STUDENTS' ATTITUDE AND INTENTIONS TOWARDS ONLINE LEARNING IN HIGHER EDUCATION: EXAMINING THE ROLE OF INDIVIDUAL AND SYSTEM CHARACTERISTICS

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ABSTRACT
This study is aimed at examining the factors predicting the university students' attitudes and intentions to use online learning system with the intervention of individual and system-related characteristics as external factors.
We used 506 responses from undergraduate and post-graduate students enrolled in public and private universities in the state of Sikkim (India). The study adopted the Technology Acceptance Model (TAM) as a theoretical foundation, and we extended it with external individual and system-specific characteristics. We employed Partial Least Square Structural Equation Modelling (PLS-SEM) to assess the relationship between the external exogenous individual (computer self-efficacy, perceived enjoyment, and computer playfulness) and systems (content quality, information quality, and system quality) characteristics with the endogenous constructs.
The theoretical model we propose effectively explains the behavioural intention ($R^2 = 0.623$) of university students using online learning systems. The results suggest that perceived enjoyment and system quality have a significant impact on the perceived usefulness and perceived ease of use of online learning system. On the other hand, computer self-efficacy, computer playfulness among individual characteristics; and content quality & information quality characteristics of online learning system do not significantly affect the perceived use and perceived ease of use of online learning system. Further, the content quality does not affect the attitude and intentions of using an online learning system.
This study provides insightful information that will help universities and governments better prepare for the adoption of online learning in the context of higher education in developing nations like India.
Keywords: Online learning, Technology Acceptance Model, computer self-efficacy, computer playfulness, perceived enjoyment, content quality, Information quality, system quality, Higher Education

Introduction

The global spread of the COVID 19 epidemic had an impact on people's lives, but it also had an impact on students' ability to learn by using alternate methods of study, experience, or instruction. Clark & Mayer (2016) defined Online learning as "*the delivery of education in a flexible and easy way through the use of the internet to support individual learning or organizational performance goals*". Nowadays, learning takes place in a digital environment where students and teachers are digitally connected. However, it is widely accepted that no educational strategy can match the pinnacle of formal education because it involves direct instruction from teachers. Many students today desire to study online and acquire degrees from international schools and institutions, but they are still unable to go since they live in remote places without adequate communication systems (Tarhini, Hone, & Liu, 2015). Therefore, for students who reside in remote places far from their educational institutions where they have enrolled, online learning is a choice because it saves time and energy. In fact, most universities and colleges around the world have embraced online education.

While imparting education through the online system, technology plays an important role. The technology acceptance model (henceforth TAM) proposed by (Davis, 1989) explains the determinants of accepting new technologies and has been extensively used by researchers. TAM argues that the perceived usefulness (individual's subjective belief that the use of this system can improve the performance of his work) and perceived ease of use (the extent to which an individual can easily use the system) will affect whether the user can accept and use the technology. The idea contends that two individual beliefs—namely, perceived usefulness and perceived ease of use—are influenced by system-specific and external factors to forecast one's attitude toward using technology. The behavioural intention to use a certain technology is influenced by attitude (Salloum, Qasim Mohammad Alhamad, Al-Emran, Abdel Monem, & Shaalan, 2019). However, recent research has revealed that online learning is a complex process comprising many components, including social factors (Schepers & Wetzels, 2007; Tarhini, Hone, & Liu, 2014, 2015), individual factors (Liaw & Huang, 2011; Sun & Zhang, 2006), facilitating conditions (Ejdys, 2021; Sun & Zhang, 2006; Tarhini et al., 2015) behavioural and cultural factors (Tarhini, Hone, Liu, & Tarhini, 2017). Understanding the development of online learning and application of information technology depends on such crucial factors (Kim & Moore, 2005).

Online learning is said to have many benefits, such as lower educational expenses, flexible access to instructional resources, response to space constraints, ease of access to content, straightforward team collaboration, and timely mutual discussions (Anderson, 2008; Bacow, Bowen, Guthrie, Long, & Lack, 2012; Dong, Cao, & Li, 2020; Means, Toyama, Murphy, Bakia, & Jones, 2009; Moore, Dickson-Deane, & Galyen, 2011; Surani & Hamidah, 2020; Xhaferi & Xhaferi, 2020). Due to the physical infrastructure present in developed nations, these advantages might be further expanded. On the other hand, prior research has indicated that online learning systems have their own unique set of issues, such as the high cost of setting up the system, internet access, and technological difficulties (Siti et al., 2021; Turnbull, Chugh, & Luck, 2021). In addition, the uncomfortable environment at home reduces children' desire for learning. Additionally, a system of online learning demands tight cooperation between teachers and students. Almaiah, Al-Khasawneh, and Althunibat (2020) noted a few obstacles to the adoption of online learning systems, such as a lack of funding, a lack of trust, managerial problems, and technological problems.

However, the adoption of online learning systems in developing nations has either partially or completely failed; their use is still ongoing and is seen as being below a satisfactory level (Tarhini et al., 2017). This alludes to a lack of knowledge of the elements influencing its adoption (Salloum et al., 2019). Additionally, most of earlier studies have concentrated on analysing the effects of certain factors on the adoption of online learning. Those variables typically vary from study to study depending on the participants and context. We employ individual (related to perception and abilities of the students) and system (related to the quality of online learning system) characteristics in the existing Technology Acceptance Model. There are a few studies exploring the influence of system and individual variables on university students' acceptance of online learning in India's higher education sector, as online learning was not widely used in the higher education system prior to the epidemic. Therefore, it is thought that a thorough theoretical model is required to comprehend the variables influencing the acceptance of online learning when human and system characteristics are involved in the Technology Acceptance Model. With this background, this paper is organized as follows: section 1 presents the introductory background to the motives of the study followed by the literature review in section 2. The research framework and hypotheses development in presented in section 3. Section 4 highlights the research methodology used for the study followed by the results in section 5. A detailed discussion and implications of the study is presented by section 6 and finally the conclusion and scope for further research in presented in section 7.

Literature Review

Online learning requires the use of various forms of technologies, internet connectivity, online platforms, and media. Like any other technology-based activity, online learning also possesses some pros and cons. In terms of benefits, online learning can foster a sense of community among students, develop independent learners, foster strong relationships between students and instructors, and increase problem-solving abilities. In terms of flaws, online learning makes it harder for students and instructors to keep up with their workload (Schroeder, Minocha, & Schneider, 2010).

The Technology Acceptance Model (TAM) and its refined versions proposed by (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989; Davis & Venkatesh, 1996) have been employed in various research studies concerned with the user acceptance of technology, and therefore, It has grown in importance as having a strong capacity for predicting how students will use technology in the classroom (Chang, Hajiyev, & Su, 2017; Farahat, 2012; Hu, Chau, Sheng, & Tam, 1999; Lai, 2017; Md Lazim, Ismail, & Tazilah, 2021; Siti et al., 2021). External and system-specific factors influence two personal beliefs i.e. perceived usefulness (henceforth PU) and perceived ease of use (henceforth PEU) to predict the attitude toward adopting a technology, according to the theory (Davis, 1989). The behavioural intention to use a certain technology is influenced by attitude alone. The definition of perceived ease of use is "*the degree to which a person feels that utilizing a specific technology will be free of effort*" whereas perceived usefulness is "*the degree to which a person believes that using a particular system would improve his or her performance*"(Davis, 1989). Numerous empirical investigations of user technology adoption have employed TAM as their theoretical foundation. Technology acceptance is defined as “an individual’s psychological state concerning his or her voluntary or intended use of a particular technology”(Hu et al., 1999). A number of studies such as (Aguilera-Hermida et al., 2021; Esteban-Millat, Martínez-López, Pujol-Jover, Gázquez-Abad, & Alegret, 2018; Farahat, 2012; Md Lazim et al., 2021; Ritter, 2017; Rizun & Strzelecki, 2020; Salloum et al., 2019; Singh, Sharma, & Paliwal, 2020; Sulistiyaningsih, Tambotoh, & Tanaamah, 2014) have been conducted for examining the relationship of external factors affecting the online learning using TAM.

