thus reinforcing the reliability of the structural model in distinguishing between the various constructs that are being investigated (M. R. Ab Hamid *et al*., 2017). The Heterotrait-Monotrait Ratio (HTMT) values presented in Table 4 indicate the discriminant validity of the structural model. With all values below 0.85, the correlations between different constructs are lower than the correlations within the same construct. This suggests that the constructs are distinct from each other, providing support for the validity of the model (Dirgiatmo, 2023).

Table 5: Result of Collinearity Assessment

Dependent variable	Independent variable	VIF
Behavioral Intentions	Performance Expectancy	1.109
	Effort Expectancy	1.139
	Habit	1.074
	Facilitating Conditions	1.176
	Social Influence	1.060
Use Behavior	Behavioral Intentions	1.975
	Facilitating Conditions	1.931
	Habit	1.063

Table 5 presents the results of the collinearity assessment for the dependent variable Behavioral Intentions and the independent constructs, as well as for the dependent variable Use Behavior and its constructs. Generally, variance inflation factor (VIF) values below 5 are considered acceptable and indicate that multicollinearity is not a significant issue. This suggests that the regression models are valid and suitable for further analysis and interpretation (Hair *et al*., 2019).

Regarding the dependent variable BI, all independent variables (performance expectancy, effort expectancy, habit, facilitating conditions, and social influence) have VIF values well below 5, ranging from 1.060 to 1.176. These low VIF values indicate that there is no significant multicollinearity among the independent variable when predicting BI.

For the dependent variable UB, the independent variables (behavioral intentions, facilitating conditions, and habit) also have VIF values below 5, ranging from 1.063 to 1.975. Therefore, multicollinearity does not appear to be a significant issue in the prediction of UB.

Structural Equation Model

This section discusses the examination of eight hypotheses in the study using structural equation modeling (SEM). These hypotheses aim to assess the relationship between dependent and independent variables regarding the behavioral intention and use behavior of eLearning among university students in Kathmandu Valley, Nepal. According to Hair Jr *et al*., (2021), SEM facilitates the validation of causal relationships among variables in a proposed model and helps mitigate measurement imprecision in the structural coefficients.

Coefficient of Determination

The R-square values in Table 6, also known as the coefficient of determination, represent the proportion of variability in the dependent variable that can be explained by the independent variables in the regression model (Nagelkerke, 1991). The R Square value lies between 0 and 1, with higher values indicating greater explanatory power. As a general rule, R Square values of 0.75, 0.50, and 0.25 can be considered substantial, moderate, and weak (Hair *et al*., 2011; Henseler *et al*., 2009).

Table 6: Coefficient of determination (R square)

Dependent variable	R Square	Results
BI	0.550	Moderate
UB	0.468	Moderate

In this study, the focus is on the dependent variable BI and UB. The R-square value for BI is 0.550, suggesting that the combined influence of the independent variables accounts for 55.0% of the variance in BI. This finding indicates a moderate fit in explaining the observed variability in behavioral intention. Similarly, for the dependent variable UB, the R-square value is 0.468, indicating that the independent variables explain 46.8% of the variance in UB, this result show a moderate level of explanatory power for use behavior.

Testing of Hypothesis in Structural Model

The study aimed to determine the path coefficients (β), t-statistics, and p-values to assess the significance of the hypotheses in the structural model. The results presented in Table 7 show that all assumptions have been statistically significant at a 5% level of significance.

Table 7: Testing of Hypothesis in Structural Model

Hypothesis	Relation	Beta	t Statistics (|O/STDEV|)	P Value	Decision
H_1(1)	PE -> BI	0.207	4.688	0.000***	Supported
H_1(2)	EE -> BI	0.102	2.384	0.017*	Supported
H_1(3)	SI -> BI	0.089	2.967	0.003***	Supported
H_1(4)	FC -> BI	0.588	12.375	0.000***	Supported
H_1(5)	FC -> UB	0.535	7.707	0.000***	Supported
H_1(6)	HB -> BI	0.078	2.144	0.033*	Supported
H_1(7)	HB -> UB	0.069	2.042	0.045	Supported
H_1(8)	BI -> UB	0.186	2.838	0.005***	Supported

Note: t-value >= 1.96 at p = 0.05 level*, t-value >= 2.58 at p = 0.01 level**, t-value >= 3.29 at p = 0.001 level***

