pISSN: 1906 - 3296 © 2020 AU-GSB e-Journal.
eISSN: 2773 – 868x © 2021 AU-GSB e-Journal.
http://www.assumptionjournal.au.edu/index.php/AU-GSB/index

Exploring The Affecting Factors of Behavioral Intention to Use Virtual Reality for Dynamic Learning: A Study of Top Three Private Universities in Yangon, Myanmar

Nang Winter Long Queau*

Received: January 24, 2024. Revised: March 2, 2024. Accepted: February 22, 2025.

Abstract

Purpose: This research aims to examine the factors affecting the students' behavioral intentions towards using virtual reality technology in replacing online learning/eLearning platforms to better engage in dynamic learning with the studies and improve their learning journey. The key variables are performance expectancy, perceived usefulness, perceived enjoyment, effort expectancy, social influence, perceived ease of use, hedonic motivation, attitude toward technology, and behavioral intention. **Research design, data, and methodology:** The quantitative questionnaire survey was provided to the target population of 500 students who are currently attending or have been attending the selected top three private universities of Yangon, Myanmar. The sampling techniques involve judgmental, snowball, quota, and convenience. Confirmatory factor analysis (CFA) and structural equation modeling were applied to analyze the data. **Results:** Perceived enjoyment has a significant effect on perceived usefulness, and attitude toward technology using VR. Effort expectancy Hedonic motivation and social influence significantly affect behavioral intention to use VR. However, there are no significant support between the relationship between performance expectancy, perceived usefulness, attitude toward technology using, perceived ease of use and behavioral intention to use VR. **Conclusion:** From the studies, the researcher can indicate that using new technology is useful and enjoyable for the users/students.

Keywords : Performance Expectancy, Effort Expectancy, Social Influence, Behavioral Intention, Virtual Reality

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Technology is very important in every sector and is more widely used in the 21st century (Ratheeswari, 2018). As for the education sector, Raja and Nagasubramani (2018) mentioned that normally, there are no original links for online learning, and educators only provide information from their official education websites. The pandemic in 2019 forced all sectors, not only education but also other sectors, to change to the new way, online platforms, to continue their current activities (Mpungose, 2021). Lecturers' reflections on use of Zoom video conferencing technology for e-learning at a South African university in the context of coronavirus. From these changes, the education sector became used to online learning platforms using Zoom/Skype/Google Classroom applications. Some educators also believe technology can improve education quality and enhance students' learning styles.

Among many popular technology tools which are mentioned in the article of Domingo and Gargante (2016), there are famous (5) technological application tools which are Artificial Intelligence (AI), Learning Management Systems (LMS), Augmented Reality (AR), Virtual Reality (VR), and Blockchain Technology. The application of AI in education to minimize wasting time and having chatbots to answer all the questions from the students in a short time. Using LMS is so common, and every kind of education becomes fond of using this system in their education sector;

1*Nang Winter Long Queau, Ph.D. Candidate in Innovative Technology Management, Graduate School of Business and Advance Technology Management, Assumption University, Thailand. Email: nwinterlq96@gmail.com

moreover, both students and tutors like to use this kind of system; hence, tutors can track their students' activity, and students can learn and do online assessments from this system. AR and VR are famous in medicine, engineering, physical activity, and studies. The last one, Blockchain technology, is kind of very new to the education industry, and so far, there is no exact record of using this technology in education.

Using technology in the education industry will increase learning activity effectively; hence, the provided study program will be more digitalized, and there is no limitation for accessing the learning materials, which means students can learn and study anywhere and anytime. What are the advantages of switching to online learning by applying modernized technology in education (Solano et al., 2017).

The integration of virtual reality (VR) technology in educational settings as a replacement for traditional online learning or eLearning platforms is a growing trend with the potential to enhance students' engagement and overall learning experiences. However, there is a significant gap in understanding the factors that influence students' behavioral intentions toward adopting VR technology for dynamic learning. The success of implementing VR in education relies heavily on students' willingness to embrace and actively engage with this technology. Identifying the key factors that impact students' behavioral intentions in this context is crucial for educational institutions and policymakers seeking to optimize the use of VR technology in the learning environment.

2. Literature Review

2.1 Performance Expectancy

The first variable of this dissertation starts with performance expectancy, which is one of the most important variables to identify as its original definition is to examine the level of satisfaction whether the users, learners, and teachers find using this technology as it is improving or not through the article of Fedorko et al. (2021) and Jihoon et al. (2021). Using a new technology will be challenging in the working environment as everything is new, and everyone is getting used to the new changes (Marlina et al., 2021). In this case, performance expectancy is the most crucial factor to indicate. According to Saraswat et al. (2021), it determines users' expectancy that the new technology usage will improve the task's performance, which is also a key factor for the organization's development. This variable is conducted from the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, formed by Venkatesh et al. (2003). This dissertation mainly focuses on students' attitudes and behavioral intentions to use this new advanced technology. In this case, performance expectancy plays a huge role in examining this title. According to this, whether the students may want to use this new technology can indicate the positive or negative effect by identifying this indicator (Sair & Danish, 2018). A study conducted by Sabas and Kiwango (2021) found that performance expectancy is a major component of the changes to the use of new technology as a system that offers alternative ways of learning to students. Through this study, performance expectancy can be stated as having a positive effect on students' attitudes and behavioral intention to use this new technology in their daily learning environment, which is also supported in the study (Ukut & Krairit, 2019). Thus, this study hypothesizes that:

H1: Performance expectancy has a significant effect on perceived usefulness of VR.

H2: Performance expectancy has a significant effect on attitude toward technology using VR.