There are growing concerns for a systematic synthesis to provide a clearer mechanism underlying technology acceptance in higher education, even though TAM has long dominated over the last three decades in explaining the creation of individuals' technology adoption behaviours in teaching and learning contexts. Hence, the researchers have examined the effect of various external factors related to online learning on the acceptance of online learning systems. In a quantitative meta-analytical study conducted by Abdullah & Ward (2016), 152 external factors influencing technology acceptance, were found. The results showed that “Self-Efficacy, Subjective norm, Enjoyment, Computer Anxiety, and Experience” are the most used external factors of TAM. The results showed that the best predictors of students' PEU of online learning systems are “Self-Efficacy, Enjoyment, Experience, Computer Anxiety, and Subjective Norm”. The best predictor of students' PU of online learning systems is “Enjoyment, Subjective Norm, Self-Efficacy, and Experience” (Abdullah & Ward, 2016; Chang et al., 2017; Farahat, 2012; Lee, Yoon, & Lee, 2009).

Online learning is said to be influenced by the characteristics of the instructor, the teaching materials, the design of the course materials, and playfulness (Lee et al., 2009). According to Chang et al. (2017), students' perceived usefulness (PU) of online learning is favourably and significantly influenced by subjective norm, experience, and enjoyment, whereas computer anxiety has the opposite effect. The perceived ease of use (PEU) of online learning is favourably and significantly influenced by experience, enjoyment, and self-efficacy. Technology innovation significantly modifies the association between Subjective norm and PU, PU, and Behavioural intentions to use online learning. Subjective norm has a positive and significant impact on behavioural intentions to utilise online learning (Chang et al., 2017). In another study, social trust influenced PU and PEU of online learning (Alshurafat, Al Shbail, Masadeh, Dahmash, & Al-Msiedeen, 2021). Salloum et al. (2019) identified 239 external unique factors in the 120 collected studies. Only eight external variables, including computer self-efficacy, subjective norm, perceived enjoyment, system quality, information quality, content quality, accessibility, and computer playfulness, were shown to be associated with TAM in at least four of the examined studies, according to the authors.

It is argued that students’ acceptance of online learning systems also varies across various Subjects/disciplines in higher education. The accounting students appreciate the use of technology and an online learning system in assessment, and their performance improved with online tests (Aisbitt & Sangster, 2005). TAM was found to be able to provide a reasonable picture of physicians' intention to employ telemedicine technology to explain physicians' decisions to accept telemedicine technology in the healthcare environment by Hu et al. (1999) in Hong Kong. PU was found to be a significant determinant of attitude and intention, but PEU was not. The students’ satisfaction in business and management discipline is significantly affected by content, the level of accuracy of the system, format, ease of use, and timeliness delivery (Hastuti, Wijiyanto, Lestari, & Sumarlinda, 2020). Due to the lack of importance given to online learning in the higher education sector during pre-covid 19 years, technical issues are considered to be the most important, followed by teachers’ lack of technical skills and their teaching style improperly adapted to the online environment (Coman, Țîru, Meseșan-Schmitz, Stanciu, & Bularca, 2020).

Considering the previously examined and summarised literature, it has been determined that most of earlier studies have concentrated on analysing the influence of certain elements on the adoption of online learning. Those variables typically changed based on the participants and the situation from study to study. Only a small number of studies (Salloum et al., 2019; Salloum & Shaalan, 2018) have looked at the impact of system and individual characteristics (content quality, information quality, and system quality) on students' attitudes and behavioural intentions toward accepting the online learning system. Therefore, the purpose of this study is to investigate the variables that influence university students' decision to use an online learning system.

Research Framework and Hypotheses Development

The Technology Acceptance Model was developed by Davis (1989) to explain how and when users will adopt and use new technology. This model investigates the users’ attitude and intention to adopt technology with perceived use and perceived ease of use along with the intervention of external factors (Figure 1).

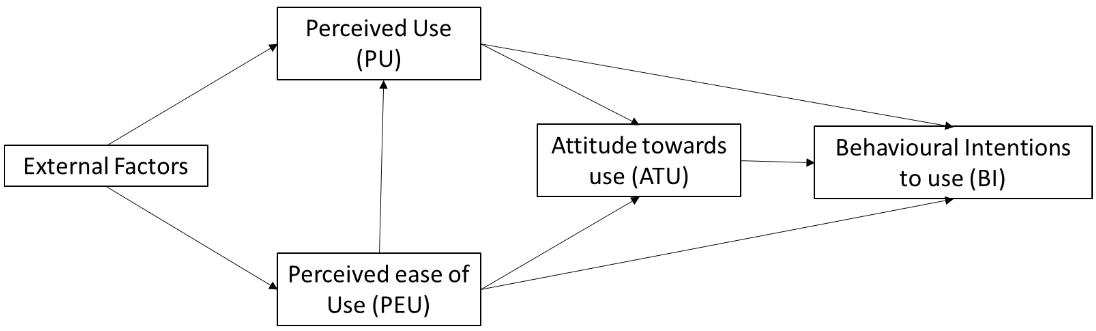

Figure 1: Technology Acceptance Model

External Factors influencing the Online learning & Hypothesis Formulation

Individual Characteristics

Computer Self-Efficacy (CSE): CSE refers to the “*individuals' beliefs about their abilities to competently use computers”* (Compeau & Higgins, 1995). Computer systems are linked to self-efficacy in this study and used as “the confidence exhibited by the users in their ability to use the online learning system”. CSE plays a key role in shaping an individual's feelings and behaviour (Compeau & Higgins, 1995). It is said that the task's likelihood of success increases with increasing efficacy expectations. Computer self-efficacy is found to have a substantial impact on the perceived usefulness and perceived ease of use of an online learning system in a variety of empirical research (Esteban-Millat et al., 2018; Mailizar, Burg, & Maulina, 2021; Park, 2009; Salloum et al., 2019; Sulistiyaningsih et al., 2014). Hence, we hypothesize the following:

H1a1: CSE has a positive effect on the PU of the online learning system.

H1a2: CSE has a positive effect on the PEU of the online learning system.

Perceived Enjoyment (PE): PE refers to the extent to which "*the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use*" (Venkatesh, 2000). PE is a crucial factor in the adoption or acceptance of online learning. PE has been shown in earlier studies (Abdullah & Ward, 2016; Chang et al., 2017; Hastuti et al., 2020; J. J. Kim, Yoon, & Kim, 2021; Md Lazim et al., 2021; Salloum et al., 2019; Siti et al., 2021) to have a substantial effect on PEU and PU of online learning. A student is more likely to have a favourable influence on the usefulness and usability of an online learning system when they realise that working on it is enjoyable. Hence, the following hypotheses were developed:

H2a1: PE has a positive effect on the PU of the online learning system.

H2a2: PE has a positive effect on the PEU of the online learning system.

Computer Playfulness (CP): CP refers to "*the degree of cognitive spontaneity in computer interactions*" (Webster & Martocchio, 1992). The term "playfulness" is used to describe ideas such as creativity, inquiry, discovery, exploration, curiosity, and difficulties (Venkatesh, 2000). The term refers to the fundamental drive behind utilising a new system. (Venkatesh & Bala, 2008). Many studies (e.g. Aguilera-Hermida et al., 2021; Ejdys, 2021; Esteban-Millat et al., 2018; Mailizar et al., 2021; Md Lazim et al., 2021; Park, 2009; Singh et al., 2020; Surani & Hamidah, 2020; Tarhini et al., 2014) suggested that perceived computer playfulness has a close link with PEU and PU. Therefore, the following hypotheses were developed:

H3a1: CP has a positive effect on the PU of the online learning system.