H_1(1): Performance Expectancy **(**PE) is the second most significant factor that influenced BI among university on Kathmandu Valley, with a beta coefficient of 0.207, a t-statistic of 4.688, and a p-value of 0.000. This verifies that PE significantly influences university students' BI to use eLearning platforms meaning that using eLearning platforms will enable students to perform better in their studies. The findings of this research are consistent with the research conducted by Mouli (2023) in Thailand, Raza *et al*., (2021) in Pakistan, Prasetyo *et al*., (2021) in Philippines, Tewari *et al*., (2023a) in India, and Hassan (2021) in Egypt. Students have a primary emphasis on enhancing their academic achievement, and they perceive eLearning platforms as a tool to assist them in achieving this goal. Based on this it can be said that administrators, specialists, academics, and eLearning system designers should focus on creating eLearning tools that can successfully and efficiently improve university students' academic performance.

H_1(2): Effort Expectancy **(**EE) significantly influenced the BI of eLearning among university students in Kathmandu Valley. This is supported by a beta coefficient of 0.102, a t-statistic of 2.384, and a p-value of 0.017. This finding is consistent with the studies conducted by Chao (2019) and other researchers such as Hunde *et al*., (2023); Mouli (2023); Ngampornchai and Adams (2016); Tewari *et al*., (2023b); (Venkatesh *et al*., 2012). Therefore, when developing or enhancing eLearning systems, universities should consider this factor and strive to make them as user-friendly as possible to ensure students are motivated to use them.

H_1(3): It was found that Social Influence (SI) significantly influences the BI of eLearning among university students in Kathmandu Valley. This is supported by a beta coefficient of 0.089, a t statistic of 2.967, and a low p-value of 0.003. These findings align with the results of previous studies conducted by (Akbar, 2021); Park (2009), which emphasize the lasting influence of peers instructors, and family members on students' perceptions and decisions regarding eLearning. The results suggest that students highly value the opinions and support of those around them, seeing their endorsement as a critical factor in their use of eLearning. Therefore, it is important to create a supportive environment and foster positive social interactions within educational settings. By doing so, we can potentially enhance students' engagement with eLearning platforms, as they perceive the support of their social circle to be essential to their academic pursuits.

H_1(4): Facilitating Conditions (FC) is the most significant factor that influence BI of eLearning among university students in Kathmandu Valley. The beta coefficient for this factor is 0.588, with a t statistic of 12.375 and a p-value of 0.000. Hunde *et al*., (2023) and Hassan (2021) have both concluded that facilitating conditions play a crucial role in predicting the actual use of eLearning platforms by university students. This finding supports the idea that students are more likely to actively seek and utilize eLearning platforms when they have access to a variety of technical devices, such as laptops, desktop computers, smartphones, and a stable internet connection. Additionally, educational institutions should provide students with adequate training, course materials, and technological support to optimize their online learning experience. It is also essential to have knowledgeable and helpful faculty and staff available to assist students in overcoming any obstacles they may face.

H_1(5): It was found that facilitating conditions significantly influenced the Use Behavior (UB) of eLearning among university students in Kathmandu Valley. This impact is evidenced by a beta coefficient of 0.535, a t-statistic of 7.707, and a p-value of 0.000. The results of this study were in line with the results of (Venkatesh *et al*., 2012; Widanengsih, 2021), which also demonstrated the direct influence of facilitating conditions on eLearning use behavior. To enhance usage behavior, universities should prioritize accessibility on various devices, solicit feedback, and seamlessly integrate eLearning into curricula. Encouraging peer support, providing technical assistance, and promoting the benefits of eLearning can also boost engagement. Therefore, universities should concentrate on these aspects to optimize eLearning adoption in Kathmandu Valley.

H_1(6): It was found that habit (HB) significantly influenced the behavioral intentions of eLearning among university students in Kathmandu Valley, as reinforced by a beta coefficient of 0.078, a t-value of 2.114, and a p-value of 0.033. This conclusion is consistent with the previous studies conducted by Mouli (2023); and Tarhini *et al*., (2017). So, the potential strategies for increasing the likelihood of using eLearning in universities in the Kathmandu Valley include implementing regular reminders and prompts to encourage engagement with eLearning platforms, setting attainable goals for consistent usage, and incorporating elements of gamification to enhance the enjoyment and habit-forming nature of learning.