2.2 Perceived Usefulness

The perceived Usefulness variable is one of the most important factors from the Technology Acceptance Model (TAM) by Davis (1989), which needs to study the users' satisfaction whether the usage of new technology enhances their job' performance or not that can be stated as its clear definition which was described in the research papers (Keni, 2020; Marikyan & Papagiannidis, 2022; Salloum & Al-Emran, 2018). This variable is essential to examine when the study focuses on changing technology and new technology used in the working environment. As this study is changing to use the new advancement technology tool in the education industry, in this case, perceived usefulness is necessary to learn the learners' views upon this usage of new technology. According to the study by Kerzˇič et al. (2019) and Tahar et al. (2020), perceived usefulness is a logical component to determine and foresee the efficiency of e-learning systems in the education sector, supporting learners' behavioral intention to use an e-learning system. The main objective of this study is to learn how this new technology tool will help and improve the students' learning competence. Some similar studies examined this perceived usefulness variable in the education industry. The study by Buabeng-Andoh (2018) pointed out that the analysis of perceived usefulness towards students' intention to learn with mobile learning showed that there is a positive significant impact; in another way, it can be stated that the learners are willing to use this new way of technology hence it improves their learning skill.

2.3 Perceived Enjoyment

A new change in the usual environment may cause unexpected outcomes to people with negative or positive impacts upon these changes to explore how useful it is and how the users may or may not enjoy these new changes. Davis et al. (1992) discovered that usefulness and enjoyment come together to examine the users can use this new technology of change easily and willing to use this new change in the future (Teo & Noyes, 2011; Wilson et al., 2021). The research of this latter part examined that the perceived enjoyment variable is essential to identify to indicate the positive impact towards users' intention to use this new technology tool for their learning. Most of the studies explored the term of enjoyment towards usage of technology during the pandemic era as most people spend their time learning via online platforms, for example, Zoom, Skype, YouTube, Learning management systems, e-learning platforms, and applications.

Another study by Basuki et al. (2022) examined the users' enjoyment in the usage of online videos during the COVID-19 duration and found that the definition of enjoyment means the higher the level of relaxation owned by information technology users, the better the user's attitude that will be related to the acceptance of the system technology. During this pandemic era, there are many internet users, and many of them spend most of their time online for different reasons, which include learning (e-learning), relaxation (watching videos), and gaming (online video games). People may use online learning not only during the pandemic but also during other ordinary times; in this case, the term enjoyment is used to identify the level of fulfillment of whether users are enjoyable to learn by using online platforms. Thus, this study hypothesizes that:

H3: Perceived enjoyment has a significant effect on perceived usefulness of VR.

H4: Perceived enjoyment has a significant effect on attitude toward technology using VR.

2.4 Attitude Towards Technology

One of the most important factors to study is the learners' attitude towards technology, a new change in their learning process. The simple definitions for this factor can be stated as measuring the person's feelings towards using this new technology about rendering or loathing upon technology changes (Andrew et al., 2018; Huedo-Martínez et al., 2018). The article by Jyothi and Renuka (2015) mentioned that attitude is a mental state of readiness and plays a vital role in determining the individual's reaction, including positive or negative responses to a particular entity. Most recent studies show that the young generation has a more positive attitude toward using new technology in their life and can be assumed to prefer to use advanced technological tools for their future (Basu & Ahmad, 2016; Kerschner & Melf-Hinrich, 2016). According to Villena-Taranilla et al. (2022), the advancement of modern technology tools in this 21st century, not only in education but in other sectors, relies on technological tools to lessen workloads and improve performance. Thus, this study hypothesizes that:

H6: Attitude toward technology has a significant effect on behavioral intention to use VR.

2.5 Perceived Ease of Use

Liesa Orús et al. (2022) mentioned the definition of perceived ease of use (PEOU) in their research. According to their findings, it can be stated that the person who uses this new technology finds it easy to use and adapts to this new change. This variable is also one of the factors from the Technology Acceptance Model (TAM), which needs to identify when a new technology applies in the organization. This factor is needed to indicate which sectors perceived ease of use could affect users' perception of the new change in technology or product according to their respective sectors mentioned in the article by Wilson et al. (2021). The degree of awareness in which a person feels a specific system is simple to use is perceived as ease of use (Huang, 2021; Keni, 2020). In another way, the perceived usefulness will influence the perceived ease of use in the TAM, and these two variables will also influence the behavioral intention of use simultaneously. As this research is mainly focused on the education sector with the application of new technology tools, there are some related studies on the examination of perceived ease of use indicator upon the use of new technology. First related studies conducted by Zardari et al. (2021) examined whether the students easily used the new way of eLearning portal for their study or not, and the result can be assumed to be a positive outcome, which means that students found that they are willing to use this eLearning portal as they are easy to use it. Thus, this study hypothesizes that:

H7: Perceived ease of use has a significant effect on behavioral intention to use VR.

2.6 Effort Expectancy

According to Kumar and Bervell (2019), and Winata and Tjokrosaputro (2021), the researchers defined effort expectancy as an individual's ease of use in using the technology without any difficulties. The effort expectancy indicator directly relates to the performance of activity as the achievement of performing is based on the level of effort (Al-Bashayreh et al., 2022). Effort expectancy is an essential indicator to identify whether the users are willing to use this technology and how they feel about using it (Wijaya et al., 2022). Many related studies were carried out for effort expectancy, especially for using new technology and how the users react to changes in their process. The study conducted by Fearnley and Amora (2020) and Yee and Abdullah (2021)

mentioned that there is a strong and positive relationship between effort expectancy and the users' intention to use ICT as a new change in their learning platforms, which seemed to give them more interesting and technology skill with convenient learning process. Another study was carried out to study the ease of studying from online learning, and the result was a positive outcome, which means that students are willing to learn from online learning. They found that online learning was easy to use and could be assessed anytime and anywhere, which was examined by Fedorko et al. (2021) and Lakhal and Khechine (2021). Bervell et al. (2020) did the research from the other side of users who are tutors, and the researchers studied their effort expectancy to use the LMS platform in their teaching way, and they also felt to use this LMS for teaching. Thus, this study hypothesizes that:
H8: Effort expectancy has a significant effect on behavioral intention to use VR.