H3a2: CP has a positive effect on the PEU of the online learning system.

System Characteristics

In this study, the system characteristics comprise three factors viz. content quality (CQ), information quality (IQ), and system quality (SQ).

Content Quality (CQ): CQ about online learning signifies "*the depth and frequent updates of the content*"(Vululleh, 2018). It includes formatting, readability, and grammatical accuracy of the learning material received by the students from their teachers through the online learning system. Previous studies have shown that content quality has a considerable effect on PU (Sami Saeed Binyamin, Rutter, & Smith, 2019; Cheng, 2011; Mailizar et al., 2021; Park, 2009; Salloum et al., 2019; Salloum & Shaalan, 2018; Venkatesh & Bala, 2008) and there is a positive relationship between CQ and PEU of online learning system (Baki, Birgoren, & Aktepe, 2018; Cheng, 2011; Coman et al., 2020; Esteban-Millat et al., 2018; J. J. Kim et al., 2021; Lee et al., 2009; Md Lazim et al., 2021; Ritter, 2017; Saleem & Saleem, 2021; Schepers & Wetzels, 2007). As a result, the following hypotheses were developed:

H4b1: CQ has a positive effect on the PU of the online learning system.

H4b2: CQ has a positive effect on the PEU of the online learning system.

Information Quality (IQ): IQ refers to "*using online learning for seeking information that may be important for learning and which is updated, to make it easier for the learner to comprehend it*"(Cho, Cheng, & Lai, 2009). Information quality also refers to "the degree to which the user receives complete, precise and well-timed information over the electronic service interface" (Liu, Chen, Sun, Wible, & Kuo, 2010). The perceived ease of use was found to be significantly impacted by the quality of the information in earlier studies on online learning that extended the TAM (Abdullah & Ward, 2016; Almaiah et al., 2020; Alshurafat et al., 2021; Baki et al., 2018; Coman et al., 2020; Siti et al., 2021). Additionally, earlier studies discovered a correlation between IQ and the belief that an online learning system is effective. (Lai, 2017; Salloum et al., 2019; Salloum & Shaalan, 2018; Shah, Bhatti, Iftikhar, Qureshi, & Zaman, 2013). As a result, the following hypotheses were developed:

H5b1: IQ has a positive effect on the PU of the online learning system.

H5b2: IQ has a positive effect on the PEU of the online learning system.

System Quality (SQ): SQ in this study refers to the "*quality characteristics such as usability, reliability, availability, and adaptability associated with online learning*". SQ is critical to the adoption and use of an online learning system, according to prior studies. Previous studies discovered that SQ has a favourable effect on how simple people perceive online learning to be (Cheng, 2011; Park, 2009; Rym, Olfa, & Mélika, 2013; Shah et al., 2013; Venkatesh & Bala, 2008). Additionally, it was discovered that SQ has a favourable impact on how beneficial people view online learning (Mahmodi, 2017; Park, 2009). As a result, the following hypotheses were developed:

H6b1: SQ has a positive effect on the PU of the online learning system.

H6b2: SQ has a positive effect on the PEU of the online learning system.

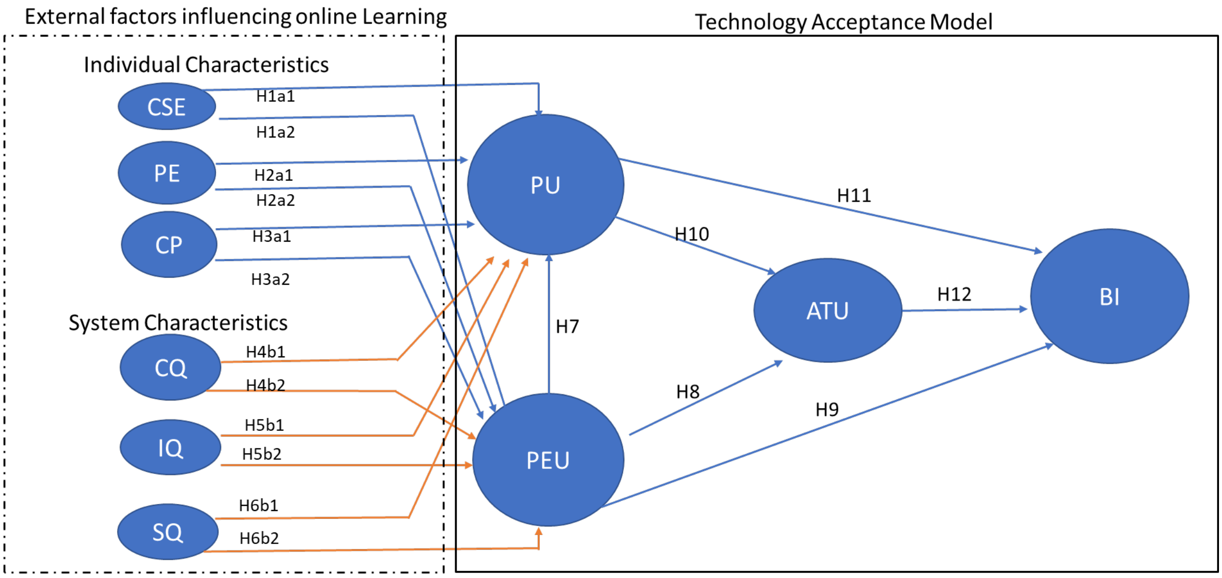

Figure 2: Research Model with the intervention of individual and system Characteristics

Technology Acceptance Model Constructs

The Technology Acceptance Model (Davis, 1989), which claims that perceived ease of use and perceived usefulness are two crucial factors that impact a person's intention to adopt new technology, is one of the most significant models of technology acceptance. The following is a detailed explanation of the hypothetical impact of the users' opinions based on the extended TAM (Figure 1):

Perceived Ease of Use (PEU): In the context of online learning, the PEU refers to "the degree to which a student perceives that the use of an online learning system would not be complicated" (Lin, Chen, & Fang, 2011). Previous studies confirmed that PEU significantly affects perceived usefulness (Abdullah & Ward, 2016; Sami S. Binyamin, Rutter, & Smith, 2019; Chang et al., 2017). It has been shown in several studies (e.g. Alharbi & Drew, 2014; J. J. Kim et al., 2021; Lai, 2017; Mailizar et al., 2021) carried out in the past that the PEU has a positive relationship with behavioural intention to use (BI), directly as well as indirectly (Alharbi & Drew, 2014). In addition, previous research indicated that there is a positive relationship between PEU and the attitudes toward using (ATU) online learning system (Hastuti et al., 2020; Lai, 2017; Md Lazim et al., 2021; Rizun & Strzelecki, 2020; Siti et al., 2021). Thus, based on the literature support on the relationship of PEU with PU, BI, and ATU, we hypothesize the following:

H7: PEU has a positive effect on the PU of the online learning system.

H8: PEU has a positive effect on the attitude towards the use (ATU) of the online learning system.