H_1(7): It was observed that habit (HB) significantly influenced the UB of eLearning among university students in Kathmandu Valley. This is evidenced by a beta value of 0.069, a t value of 2.042, and a p-value of 0.045, which suggests that habit formation is also a key driver of the use behavior of eLearning among these students. This finding is matched with the findings of (Deng *et al.*, 2023; Limayem & Cheung, 2011). The positive relationship between habit formation and eLearning use behavior highlights the importance of fostering consistent engagement with online educational platforms.

H_1(8): Behavioral Intention (BI) significantly influenced the UB of eLearning among university students in Kathmandu Valley, indicated by a beta value of 0.186, t value of 2.838, and a low p-value of 0.005. This underscores the importance of understanding and addressing students' intentions towards eLearning platforms. This finding aligns with the discoveries of Bhurtel and Uprety (2021); (Mouli, 2023; Venkatesh *et al*., 2012), which also found a positive influence of behavioral intention on the use of eLearning. Universities can provide incentives or recognition for active participation and achievement in eLearning initiatives, thereby motivating students to consistently utilize eLearning platforms for their academic pursuits.

Model Fit Summary

Table 8: Model Fit Summary

	Saturated Model	Estimated Model
SRMR	0.069	0.070
d_ULS	3.183	3.255
d_G	1.326	1.327
Chi-Square	2610.449	2613.520
NFI	0.907	0.901

Table 8 presents the model fit summary of the Structural Equation Modeling based on various criteria, including SRMR, d_ULS, d_G, Chi-Square, and NFI values. The SRMR values for both the saturated and estimated models are closely aligned and fall below the commonly recommended threshold of 0.08 for an acceptable fit. This suggests that both models exhibit a good fit (Shi *et al*., 2018). The d_ULS and d_G values for the estimated model also align reasonably well with those of the saturated model, indicating an acceptable fit. The Chi-Square values for the saturated models are high, confirming their perfect fit. Additionally, the Normed Fit Index (NFI) value for the estimated model surpasses the commonly recommended threshold of 0.90, suggesting an acceptable fit (Hair, 2009).

CONCLUSION

The main objective of this study is to examine the factors that influence university students' behavioral intention and use behavior towards eLearning in Kathmandu Valley, using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The study focuses on key variables defined by the UTAUT model such as performance expectancy, effort expectancy, social influence, facilitating conditions, habit, behavioral intention, and use behavior. The findings reveal several significant factors that influence students' behavioral intentions and use behavior of eLearning. Behavioral intention is significantly influenced by performance expectancy, effort expectancy, social influence, facilitating conditions, and habit, with facilitating conditions being the most influential factor. Similarly, use behavior is significantly influenced by facilitating conditions, behavioral intention, and habit, with facilitating conditions being the most significant factor. The study emphasizes the critical need for strategies that enhance both the behavioral intention and use behavior of eLearning. Administrators, specialists, academics, and eLearning system designers should prioritize the development of eLearning tools that effectively improve the academic performance of university students. As universities develop or refine their eLearning systems, they must prioritize simplicity to encourage student usage. This includes incorporating consistent reminders, setting clear goals, providing training, and integrating gamification elements to enhance engagement and cultivate a habit of using eLearning platforms. Addressing these aspects is vital to facilitate the widespread adoption and effective utilization of eLearning among university students in Kathmandu Valley, ultimately leading to improved academic performance and learning outcomes.

Furthermore, this study's quantitative nature may have overlooked certain factors that could have been significant in the specific context. For instance, factors such as flexibility, perceived usefulness, course quality, and interaction with faculty should be considered when assessing student satisfaction, as they could influence behavioral intention and use behavior toward eLearning. To gain a deeper understanding of this issue, conducting a qualitative study could provide valuable insights. Additionally, it is important to highlight that this study did not examine the moderating/mediating effects of age, gender, voluntariness, and experience. So, this should be examined in a large-scale study involving a diverse population and various subgroups.

Authors' Contribution:

Mr. Pokhrel conceptualized the research, conducted the analysis, and prepared the draft transcript. Mr. Acharya worked on the literature review and revised the draft. Both authors collectively finalized the article.

Conflict of Interest:

Authors certify that there are no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in the manuscript.

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