2.7 Hedonic Motivation

The term hedonic motivation in technology can be defined as an individual's desire to use the system in order to fulfill their desire and satisfy the needs such as feelings of emotions, prestige, and other subjective feelings are included according to the research papers (Azizi et al., 2020; Halverson & Graham, 2019; Sitar-Taut, 2021). This indicator also relates to the user's intention to use the system, which can be assumed as a hedonic motivation indicator, which is an important determinant in examining the users' feelings and behavioral intention (Koch et al., 2020). Hedonic motivation is also an essential indicator to identify as it gives a clear view of whether the users feel the perceived enjoyment from using new changes or any difficulties with it. Nikolopoulou et al. (2021) and Munoz-Carril et al. (2021) studied the teachers' hedonic motivation for using mobile internet as an adoption technology for teaching. In this research, the authors found that hedonic motivation is important because it directly affects and significantly predicts the teachers' intention to use the mobile internet for their teaching. According to Azizi et al. (2020), the researchers proved that the hedonic motivation factor is important as they found that there is a significant impact on the student's intention to use the blended learning method. The results showed that the students found this approach to enjoyable learning. Studying this factor can also predict the learners' attitude toward using the learning system and their intention to use it for further studies (Alowayr & Al-Azawei, 2021; Herting et al., 2021). Thus, this study hypothesizes that:
H9: Hedonic motivation has a significant effect on behavioral intention to use VR.

2.8 Social Influence

The simple meaning of this social influence indicator can be stated as a process of changing one's behavior due to the other's influence of doing and saying according to the new changes within their environment. This factor is one of the crucial indicators of the TAM model. It is identified in every other sector as it determines the users' acceptance and usage behavior upon their new changes (Jaradat & Rababaa, 2013). The authors defined this indicator as having a vital role in identifying the users' feelings upon using the technology changes (Abdelsalama et al., 2019; Escobar-Rodríguez et al., 2014). In the research, they identified the students' social influence and whether they were satisfied with using Facebook, a social media platform, as a learning tool because this change is directly concerned with the users/students and is important to identify (Huang, 2021). Tan (2013) examined the students' feelings upon using an English e-learning platform in Taiwan. The purpose is to improve their English language skill and understanding of the usage of e-learning platforms. Thus, this study hypothesizes that:
H10: Social influence has a significant effect on behavioural intention to use VR.

2.9 Behavioral Intention

The behavioral intention factor can be identified as an individual who is willing to use the new change of system continuously; in another way, this is also a psychological theory that links beliefs to behaviors (Albelbisi & Yusop, 2018) as this factor is directly depending on the other determinant factors but also plays a crucial role in every sector which is completely relating with the users (Tusyanah et al., 2021). This factor is also related to the UTAUT or TAM model, which can be applied to identify the user's behavioral intention to use this new system (Jaradat & Rababaa, 2013). Ikhsan et al. (2021) examined the students' behavioral intention toward the use of a mobile learning management system as a new replacement for technology changes in their learning process by applying the UTAUT model to identify which factors are affecting the behavior intention to use this new approach in positive or negative impact. From this research, the most common factors, performance expectancy, effort expectancy, social influence, and facilitating conditions, significantly influence the students' behavioral intention.

3. Research Methods and Materials

3.1 Research Framework

A simple definition of the conceptual framework can be defined as it is the backbone of the research paper. All the dependent and independent variables were examined and structured from the based model, and a framework has been created (Halverson & Graham, 2019). A conceptual framework is essential to every research paper as it gives a systemic and structured format.

In this paper, the researcher built this conceptual framework based on the model (TAM & UTAUT) and referenced the other authors' previous studies and articles.

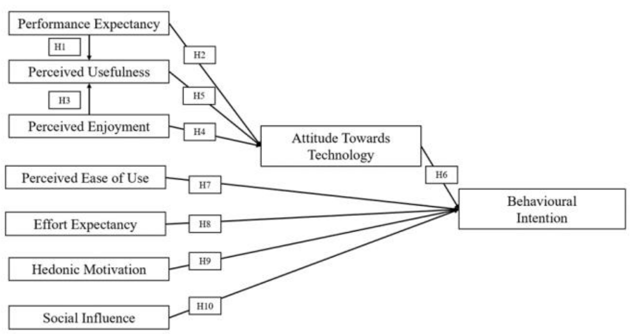

Figure 1: Conceptual Framework

H1: Performance expectancy has a significant effect on perceived usefulness of VR.
H2: Performance expectancy has a significant effect on attitude toward technology using VR.
H3: Perceived enjoyment has a significant effect on perceived usefulness of VR.
H4: Perceived enjoyment has a significant effect on attitude toward technology using VR.
H5: Perceived usefulness has a significant effect on attitude toward technology using VR.
H6: Attitude toward technology has a significant effect on behavioral intention to use VR.
H7: Perceived ease of use has a significant effect on behavioral intention to use VR.
H8: Effort expectancy has a significant effect on behavioral intention to use VR.
H9: Hedonic motivation has significant effect on behavioral intention to use VR.
H10: Social influence has significant effect on behavioral intention to use VR.

3.2 Research Methodology

The research objective and framework have been constructed based on the journal article with a similar study background. According to the research structure, a quantitative research method has been decided to be used for this paper. As for the quantitative data collection, a questionnaire survey has been used to gather the data from the respondents by conducting an online questionnaire survey using Google Forms to collect data from the target group.

Prior to data collection, a panel of three experts assessed the Index of Item-Objective Congruence (IOC) to ensure that each item effectively measures its intended construct, thereby contributing to the validity of the assessment. In the pilot test involving 50 participants, Cronbach's Alpha yielded a score of 0.7 and above, indicating the reliable measurement of the intended construct and enhancing the overall trustworthiness of the test results (Nunnally & Bernstein, 1994). Subsequently, confirmatory factor analysis and structural equation modeling were employed to analyze the data, assess the model's fit, and ascertain the causal relationships between variables.