H9: PEU has a positive effect on the behavioural intention to use (BI) the online learning system

Perceived Usefulness (PU): According to Lin et al. (2011), PU refers to "the degree to which individuals believe that the use of online learning system support and improves their learning objectives". Students will only adopt the online learning system when they believe that using it would enhance their academic achievement. The idea is that an individual's positive attitude would be viewed as being higher the more valuable they believed the online learning system to be. The association between PU and the mindset for utilising online learning methods has substantial empirical backing (Hastuti et al., 2020; Lai, 2017; Md Lazim et al., 2021; Rizun & Strzelecki, 2020; Singh et al., 2020; Siti et al., 2021; Wong, 2016). Hence, the following hypothesis is developed:

H10: PU has a positive effect on the attitude toward using (ATU) the online learning system.

Previous online learning studies (e.g. (Alharbi & Drew, 2014; J. J. Kim et al., 2021; Lai, 2017; Mailizar et al., 2021) indicated that there is a significant positive correlation between PU and the behavioural intention to use the online learning system (BI). Hence, the following hypothesis is formulated:

H11: PU has a positive effect on the behavioural intention to use (BI) the online learning system.

Attitude Towards Use (ATU): Attitude refers to “the degree to which a person has a positive or negative feeling towards online learning systems”(Hussein, 2017). Numerous research have demonstrated that behaviour intention is directly impacted by attitude (Alharbi & Drew, 2014; Deshpande, Bhattacharya, & Yammiyavar, 2012; Lai, 2017; Mailizar et al., 2021). Hence, the following hypothesis is formulated:

H12: Attitude towards use (ATU) has a positive effect on the behavioural intention to use (BI) the online learning system.

Behavioural Intention (BI): Behavioural Intention (BI) is “*a cognitive process of individuals’ readiness to perform specific behaviour and is an immediate antecedent of usage behaviour*” (Abbasi et al., 2011). Behavioural intention (BI) is a term used to describe the learners' intention to utilise online learning systems, and it includes continued use in the present and the future (Liao & Lu, 2008). A system's or technology's success is mostly dependent on BI (Abdullah & Ward, 2016; Coman et al., 2020; Lee et al., 2009; Md Lazim et al., 2021; Tarhini et al., 2015).

Research Methodology

Research Design

We used a quantitative research design using a cross-sectional survey in this current study. This method was chosen because it is thought to be capable of producing reliable, valid, and generalizable results (Fraenkel et al., 2011).

Data Collection

Students enrolled in Sikkim's public and private universities, including Sikkim University, Sikkim Manipal University, Shri Ramasamy Memorial (SRM) University, ICFAI University, and Sikkim Professional University, make up the study's target group. Self-administrated surveys were given out to the students between the months of January through March 2021 in order to collect the data. The information from the undergraduate, graduate, and PhD students was gathered using an online survey including questionnaires. The convenience of an online survey and its compatibility with various devices made it the chosen method (Fraenkel, Wallen, & Hyun, 2011). During the pandemic, the students were approached through a message on WhatsApp to be shared among the students' group with a link to the questionnaire. The questionnaire survey remained open for two-three months. A total of 534 responses were received and the data analysis was performed on 506 valid cases after data cleaning. The details of the responses received are given in Table 1.

Table 1: Participants' Details

Variables	Categories	Count	Column N %
Institution	Sikkim University	331	65.4%
	Sikkim Manipal University	111	21.9%
	SRM University, Sikkim	17	3.4%
	ICFAI University, Sikkim	27	5.3%
	Sikkim Professional University	20	4.0%
	Total	506	100.0%
Type	Public	331	65.4%
	Private	175	34.6%
	Total	506	100.0%
Education	UG	262	51.8%
	PG	244	48.2%
	Total	506	100.0%
Gender	Male	177	35.0%
	Female	329	65.0%
	Total	506	100.0%

Study Instrument
A survey tool was created in order to test the research's hypothesis. The survey was divided into two parts. The participants' basic information, such as their university, level of education, gender, and age, was covered in the first portion. The items pertaining to the use of the online learning system are included in the second section. A five-point Likert scale was used to score the items in the second portion, with 1 denoting "strongly disagree" and 5 denoting "strongly agree." To measure the ten components in the research model, the survey instrument had 45 items. The sources of these constructs are shown in Table 2. The items from the earlier studies were modified to make them consistent with the requirements of the current study.

Tools for Data Analysis
To examine the created proposed technology acceptance model for students' acceptance of online learning, we use the Partial Least Squares-Structural Equation Modelling (PLS-SEM) approach. The PLS-SEM is used to evaluate the measurement and structural models in this study. The fact that PLS-SEM allows contemporaneous analysis for both measurement and structural model, which leads to more accurate estimations, was the reason for its adoption in this study.

Table 2: Constructs, Items, and Sources of Scale

Construct	No. of items	Source
Attitude towards use (ATU)	4	(Hastuti et al., 2020; Hussein, 2017; Lai, 2017; Md Lazim et al., 2021; Rizun & Strzelecki, 2020; Singh et al., 2020; Siti et al., 2021)
Behavioural Intention to use (BI)	4	(Abbasi, Chandio, Soomro, & Shah, 2011; Alharbi & Drew, 2014; Deshpande et al., 2012; J. J. Kim et al., 2021; Lai, 2017; Mailizar et al., 2021)
Perceived Usefulness (PU)	4	(Abbasi et al., 2011; Alharbi & Drew, 2014; Davis & Venkatesh, 1996; Farahat, 2012; Hastuti et al., 2020; Siti et al., 2021)
Perceived Ease of Use (PEU)	4	(Abdullah & Ward, 2016; Farahat, 2012; J. J. Kim et al., 2021; Lai, 2017; Lin et al., 2011; Venkatesh & Bala, 2008)
Computer Self-efficacy (CSE)	5	(Chang et al., 2017; Ejdys, 2021; Rizun & Strzelecki, 2020; Salloum et al., 2019; Salloum & Shaalan, 2018; Venkatesh, 2000)
Perceived Enjoyment (PE)	4	(Chang et al., 2017; Lai, 2017; Rizun & Strzelecki, 2020; Salloum & Shaalan, 2018; Wang, Lew, Lau, & Leow, 2019)
Computer Playfulness (CP)	5	(Salloum et al., 2019; Salloum & Shaalan, 2018; Venkatesh, 2000; Webster & Martocchio, 1992)
Content Quality (CQ)	5	(Sami Saeed Binyamin et al., 2019; Hastuti et al., 2020; Salloum et al., 2019; Salloum & Shaalan, 2018)
Information Quality (IQ)	5	(Roca, Chiu, & Martínez, 2006; Salloum et al., 2019; Salloum & Shaalan, 2018; Shah et al., 2013)
System Quality (SQ)	5	(Mailizar et al., 2021; Roca et al., 2006; Salloum et al., 2019; Shah et al., 2013)

Results
Measurement Model Evaluation
For the measurement of attitude, perception, intents, etc. in the behavioural sciences, there are two types of validities that are necessary: convergent validity and discriminant validity (Hair, Risher, Sarstedt, & Ringle, 2019). The sections below address these concerns:

Convergent Validity
When assessing the convergent validity of a reflective scale, various measures must be considered. These metrics include Cronbach's alpha, composite reliability (CR), factor loading of the construct's individual items, and average extracted variance (AVE). Cronbach's alpha should be set to 0.7 to check the construct's items' internal consistency (Hair et al., 2019). Here, one CSE2 item reported that the Cronbach's alpha was smaller than recommended (alpha=0.659), hence it was removed from the CSE construct. Additionally, the values of the factor loadings and composite reliability should be equal to or greater than 0.7 to establish the convergent validity of the constructs, while the values of the AVE must be greater than 0.5 to be accepted (J. F. Hair, Risher, Sarstedt, & Ringle, 2019). The convergent validity results are displayed in Table 3. The loadings for the measurement items were shown in

this study to be higher than the suggested value. Additionally, it was shown that the composite reliability (CR), Cronbach's alpha, and AVE values were higher than suggested. This confirms the convergent validity.