3.3 Population and Sample Size

The calculation mentioned above has been done based on the required information for this research paper. The researcher entered 0.2 as the anticipated effect size, 0.8 as the desired statistical power level, eight as several latent variables, 31 as several observed variables, and 0.05 as the probability level. After the calculation, the result came out as 444, while the minimum sample size was 108. Although the sample size was 444, the researcher set the appropriate sample size based on the previous studies and articles. Thus, the researcher concluded that the sample size should follow 500, which will be the most appropriate sample size for this research.

3.4 Sampling Technique

The researcher decided to follow the quantitative research data collection for the research paper. Quantitative research is the analysis wherein a mathematical, statistical, or computational method is used to study a measurable or quantifiable dataset (Rashid et al., 2021). The sampling techniques involve judgmental, snowball, quota, and convenience. The judgmental and convenience sampling is to select 500 students who are currently attending or have been attending the selected top three private universities of Yangon, Myanmar. Quota sampling is used to distribute three universities in an even proportion. Snowball sampling is to encourage participants to share the online survey to their peers.

4. Results and Discussion

4.1 Demographic Information

The simple demographic questions include age, gender, race, marital status, income, education, and employment. These demographic questions are only necessary concerning the research title and objectives (Torrentira, 2020).

Among the 500 individuals, 240 are male (48%), and 260 are female (52%), ensuring a balanced representation of both perspectives. Majority fall within 25 to 34 (43.4%), followed closely by 30 to 34 (39.2%), with smaller percentages in age brackets 18-24 (3%), 35-49 (14%), and 50 and above (0.4%).

Participants exhibit diverse educational backgrounds, with 3.6% holding a bachelor's degree, 93.2% attaining a master's, and 3.2% achieving a doctorate. Income diversity is observed, with 2.2% earning 500,000 MMK and below, 80.6% falling within 500,001 MMK to 10,000,000 MMK, and 17.2% earning above 10,000,000 MMK. The demographic profile is shown in the following table.

Table 1: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	240	48 %
	Female	260	52 %
Age Group	18 – 24	15	3 %
	25 – 29	217	43.4 %
	30 – 34	196	39.2 %
	35 – 49	70	14 %
	50 and above	2	0.4 %
Education Level Platforms	Bachelor	18	3.6 %
	Master	466	93.2 %
	Doctorate	16	3.2 %
Income	500, 000 MMK and below	11	2.2%
	Bet. 500, 001 MMK and 10, 000, 000 MMK	403	80.6%
	Above 10, 000, 000 MMK	86	17.2%

4.2 Confirmatory Factor Analysis (CFA)

Hair et al. (2010) highlighted the effectiveness of confirmatory factor analysis (CFA) in appropriately addressing small-scale variables. The results presented in Table 2 indicate that the construction exhibits internal consistency, adhering to the widely accepted guideline that Cronbach's Alpha should be 0.70 or higher (Nunnally & Bernstein, 1994). Factor loadings for each variable surpassed 0.5, with a t-value exceeding 1.98 and a p-value below 0.5 (Hair et al., 2010). Furthermore, composite reliability (CR) exceeded 0.7, and the average variance extracted (AVE) surpassed 0.4 for all constructs, as recommended by Fornell and Larcker (1981). These findings collectively signify the achievement of desirable statistical estimates.

Table 2: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Performance Expectancy (PE)	(Onaolapo & Oyewole, 2018)	4	0.918	0.791-0.917	0.916	0.732
Perceived Enjoyment (PENJ)	(Bower et al., 2020)	4	0.927	0.836-0.891	0.924	0.753
Perceived Usefulness (PU)	(Bervell et al., 2020)	4	0.929	0.846-0.884	0.921	0.746
Perceived Ease of Use (PEOU)	(Escobar-Rodríguez et al., 2014)	3	0.907	0.864-0.903	0.914	0.779
Effort Expectancy (EE)	(Fearnley & Amora, 2020)	3	0.921	0.873-0.917	0.923	0.800
Attitude Toward Technology (ATT)	(Fussell & Truong, 2021)	3	0.918	0.866-0.910	0.918	0.789
Hedonic Motivation (HM)	(Huang, 2021)	3	0.926	0.895-0.917	0.930	0.816
Social Influence (SI)	(Herting et al., 2021)	3	0.925	0.889-0.902	0.925	0.804
Behavioural Intention (BI)	(Madini & Alshaikhi, 2017)	4	0.935	0.855-0.912	0.942	0.802

The statical values for each fit index can be considered a very good stage; hence, all indices fall within the acceptable range. The model fit was evaluated by comparing the statistical values of goodness-of-fit indices in Table 3 to acceptable criteria. These values include CMIN/DF = 2.175, GFI = 0.916, AGFI = 0.879, NFI = 0.960, CFI = 0.978, TLI = 0.970, and RMSEA = 0.049

Table 3: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<3.00 (Hair et al., 2010)	2.175
GFI	>0.85 (Bagozzi & Yi, 1988)	0.916
AGFI	>0.80 (Sica & Ghisi, 2007)	0.879
RMSEA	<0.08 (Pedroso et al., 2016)	0.049
CFI	>0.90 (Bentler, 1990)	0.978
NFI	>0.90 (Bentler & Bonett, 1980)	0.960
TLI	>0.90 (Bentler & Bonett, 1980)	0.970
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, RMSEA = Root mean square error of approximation, CFI = Comparative fit index, NFI = Normed fit index and TLI = Tucker-Lewis index

Discriminant validity, by the criteria established, is affirmed when the square root of the Average Variance Extracted (AVE) surpasses the coefficients of intercorrelated constructs (Hamid et al., 2017). The findings, as presented in the following Table 4, demonstrate that for all constructs along the diagonal line, the square root of AVE exceeded the inter-scale correlations. This outcome provides unequivocal evidence of the study's successful establishment of discriminant validity (Fornell & Larcker, 1981).

Table 4: Discriminant Validity

	PE	PENJ	PU	PEOU	EE	ATT	HM	SI	BI
PU	**0.855**								
PENJ	0.794	**0.867**							
PU	0.767	0.815	**0.863**						
PEOU	0.688	0.729	0.742	**0.882**					
EE	0.674	0.678	0.727	0.769	**0.894**				
ATT	0.663	0.746	0.713	0.779	0.771	**0.888**			
HM	0.671	0.695	0.767	0.671	0.715	0.763	**0.903**		
SI	0.672	0.753	0.718	0.754	0.700	0.777	0.717	**0.896**	
BI	0.728	0.720	0.794	0.695	0.736	0.688	0.759	0.713	**0.895**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

Liesa Orús et al. (2022) stated in their studies that structural Equation Modelling (SEM) is a sophisticated multivariate statistical analysis technique commonly utilized to investigate intricate structural relationships within various fields of study. This method integrates principles derived from factor analysis and multiple regression analysis, thus serving as a potent analytical instrument for meticulously examining the intricate structural linkages between observable variables and latent constructs (Marsh et al., 2019). The statistical values before adjustment can be seen in the following table. The structural model's fit was assessed using well-established goodness-of-fit indices, consistent with those employed in Confirmatory Factor Analysis (CFA). These indices, including CMIN/df, GFI, AGFI, NFI, CFI, TLI, and RMSEA, were utilized to evaluate the fit of the model, which involved nine latent variables: performance expectancy, perceived enjoyment, perceived usefulness, perceived ease of use, effort expectancy, attitude toward technology, hedonic motivation, social influence, and behavioral intention to use.

Table 5: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	<3.00 (Hair et al., 2010)	4.178
GFI	>0.85 (Bagozzi & Yi, 1988)	0.865
AGFI	>0.80 (Sica & Ghisi, 2007)	0.811
RMSEA	<0.08 (Pedroso et al., 2016)	0.078
CFI	>0.90 (Bentler, 1990)	0.938
NFI	>0.90 (Bentler & Bonett, 1980)	0.921
TLI	>0.90 (Bentler & Bonett, 1980)	0.919
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, RMSEA = Root mean square error of approximation, CFI = Comparative fit index, NFI = Normed fit index and TLI = Tucker-Lewis index

4.4 Research Hypothesis Testing Result

The strength of the relationships between the independent and dependent variables posited in the hypothesis was assessed using regression or standardized path coefficients. As detailed in Table 6, five proposed hypotheses received empirical support. Notably, behavioral intention to use VR technology in education was influenced by effort expectancy, hedonic motivation, social influence, perceived enjoyment effect on perceived usefulness of VR, and attitude toward technology.

Table 6: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PE→PU	- 0.383	- 6.897 *	Not Supported
H2: PE→ATT	- 1.150	- 9.816*	Not Supported
H3: PENJ→PU	1.124	14.823 *	Supported
H4: PENJ→ATT	2.124	9.213 *	Supported
H5: PU→ATT	- 0.764	- 4.482 *	Not Supported
H6: ATT→BI	- 0.454	- 4.841 *	Not Supported
H7: PEOU→BI	0.188	2.634	Not Supported
H8: EE→BI	0.344	5.496 *	Supported
H9: HM→BI	0.555	8.808 *	Supported
H10: SI→BI	0.413	4.932 *	Supported

Note: * $p<0.05$
Source: Created by the author

H1: Performance Expectancy significantly affects the Perceived Usefulness of VR.

The result of performance expectancy presented in the above table, t = -6.897 and Coefficients = -0.383, can be ruled as there is no effect on perceived usefulness based on the value of the t-test and the coefficient. Therefore, this hypothesis is stated as not supported. This finding was aligned with the previous studies by Bervell et al. (2020), Lakhal and Khechine (2021), and Udang (2022). Students believe that using VR technology will improve their learning curve; however, most of them thought it would not be that useful in the longer term.

H2: Performance Expectancy significantly affects Attitude Toward Technology using VR.

The result of performance expectancy presented in the above table, t = -9.816 and Coefficients = -1.150, can be ruled as there is no effect upon attitude toward technology based on the value of the t-test and the coefficient. Therefore, this hypothesis is stated as not supported. In the earlier section, the studies by Venkatesh et al. (2012) and Fussell and Truong (2021) stated that the researchers found the same findings from their research on the students. The result shows that some students assumed that using VR improves performance. However, when it comes to using technology, some could be more enjoyable and dislike using new technology in their learning.

H3: Perceived Enjoyment significantly affects the Perceived Usefulness of VR.

The result of perceived enjoyment presented in the above table, t = 14.823 and Coefficients = 1.124, can be ruled as a positive effect on perceived usefulness, based on the test value and the coefficient. Therefore, this hypothesis is confirmed as supported. This finding aligns with most study articles (Al-Bashayreh et al., 2022; Mpungose, 2021; Rizun & Strzelecki, 2020). Almost all the students enjoy using VR technology for their learning, and from this happiness, they are all willing to use it.

H4: Perceived Enjoyment significantly affects Attitude Toward Technology using VR.

The result of perceived enjoyment presented in the above table, t = 9.213 and Coefficients = 2.124, can be ruled as there is a positive effect upon attitude toward a technology based on the value of the t-test and the coefficient. Therefore, this hypothesis is confirmed as supported. The earlier finding confirmed that students are willing to use VR technology, and it changes their attitude toward technology, which is affiliated with the study by Holdack et al. (2020) and Novikova et al. (2022)

H5: Perceived Usefulness significantly affects Attitude Toward Technology using VR.

The result of perceived usefulness presented in the above table, t = -4.482 and Coefficients = -0.764, can be ruled as there is no effect upon attitude toward a technology based on the value of the t-test and the coefficient. Therefore, this hypothesis is stated as not supported. The earlier hypothesis with PU got some negative results with using VR technology, and the attitude toward technology got the same result, which has also been mentioned in the study (Albelbisi & Yusop, 2018; Marlina et al., 2021).

H6: Attitude Toward Technology significantly affects Behavioural Intention to use VR.