Table 3: Convergent Validity Results

Constructs	Items	Factor loading	Cronbach Alpha	CR	AVE
Attitude toward use (ATU)	ATU1	0.813	0.831	0.888	0.664
	ATU2	0.778			
	ATU3	0.803			
	ATU4	0.864			
Behavioural Intentions to use (BI)	BI1	0.802	0.825	0.884	0.656
	BI2	0.762			
	BI3	0.831			
	BI4	0.843			
Computer playfulness (CP)	CP1	0.757	0.846	0.890	0.620
	CP2	0.741			
	CP3	0.828			
	CP4	0.833			
	CP5	0.772			
Content Quality (CQ)	CQ1	0.789	0.838	0.885	0.607
	CQ2	0.744			
	CQ3	0.804			
	CQ4	0.784			
	CQ5	0.773			
Computer self-efficacy (CSE)	CSE1	0.730	0.830	0.887	0.664
	CSE3	0.825			
	CSE4	0.847			
	CSE5	0.851			
Information Quality (IQ)	IQ1	0.765	0.845	0.890	0.618
	IQ2	0.794			
	IQ3	0.827			
	IQ4	0.780			
	IQ5	0.761			
Perceived Enjoyment (PE)	PE1	0.770	0.815	0.878	0.642
	PE2	0.800			
	PE3	0.832			
	PE4	0.803			
Perceived ease of use (PEU)	PEU1	0.799	0.787	0.862	0.611
	PEU2	0.731			
	PEU3	0.751			
	PEU4	0.842			
Perceived usefulness (PU)	PU1	0.846	0.860	0.905	0.704
	PU2	0.834			
	PU3	0.825			
	PU4	0.850			
System quality (SQ)	SQ1	0.842	0.910	0.933	0.736
	SQ2	0.835			
	SQ3	0.878			
	SQ4	0.859			
	SQ5	0.876			

Discriminant Validity

Discriminant validity is the extent to which one construct differs from all other constructs in the study model (Ketchen, 2013). The Fornell-Larcker criterion and Cross-Loadings are the two measures we utilised to determine the discriminant validity. As shown in Table 4, the present study satisfies the Fornell-Larcker criterion for discriminant validity, which states that each construct's square root of AVE (diagonal value) in the correlation matrix should be greater than the correlation of latent constructs.

Table 4: Fornell-Larcker criterion for Discriminant Validity

	ATU	BI	CP	CQ	CSE	IQ	PE	PEU	PU	SQ
ATU	**0.815**									
BI	0.777	**0.810**								
CP	0.721	0.719	**0.787**							
CQ	0.566	0.601	0.634	**0.779**						
CSE	0.592	0.587	0.668	0.680	**0.815**					
IQ	0.628	0.629	0.664	0.761	0.662	**0.786**				
PE	0.636	0.632	0.757	0.684	0.621	0.723	**0.802**			
PEU	0.609	0.573	0.635	0.640	0.679	0.742	0.699	**0.782**		
PU	0.649	0.612	0.723	0.670	0.645	0.712	0.712	0.754	**0.839**	
SQ	0.689	0.624	0.694	0.616	0.637	0.668	0.694	0.748	0.783	**0.858**

As another measure to check the discriminant validity, we examined the cross-loadings of the items with the constructs. According to Hair et al. (2014), an item's outer loadings on a construct should be higher than all its cross-loadings with other constructs. Table 5 presents the results of cross-loading of the items on the latent constructs. The items in the respective construct showed no cross-loading with other constructs, hence confirming the discriminant validity of the constructs.

Table 5: Cross-Loading Results

	ATU	BI	CP	CQ	CSE	IQ	PE	PEU	PU	SQ
ATU1	**0.813**	0.621	0.538	0.501	0.485	0.505	0.480	0.483	0.526	0.553
ATU2	**0.778**	0.577	0.532	0.452	0.474	0.500	0.526	0.474	0.486	0.492
ATU3	**0.803**	0.631	0.624	0.427	0.473	0.512	0.513	0.497	0.557	0.587
ATU4	**0.864**	0.697	0.648	0.467	0.498	0.531	0.556	0.528	0.544	0.609
BI1	0.662	**0.802**	0.601	0.486	0.484	0.538	0.541	0.528	0.536	0.542
BI2	0.575	**0.762**	0.483	0.494	0.453	0.484	0.447	0.408	0.419	0.421
BI3	0.656	**0.831**	0.605	0.474	0.455	0.482	0.519	0.448	0.510	0.533
BI4	0.617	**0.843**	0.631	0.496	0.510	0.532	0.534	0.465	0.509	0.516
CP1	0.519	0.592	**0.757**	0.512	0.511	0.482	0.542	0.487	0.546	0.527
CP2	0.547	0.561	**0.741**	0.448	0.477	0.483	0.607	0.475	0.496	0.485
CP3	0.612	0.598	**0.828**	0.460	0.526	0.502	0.610	0.488	0.582	0.564
CP4	0.615	0.574	**0.833**	0.534	0.550	0.572	0.629	0.530	0.626	0.577
CP5	0.540	0.510	**0.772**	0.535	0.560	0.567	0.592	0.514	0.586	0.569
CQ1	0.408	0.430	0.464	**0.789**	0.533	0.600	0.499	0.462	0.467	0.460
CQ2	0.385	0.420	0.422	**0.744**	0.487	0.572	0.450	0.493	0.498	0.494
CQ3	0.530	0.552	0.622	**0.804**	0.567	0.659	0.638	0.573	0.606	0.543
CQ4	0.426	0.489	0.465	**0.784**	0.547	0.554	0.523	0.488	0.561	0.471
CQ5	0.440	0.431	0.471	**0.773**	0.510	0.570	0.537	0.462	0.454	0.418
CSE1	0.431	0.438	0.556	0.510	**0.730**	0.505	0.462	0.470	0.482	0.430
CSE3	0.443	0.460	0.495	0.532	**0.825**	0.505	0.491	0.536	0.492	0.479
CSE4	0.505	0.458	0.535	0.556	**0.847**	0.557	0.531	0.593	0.553	0.563

CSE5	0.540	0.553	0.592	0.614	**0.851**	0.586	0.535	0.603	0.569	0.590
IQ1	0.509	0.519	0.511	0.666	0.528	**0.765**	0.580	0.562	0.594	0.538
IQ2	0.467	0.454	0.505	0.608	0.530	**0.794**	0.532	0.544	0.518	0.502
IQ3	0.507	0.519	0.552	0.619	0.538	**0.827**	0.624	0.613	0.578	0.515
IQ4	0.475	0.472	0.517	0.564	0.501	**0.780**	0.544	0.579	0.543	0.518
IQ5	0.506	0.502	0.521	0.533	0.505	**0.761**	0.553	0.612	0.559	0.549
PE1	0.440	0.449	0.519	0.476	0.445	0.497	**0.770**	0.512	0.464	0.481
PE2	0.542	0.493	0.630	0.556	0.479	0.605	**0.800**	0.539	0.574	0.551
PE3	0.543	0.563	0.645	0.512	0.499	0.571	**0.832**	0.581	0.610	0.602
PE4	0.507	0.512	0.622	0.638	0.560	0.632	**0.803**	0.600	0.618	0.579
PEU1	0.507	0.471	0.560	0.513	0.546	0.650	0.622	**0.799**	0.651	0.632
PEU2	0.403	0.395	0.436	0.516	0.550	0.528	0.533	**0.731**	0.489	0.483
PEU3	0.472	0.440	0.446	0.445	0.444	0.522	0.480	**0.751**	0.524	0.546
PEU4	0.512	0.479	0.531	0.530	0.582	0.609	0.546	**0.842**	0.672	0.659
PU1	0.561	0.520	0.649	0.552	0.557	0.614	0.627	0.672	**0.846**	0.684
PU2	0.523	0.459	0.558	0.550	0.530	0.586	0.586	0.613	**0.834**	0.628
PU3	0.509	0.499	0.605	0.513	0.518	0.551	0.558	0.610	**0.825**	0.653
PU4	0.580	0.569	0.613	0.629	0.560	0.634	0.616	0.633	**0.850**	0.663
SQ1	0.571	0.507	0.571	0.510	0.481	0.537	0.561	0.597	0.668	**0.842**
SQ2	0.544	0.512	0.544	0.517	0.521	0.517	0.558	0.589	0.646	**0.835**
SQ3	0.584	0.520	0.611	0.509	0.564	0.580	0.590	0.666	0.675	**0.878**
SQ4	0.608	0.543	0.601	0.549	0.579	0.617	0.619	0.671	0.661	**0.859**
SQ5	0.644	0.590	0.642	0.558	0.583	0.610	0.645	0.681	0.710	**0.876**