The result of attitude toward technology that was presented in the above table, t = -4.841 and Coefficients = -0.454, can be ruled as there is no effect on behavioral intention to use, which is based on the value of the t-test and the coefficient. Therefore, this hypothesis is stated as not supported. Fearnley and Amora (2020) and Lakhal and Khechine (2021) found a similar result in that most of the students are enjoyable; however, for longer usage, they all prefer the normal way of learning. Nevertheless, some persistently prefer to use VR technology for their learning, which is also found in this study (Zardari et al., 2021).

H7: Perceived Ease of Use significantly affects Behavioral Intention to use VR.

The result of perceived ease of use presented in the above table, t = 2.634 and Coefficients = 0.188, can be ruled as there is no effect on behavioral intention to use, based on the t-test value and the p-value significance. Therefore, this hypothesis is stated as not supported. Abdelsalama et al. (2019) and Villena-Taranilla et al. (2022) also found a similar result with this finding. Hence, some students are not comfortable using new technology, and VR technology itself is not very easy to use; henceforth, they need to wear it, and the weight gives them the reluctance to use it.

H8: Effort Expectancy significantly affects Behavioral Intention to use VR.

The result of effort expectancy presented in the above table, t = 5.496 and Coefficients = 0.344, can be ruled as there is a positive effect on behavioral intention to use, which is based on the value of the t-test and the coefficient. Therefore, this hypothesis is confirmed as supported. Most of the studies show that most students found that using VR technology is easy and understandable, which positively affects effort expectancy, and that aligns with several studies (Bower et al., 2020; Nuraziza et al., 2021).

H9: Hedonic Motivation significantly affects behavioral Intention to use VR.

The result of hedonic motivation that was presented in the above table, t = 8.808 and Coefficients = 0.555, can be ruled as there has a positive effect on behavioral intention to use, which is based on the value of the t-test and the coefficient. Therefore, this hypothesis is confirmed as supported. Hedonic motivation received the highest values among the other variables, and it is crucial to student's behavioral intention to use VR technology (Huedo-Martínez et al., 2018; Raja & Nagasubramani, 2018; Solano et al., 2017). Some researchers believed that the students' motivation for using new technology plays an important role in behavioral intention.

H10: Social Influence significantly affects behavioral Intention to use VR.

The result of social influence presented in the above table, t = 4.932 and Coefficients = 0.413, can be ruled as there is a positive effect on behavioral intention to use based on the value of the t-test and the coefficient. Therefore, this hypothesis is confirmed as supported. Hence, VR technology is one of the most popular in the 21st century technologies, and some industries started using it for their business entertainment and gaming and are now expanding into the educational sector. All the students alleged that they all need to keep updated with the newest technology, which also benefits their learning activity and advances their hard skills or technology usage (Kustandi et al., 2020; Marlina et al., 2021).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The findings of the study revealed several important insights. Perceived enjoyment emerged as a significant factor influencing both perceived usefulness and attitude toward technology when using VR. Furthermore, effort expectancy, hedonic motivation, and social influence were identified as significant factors affecting students' behavioral intention to use VR. However, no significant relationships were found between performance expectancy, perceived usefulness, attitude toward technology, perceived ease of use, and behavioral intention to use VR.

From these results, it can be inferred that students perceive the use of VR technology as both enjoyable and useful. The positive impact of perceived enjoyment on perceived usefulness and attitude toward technology suggests that enhancing the enjoyment factor in the use of VR can potentially contribute to more favorable attitudes and perceptions among students. Additionally, the significance of effort expectancy, hedonic motivation, and social influence underscores the importance of addressing these factors when implementing VR in educational settings to encourage students' intention to use this technology.

In summary, this research provides valuable insights for educators, policymakers, and technology developers aiming to integrate VR into educational practices. Understanding the factors influencing students' behavioral intentions is crucial for the successful adoption of VR technology, ultimately contributing to a more engaging and effective learning environment. The study's outcomes contribute to the ongoing discourse on technology-enhanced learning and offer practical implications for the design and implementation of VR-based educational initiatives.

5.2 Recommendation

The successful incorporation of virtual reality (VR) technology into education demands a concise set of recommendations to guide educators, policymakers, and technology developers. Here, we offer a brief yet comprehensive essay outlining key suggestions derived from our research:

To maximize students' engagement with VR technology, it is crucial to prioritize the development of content that is not only educational but also enjoyable and immersive. Creating experiences that captivate students' interest and curiosity can significantly contribute to a positive perception of VR in the learning environment.

To ensure a seamless integration of VR into educational practices, efforts should be directed towards minimizing the perceived effort required by students. This involves refining user interfaces, providing clear instructional materials, and implementing comprehensive training programs. Simplifying the user experience will contribute to increased comfort and proficiency in using VR tools.

Recognizing the impact of social dynamics on learning, educators and developers should focus on fostering collaborative and social learning experiences within VR platforms. Peer engagement, group activities, and shared learning experiences can positively influence students' attitudes and enhance the overall effectiveness of VR in education.

The design of VR content should not only be informative but also tailored to evoke positive emotions and tap into students' intrinsic motivation. Incorporating elements that align with hedonic motivation can contribute to a more favorable perception of VR technology, motivating students to actively participate and learn through this innovative medium.

Clear communication regarding the practical utility and benefits of using VR for learning is essential. Educators should actively demonstrate how VR enhances understanding, engagement, and knowledge retention. By emphasizing the tangible advantages, students are more likely to perceive VR as a valuable tool in their educational journey.

Acknowledging the learning curve associated with new technology, institutions should offer continuous training and support for students using VR. Workshops, tutorials, and accessible help resources can address usability concerns, ensuring a smooth and satisfying experience with VR tools.