Structural Model Evaluation
The key criteria for assessing the structural model in PLS-SEM are the collinearity diagnostics, the significance of the path coefficients, the level of the R^2 values, the f^2 effect size, and the predictive relevance (Q^2) (Hair et al., 2019). The collinearity statistics are presented in Table 6. Each predictor construct's variance inflation factor (VIF) value is higher than 0.20 and lower than 5 as suggested by (Hair et al., 2014), hence there is no problem with lateral multicollinearity among the constructs.

Path Coefficients and t-statistics
The results of path coefficients and coefficients of determination (R^2) are shown in Figure 2. Among the individual characteristics, the path coefficients of CSE→PU and CP→PEU were negative i.e., -0.005 and -0.065 respectively whereas CQ among system characteristics was negatively related to PEU with a path coefficient of -0.031. All the constructs of the TAM model showed positive path coefficients. We have used bootstrapping to assess the significance of path coefficients. The path coefficients and their t-statistics for a one-tailed t-test at a 5% level of significance are shown in Table 6. The path coefficient of CSE→PU (β= -0.005, t-value=0.095) and PE→PU (β=0.050, t-value=0.940); and CP→PEU (β=-0.065, t-value=1.270) are not significant (t-value <1.645) among individual characteristics. Among the system characteristics, the path coefficients of CQ→PEU (β= -0.031, t-value=0.626) and IQ→PU (β=0.083, t-value=1.416) are not statistically significant at 5% level of significance. Having a t-value <1.645 for a significant level of 5% (α = 0.05) in the one-tailed test indicates that CSE, PE, and IQ do not significantly affect PU; and CP and CQ do not significantly affect PEU.

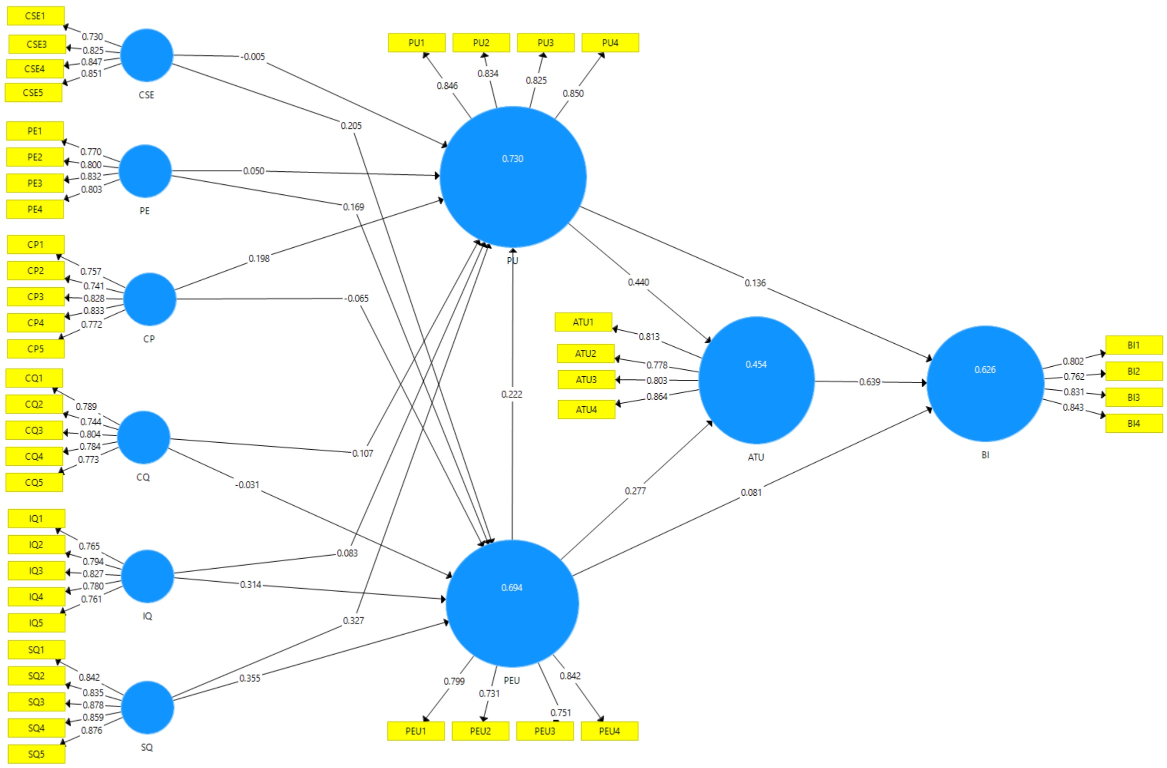

Figure 3: Path coefficients and R^2 of Extended TAM

While examining the effect of individual and systems characteristics on PU as an endogenous construct in the structural model, Fig. 2 shows that R^2 is 0.730, indicating that the PEU, individual characteristics (CSE, PE, and CP) and system characteristics (CQ, IQ, and SQ) together explain 73.0% of the variance in PU. Among the individual characteristics, CP (β = 0.198, t-value = 4.079) is the strongest predictor of PU whereas CSE and PE are not. This shows that our hypothesis H3a1 is supported whereas H1a1 and H2a1 are not.

Table 6: Collinearity, Path coefficients, t-statistics and Effect Size of Exogenous constructs

Hypothesis	Relationship	VIF	Original Sample β	Standard Deviation	t-statistics	Effect size (f^2)
H1a1	CSE → PU	2.546	-0.005	0.052	0.092	0.000
H1a2	CSE →PEU	2.409	0.205	0.047	4.386	0.057
H2a1	PE → PU	3.281	0.050	0.053	0.940	0.003
H2a2	PE → PEU	3.188	0.169	0.055	3.091	0.029
H3a1	CP → PU	2.973	0.198	0.049	4.079	0.049
H3a1	CP → PEU	2.959	-0.065	0.051	1.270	0.005
H4b1	CQ → PU	2.889	0.107	0.050	2.142	0.015
H4b2	CQ → PEU	2.886	-0.031	0.050	0.626	0.001
H5b1	IQ → PU	3.481	0.083	0.058	1.416	0.007
H5b2	IQ → PEU	2.546	0.314	0.062	5.077	0.102
H6b1	SQ → PU	2.888	0.327	0.068	4.798	0.138
H6b2	SQ → PEU	2.476	0.355	0.054	6.604	0.166
H7	PEU → PU	3.273	0.222	0.058	3.823	0.056
H8	PEU →ATU	2.317	0.277	0.061	4.513	0.061
H9	PEU → BI	2.457	0.081	0.050	1.733	0.007
H10	PU → ATU	2.317	0.440	0.057	7.677	0.153
H11	PU → BI	2.671	0.136	0.055	2.490	0.019
H12	ATU → BI	1.831	0.639	0.042	15.297	0.596

The model reveals that SQ is the strongest predictor of PU (β = 0.327, t-value = 4.798) followed by CQ (β = 0.107, t-value = 2.142) among the system characteristics whereas IQ (β = 0.083, t-value = 1.416) does not contribute significantly. This implies that our hypotheses H5a1 and H6a1 of positive relationship with PU were supported whereas H4a1 was not. From the TAM constructs, PEU (β = 0.222, t-value = 3.823) is the significant predictor of PU, meaning thereby, supporting our H7 hypothesis. This confirms that PEU from TAM, CP from individual characteristics; and SQ and CQ from System characteristics have a strong positive relationship with PU.

Regarding PEU as an endogenous construct, the R^2 is 0.6944 as shown in Table 7, indicating that Individual characteristics (CSE, PE, and CP) and system characteristics (CQ, IQ, and SQ) together explain 69.44% of the variance in PEU. Among the individual characteristics, CSE (β = 0.205, t-value = 4.386) is the strongest predictor of PEU followed by PE (β = 0.169, t-value = 3.091) whereas CP (β = -0.065, t-value = 1.270) is not. This implied that our hypotheses (H1a2 and H2a2) of CSE and PE having a positive relationship with PEU were supported whereas H3a2 was not supported. On the other hand, among the system characteristics, SQ (β = 0.355, t-value = 6.604) is the strongest predictor of PEU followed by IQ (β = 0.314, t-value = 5.077). CQ (β = -0.031, t-value = 0.626) is negatively related to PEU and does not contribute significantly to predicting the PEU. This indicated that the hypotheses H5b2 and H6b2 of IQ and SQ having a positive relationship with PEU were supported whereas H4b2 was not supported. This confirms that CSE & PE from individual characteristics and SQ & IQ from system characteristics have a strong and significant positive relationship with PEU.

To examine the predictive accuracy of the model, Fig. 2, shows that R^2 is 0.625 for BI. This indicates that the three exogenous constructs (PU, PEU, and ATU) explain 62.5% of the variance in BI. The inner model shows that ATU is the only strongest predictor of BI (β = 0.639, t-value = 15.297) followed by PU (β = 0.136, t-value = 2.490) and PEU (β = 0.081, t-value = 1.617, p value=0.053). This supports our hypotheses H10, H11, and H12. Having a t-value >1.645 for a significant level of 5% (α = 0.05) in the one-tailed test indicates that PU, PEU, and ATU possess a strong positive relationship with BI.

As an endogenous construct, the model identifies ATU as having an R^2 of 0.453. This means that the variance in ATU is explained by the two constructs (PEU and PU) to the extent of 45.3%. The model also shows that PEU is the second-strongest predictor of ATU, coming in at 0.277, t-value 4.513, and PU at 0.440, t-value 7.677. We can conclude that PU and PEU had a significant relationship with ATU based on the fact that our hypotheses H8 and H9 are supported by t-values > 1.645 for a significant level of 5 percent in the one-tailed test.

Coefficient of Determination (R^2), Predictive Relevance (Q^2), and Effect Size (f^2)

The coefficient of determination (R^2) measure denotes the model's predictive power and the amount of variance in the endogenous constructs that is explained by each associated exogenous construct (Hair et al., 2014). Chin (1998) asserts that the R2 value is regarded as "strong" when it exceeds 0.67, "moderate" when it falls between 0.33 and 0.67, and "poor" when it falls between 0.19 and 0.33.

As shown in Table 7, the R^2 values for the attitude towards use (ATU), and behavioural intention to use (BI), were found to be moderate (between 0.33 and 0.67); and PEU and PU were found to be high (more than 0.67).

Table 7: R^2 of the endogenous latent variables

Constructs	R^2	R^2Adjusted	Predictive Accuracy	Predictive Relevance (Q^2)
ATU	0.45391	0.45174	Moderate	0.296
BI	0.62595	0.62372	Moderate	0.403
PEU	0.69445	0.69078	High	0.414
PU	0.73007	0.72628	High	0.505

To assess the predictive relevance of endogenous constructs, we used blindfolding with default omission distance (7) to obtain cross-validated redundancy measures for each endogenous construct. As shown in Table 7, the resulting Q^2 values larger than 0 indicate that the exogenous constructs have predictive relevance for the endogenous construct under consideration.

Moreover, to evaluate the effect size of individual and system characteristics on PU and PEU; and of PEU & PU on ATU and BI, we used Cohen's f^2 (Cohen, 2013). The effect size f^2 enables determining the contribution of an external construct to the R^2 value of an endogenous latent variable. The exogenous construct's influence on the endogenous construct is indicated by the f^2 values of 0.02, 0.15, and 0.35, respectively. The effect of SQ→PEU and PU→ATU was small whereas the effect of ATU→BI was large. The effects of the remaining exogenous constructs on PU, PEU, ATU, and BI were small as shown in Table 6.

Discussion

The current study aims to assess characteristics that influence university students' behavioural intention to accept online learning with the intervention of individual and system-specific characteristics. This study differs from others in that it looked at students at public and private universities in a developing country where online learning was not widely used before the COVID-19 outbreak. As a result, further research is needed into this topic to have a better knowledge of the elements that influence student acceptance of online learning. We used the TAM model (Davis et al., 1989) to investigate this issue, which included external elements such as individual characteristics and online learning system-specific characteristics.

The hypotheses related to TAM and the external factors (individual and system characteristics) were examined and the results are presented in Table 8. This study shows four important points of discussion. First, Perceived usefulness (PU) is significantly affected by computer playfulness (CP) from individual characteristics; and by the content quality (CQ) and system quality (SQ) from the system characteristics of online learning. This finding supports the existing literature.

Table 8: Results of Hypotheses testing

Hypothesis	Effect	Hypothesized Relation	Path coefficient	p Values	Decision
H1a1	CSE → PU	Positive	-0.005	0.463	Not supported
H1a2	CSE →PEU	Positive	0.205	0.000	Supported
H2a1	PE → PU	Positive	0.050	0.174	Not supported
H2a2	PE → PEU	Positive	0.169	0.001	Supported
H3a1	CP → PU	Positive	0.198	0.000	Supported
H3a1	CP → PEU	Positive	-0.065	0.102	Not supported
H4b1	CQ → PU	Positive	0.107	0.016	Supported
H4b2	CQ → PEU	Positive	-0.031	0.266	Not supported
H5b1	IQ → PU	Positive	0.083	0.079	Not supported
H5b2	IQ → PEU	Positive	0.314	0.000	Supported
H6b1	SQ → PU	Positive	0.327	0.000	Supported
H6b2	SQ → PEU	Positive	0.355	0.000	Supported
H7	PEU → PU	Positive	0.222	0.000	Supported
H8	PEU → ATU	Positive	0.277	0.000	Supported
H9	PEU → BI	Positive	0.081	0.042	Supported
H10	PU → ATU	Positive	0.440	0.000	Supported
H11	PU → BI	Positive	0.136	0.007	Supported
H12	ATU → BI	Positive	0.639	0.000	Supported

However, among the individual characteristics of the students, their Computer Self-efficacy (CSE) and Perceived enjoyment (PE); and information quality (IQ) among system characteristics did not significantly affect PU. This finding contradicts the previous studies that showed CSE, PE and IQ have a positive impact on users' PU of online learning (Abdullah & Ward, 2016; Chang et al., 2017; Ejdys, 2021; J. J. Kim et al., 2021; Rizun & Strzelecki, 2020; Salloum et al., 2019; Salloum & Shaalan, 2018; Venkatesh, 2000; Wang et al., 2019). However, there are pieces of evidence in the extant body of knowledge that indicated that CSE and PE do not have a significant impact on PU of online learning. For instance, Binyamin, Rutter, & Smith, (2018) and Thakkar & Joshi (2018) found that individuals' CSE does not significantly affect the PU of the online learning system. Maheshwari (2021) argued that although PE has a significant positive relationship with PU, PE is affected by ICT infrastructure and internet speed and access, which indirectly influences students' intentions to learn online. Furthermore, the impact of information quality (IQ) on PU is fully mediated by the ICT infrastructure and service delivery quality of the online learning system (Alsabawy, Cater-Steel, & Soar, 2016). Therefore, universities must be aware of the crucial influence of ICT infrastructure services and examine how investing in these services might improve online learning system and information quality, as well as online learning systems' perceived usefulness.