5.3 Limitation and Further Study

First and foremost, the scope of this research is limited; hence, the researcher ought to select the private university sector to get the exact number of students due to the current situation in Yangon, Myanmar. Therefore, the researcher must select the top three private universities to narrow the student population to get the exact detailed response to this research finding. This research aims to explore the implementation of VR technology in the education sector. Nevertheless, the selected region, Yangon, does not currently have VR technology in education; therefore, the researcher needs to aim for the younger generation to get a quality response and match the limited sample size. The popularity of VR is only overwhelming among the younger generation, and they all are familiar with the usage of VR; however, it is in different sectors, such as the gaming and entertainment sectors.

References

Abdelsalama, M., Khedrb, A. E., Emamb, O., & Helmy, Y. (2019). A General Approach Students' Attitude towards to Virtual Reality Technology in Distance Education Environment. *Future Computing and Informatics Journal, 4*(1), 10-15.

Al-Bashayreh, M., Almajali, D., Altamimi, A., Masa'deh, R., & Al-Okaily, M. (2022). An Empirical Investigation of Reasons Influencing Student Acceptance and Rejection of Mobile Learning Apps Usage. *Sustainability, 14*(7), 4325. https://doi.org/10.3390/su14074325

Albelbisi, N. A., & Yusop, F. D. (2018). Secondary School Students' Use of and Attitudes toward Online Mathematics Homework. *The Turkish Online Journal of Educational Technology, 17*(1), 144-153.

Alowayr, A., & Al-Azawei, A. (2021). Predicting mobile learning acceptance: An integrated model and empirical study based on the perceptions of higher education students. *Australasian Journal of Educational Technology, 37*(3), 38-55. https://doi.org/10.14742/ajet.6154

Andrew, M., Taylorson, J., Langille, D. J., Grange, A., & Williams, N. (2018). Student attitudes towards technology and their preferences for learning tools/devices at two universities in the UAE. *Journal of Information Technology Education: Research, 17,* 309-344. https://doi.org/10.28945/4111

Azizi, S. M., Roozbahani, N., & Khatony, A. (2020). Factors affecting the acceptance of blended learning in medical education: application of UTAUT2 model. *BMC Medical Education, 20*(1), 367-376. https://doi.org/10.1186/s12909-020-02302-2

Bagozzi, R., & Yi, Y. (1988). On the Evaluation of Structural Equation Models. *Journal of the Academy of Marketing Sciences, 16,* 74-94. http://dx.doi.org/10.1007/BF02723327

Basu, N., & Ahmad, G. (2016). Attitude towards Using New Technology among Higher Secondary School Teachers in District Budgam. *Journal of Information Engineering and Applications, 6*(2), 16-21.

Basuki, R., Tarigan, Z. J., Siagian, H., Limanta, L. S., Setiawan, D., & Mochtar, J. (2022). The effects of perceived ease of use, usefulness, enjoyment, and intention to use online platforms on behavioral intention in online movie watching during the pandemic era. *International Journal of Data and Network Science, 6,* 253-262. https://doi.org/10.5267/j.ijdns.2021.9.003

Bentler, P. M. (1990). Comparative Fit Indexes in Structural Models. *Psychological Bulletin, 107,* 238-246. http://dx.doi.org/10.1037/0033-2909.107.2.238

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin, 88*(3), 588-606. https://doi.org/10.1037/0033-2909.88.3.588

Bervell, B., Nyagorme, P., & Arkorful, V. (2020). LMS-Enabled Blended Learning Use Intentions among Distance Education Tutors: Examining the Mediation Role of Attitude Based on Technology-Related Stimulus-Response Theoretical Framework. *Contemporary Educational Technology, 12*(2), ep273. https://doi.org/10.30935/cedtech/8317

Bower, M., DeWitt, D., & Lai, J. W. (2020). Reasons associated with preservice teachers' intention to use immersive virtual reality in education. *British Journal of Educational Technology, 51*(6), 2215-2233. https://doi.org/10.1111/bjet.13009

Buabeng-Andoh, C. (2018). Predicting students' intention to adopt mobile learning: A combination of theory of reasoned action and technology acceptance model. *Journal of Research in Innovative Teaching & Learning, 11*(2), 2397-7604.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace. *Journal of Applied Social Psychology, 22*(14), 1111-1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

Domingo, M. G., & Gargante, A. B. (2016). Exploring the use of educational technology in primary education: Teachers' perception of mobile technology learning impacts and applications' use in the classroom. *Computers in Human Behavior, 56,* 21-28. https://doi.org/10.1016/j.chb.2015.11.023

Escobar-Rodríguez, T., Carvajal-Trujillo, E., & Monge-Lozano, P. (2014). Factors that influence the perceived advantages and relevance of Facebook as a learning tool: An extension of the UTAUT. *Australasian Journal of Educational Technology, 30*(2), 136-151. https://doi.org/10.14742/ajet.585

Fearnley, M. R., & Amora, J. T. (2020). Learning Management System Adoption in Higher Education Using the Extended Technology Acceptance Model. *Journal of Education: Technology in Education, 8*(2), 89-106. https://doi.org/10.22492/ije.8.2.05

Fedorko, I., Bačik, R., & Gavurova, B. (2021). Effort expectancy and social influence factors as main determinants of performance expectancy using electronic banking. *Banks and Bank Systems, 16*(2), 27-37. https://doi.org/10.21511/bbs.16(2).2021.03

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Fussell, S. G., & Truong, D. (2021). Using virtual reality for dynamic learning: an extended technology acceptance model. *Springer, 26,* 249-267. https://doi.org/10.1007/s10055-021-00554-x

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis* (7th ed.). Pearson.

Halverson, L. R., & Graham, C. R. (2019). Learner Engagement in Blended Learning Environments: A Conceptual Framework. *Online Learning, 23*(2), 145-178. https://doi.org/10.24059/olj.v23i2.1481

Hamid, M. A., Sami, W., & Sidek, M. M. (2017). Discriminant Validity Assessment: Use of Fornell & Larcker criterion versus HTMT Criterion. *Journal of Physics: Conference Series, 890,* 012163. https://doi.org/10.1088/1742-6596/890/1/012163

Herting, D. C., Pros, R. C., & Tarrida, A. C. (2021). Habit and social influence as determinants of PowerPoint use in higher education: A study from a technology acceptance approach. *Interactive Learning Environments, 31*(1), 1-17.