Table 9: Total Indirect effects of individual and system characteristics on ATU & BI

Indirect path	Sample mean	Standard Deviation	T Statistics	P Values
CP → ATU	0.064	0.031	2.063	0.020
CP → BI	0.061	0.029	2.068	0.020
CP → PU	-0.013	0.011	1.257	0.105
CQ → ATU	0.036	0.032	1.117	0.132
CQ → BI	0.035	0.030	1.115	0.133

CQ → PU	-0.006	0.012	0.566	0.286
CSE → ATU	0.074	0.030	2.505	0.006
CSE → BI	0.069	0.028	2.530	0.006
CSE → PU	0.044	0.016	2.802	0.003
IQ → ATU	0.150	0.035	4.402	0.000
IQ → BI	0.141	0.034	4.241	0.000
IQ → PU	0.067	0.023	3.033	0.001
PE → ATU	0.086	0.031	2.710	0.003
PE → BI	0.081	0.029	2.778	0.003
PE → PU	0.037	0.017	2.255	0.012
PEU → ATU	0.095	0.027	3.641	0.000
PEU → BI	0.265	0.043	6.306	0.000
PU → BI	0.280	0.037	7.569	0.000
SQ → ATU	0.278	0.044	6.257	0.000
SQ → BI	0.262	0.043	6.032	0.000
SQ → PU	0.076	0.020	3.848	0.000

Second, CSE, PE from individual characteristics, and IQ and SQ from system characteristics showed a significant positive effect on PEU which is also supported by many studies (Abdullah & Ward, 2016; Chang et al., 2017; Esteban-Millat et al., 2018; Hastuti et al., 2020; J. J. Kim et al., 2021; Mailizar et al., 2021; Md Lazim et al., 2021; Park, 2009; Salloum et al., 2019; Siti et al., 2021; Sulistiyaningsih et al., 2014). However, our study revealed that CP from individual characteristics and CQ from system characteristics do not significantly affect the PEU of the online learning system. This finding is also not in line with the mainstream literature regarding the acceptance of online learning that indicates a significant influence of CP on PEU (Ejdys, 2021; Lai, 2017; Wang et al., 2019). Although computer playfulness (CP) is expected to have a significant impact on PEU, our findings show that CP does not affect the perceived ease of use of an online learning system, implying that university students were unable to achieve an acceptable level of intrinsic motivation while learning online during the COVID-19 pandemic. As a result, our study also confirms the findings of Al-Gahtani (2016) who suggested that students perceive the online learning system as difficult and complicated because it lacks the fun that would ordinarily encourage them to consider it as easy to use. Furthermore, CQ also does not affect the students' perceived ease of use of online learning. This may be due to less importance or the non-existence of online learning systems in most of the universities before the COVID-19 pandemic. A sudden switch from the traditional classroom system to online learning also puzzled the teachers and this had an impact on developing the quality of content for their course. Therefore, this finding is important in terms of enhancing the content quality so that the online learning system can be perceived by the students as easy to use.

Third, this study reveals that perceptions of ease of use and usefulness had a substantial impact on participants' attitudes toward utilising online learning (ATU) and behavioural intentions (BI) of acceptance of it. Additionally, the best predictor of ATU and BI was PU. This result supports our hypothesis that PEU and PU of online learning greatly influenced students' attitudes and behavioural intentions toward using it. Additionally, prior research has demonstrated the significance of PU and PEU on attitudes toward using online learning (Abdullah & Ward, 2016; Alsabawy et al., 2016; Alshurafat et al., 2021; Salloum et al., 2019; Siti et al., 2021; Vululleh, 2018; Wang et al., 2019).

Fourth, while examining the total indirect effect of the exogenous constructs on ATU and BI of acceptance of online learning (Table 9), this study revealed that individual characteristics (CSE, PE, and CP) and system characteristics (IQ and SQ) have a significant effect on ATU & BI of using online learning system. Accordingly, this finding agrees with our prediction that CSE, PE, CP, SQ, IQ PEU, and PU of online learning significantly affected students' attitudes and behavioural intentions towards accepting online learning. However, CQ from system characteristics did not show any significant impact on ATU & BI which is in contrast to the studies that support the significant effect of CQ on attitude and intentions to use online learning (Sami Saeed Binyamin et al., 2019; Hastuti et al., 2020; Lin et al., 2011; Salloum et al., 2019; Salloum & Shaalan, 2018). While examining the direct effect, we also found that the perception of students towards the quality of content is negatively related to the perceived ease of use and does not affect PEU significantly (Table 9). This finding is an important contribution of the present study in terms of alarming the policymakers to focus more on enhancing the quality of content developed for online learning and delivered by the faculty members in the universities.

Concluding Remark

This study suggests a paradigm for analysing attitudes toward and plans for implementing online learning among university students. The technology acceptance model (TAM) was used for analysis, with system (content quality, information quality, and system quality) and individual (computer self-efficacy, perceived enjoyment, and computer playfulness) characteristics included as external constructs. The suggested theoretical model successfully explains university students' behavioural intention to use the online learning system ($R^2 = 0.623$). The findings suggested that perceived enjoyment and system quality strongly affected students' perceived usefulness and perceived ease of use of online learning. On the other hand, computer self-efficacy, computer playfulness among individual characteristics; and content quality & information quality characteristics of online learning system do not significantly affect the perceived use and perceived ease of use of online learning system. Further, the content quality does not affect the attitude and intentions of using an online learning system. The insignificant impact of these individual and system characteristics on students' intention to use online learning may signify a shift in the thinking paradigm among skilled students and tech-savvy with digital technologies (Gan & Balakrishnan, 2018; Mailizar et al., 2021). Another reason may be that the students were left with no choice except to online learning during the COVID-19 pandemic. In such circumstances, when students did not have any other choice, perceived usefulness, perceived ease of use and content quality of online learning might become less important factors for them in accepting the use of online learning. This study also demonstrated that students' perceptions of the usability and simplicity of online learning had a substantial impact on their attitudes. We draw the conclusion that the quality of the online learning system is essential to ensuring the long-term viability of online learning during the epidemic and beyond. Universities must therefore continue to enhance the quality of the online learning system.

This study had several restrictions. First, because convenience sampling was used, the sampling was limited to only the students of Sikkim's public and private universities. Therefore, it is advised that future research concentrate on gathering samples from many other states (plain places where network connectivity is not a problem) in order to make the findings more applicable to other contexts. Second, the study carried out a survey, but the information was gathered during a pandemic by distributing the links. During the COVID-19 pandemic, online learning may have been the sole emergency management tool that allowed for the continuation of teaching and learning even in the absence of a well-established ICT infrastructure. As a result, qualitative research methodologies may be used in future to examine the intentions to adopt online learning post-COVID-19.

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