Holdack, A., Stoyanov, K., & Fromme, H. F. (2020). The role of perceived enjoyment and perceived informativeness in assessing Holdack, E., Lurie the acceptance of AR wearables. *Journal of Retailing and Consumer Services, 65*(1), 102259. https://doi.org/10.1016/j.jretconser.2020.102259

Huang, C.-H. (2021). Using PLS-SEM Model to Explore the Influencing Factors of Learning Satisfaction in Blended Learning. *Education Sciences, 11*(5), 249. https://doi.org/10.3390/educsci11050249

Huedo-Martínez, S., Molina-Carmona, R., & Llorens-Largo, F. (2018). Study on the Attitude of Young People Towards Technology. *Learning and Collaboration Technologies, 10925,* 26-43. https://doi.org/10.1007/978-3-319-91152-6_3

Ikhsan, R. B., Prabowo, H., & Yuniarty, Y. (2021). Drivers of the Mobile-Learning Management System's Actual Usage: Applying the UTAUT Model. *ICIC International, 12*(11), 1067-1074.

Jaradat, M.-I. R., & Rababaa, M. S. (2013). Assessing Key Factor that Influence on the Acceptance of Mobile Commerce Based on Modified UTAUT. *International Journal of Business and Management, 8*(23), 102-112.

Jihoon, K., Yong, K. J., & Connaughton, D. P. (2021). Performance Expectancy of Officiating Technology in Spector-Based Sport Events: Scale Development and Validation. *Communication & Sport, 11*(3), 528-550. https://doi.org/10.1177/21674795211022006

Jyothi, V., & Renuka, D. (2015). Role of Computer Technology in Developing Positive Attitude towards Mathematics. *International Journal of Scientific & Engineering Research, 6*(9), 77-79.

Keni, K. (2020). How Perceived Usefulness and Perceived Ease of Use Affecting Intent to Repurchase? *Jurnal Manajemen, 14(*3), 481-496. https://doi.org/10.24912/jm.v24i3.680

Kerschner, C., & Melf-Hinrich, E. (2016). A framework of attitudes towards technology in theory and practice. *Ecological Economics, 126,* 139-151. https://doi.org/10.1016/j.ecolecon.2016.02.010

Kerzˇič, D., Tomazˇevič, N., Aristovnik, A., & Umek, L. (2019). Exploring critical factors of the perceived usefulness of blended learning for higher education students. *PLoS ONE, 14*(11), e0223767. https://doi.org/10.1371/journal.pone.0223767

Koch, J., Frommeyer, B., & Schewe, G. (2020). Online Shopping Motives during the COVID-19 Pandemic—Lessons from the Crisis. *Sustainability, 12*(24), 10247. https://doi.org/10.3390/su12241024710247), 1-20.

Kumar, J. A., & Bervell, B. (2019). Google Classroom for mobile learning in higher education: Modelling the initial perceptions of students. *Education and Information Technologies, 1*(2), 1793-1817. https://doi.org/10.1007/s10639-018-09858-z

Kustandi, C., Fadhillah, D. N., Situmorang, R., Prawiradilaga, D. S., & Hartati, S. (2020). VR Use in Online Learning for Higher Education in Indonesia. *International Journal of Interactive Mobile Technologies, 14*(1), 31-46. https://doi.org/10.3991/ijim.v14i01.11337

Lakhal, S., & Khechine, H. (2021). Technological factors of students' persistence in online courses in higher education: The moderating role of gender, age, and prior online course experience. *Education and Information Technologies, 26*(3), 1-18.

Liesa Orús, M., Latorre Cosculluela, C., Sierra Sánchez, V., & Vázquez Toledo, S. (2022). Links between ease of use, perceived usefulness and attitudes towards technology in older people in university: *A structural equation modelling approach. Education and Information Technologies, 28,* 1-18.

Madini, A. A., & Alshaikhi, D. (2017). Female ESP Postgraduates' Acceptance of Virtual Reality Learning: Aye or Nay. *International Journal of Humanities and Social Sciences, 9*(6), 12-31.

Marikyan, D., & Papagiannidis, S. (2022). *TheoryHub Book. Technology Acceptance Model: A review, 1-12* (1st ed.). Retrieved from Technology Acceptance Model.

Marlina, E., Tjahjadi, B., & Ningsih, S. (2021). Factors Affecting Student Performance in E-Learning: A Case Study of Higher Educational Institutions in Indonesia. *Journal of Asian Finance, Economics and Business, 8*(4), 0993-1001.

Marsh, H. W., Guo, J., Dicke, T., Parker, P. D., & Craven, R. G. (2019). Confirmatory Factor Analysis (CFA), Exploratory Structural Equation Modeling (ESEM), and Set-ESEM: Optimal Balance Between Goodness of Fit and Parsimony. *Multivariate Behavioral Research, 55*(1), 102-119. https://doi.org/10.1080/00273171.2019.1602503

Mpungose, C. B. (2021). Lecturers' reflections on use of Zoom video conferencing technology for e-learning at a South African university in the context of coronavirus. *African Identities, 21*(2), 266-282. https://doi.org/10.1080/14725843.2021.1902268

Munoz-Carril, P.-C., Hernandez-Selles, N., Fuentes-Abeledo, E.-J., & Gonzalez-Sanmamed, M. (2021). Factors influencing students' perceived impact of learning and satisfaction in Computer Supported Collaborative Learning. *Computers & Education, 174*(104310), 1-13.

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2021). Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers' intention to use mobile internet. *Computers and Education Open, 2*, 100041. https://doi.org/10.1016/j.caeo.2021.100041

Novikova, I. A., Bychkova, P. A., & Novikov, A. L. (2022). Attitudes towards Digital Educational Technologies among Russian University Students before and during the COVID-19 Pandemic. *Sustainability, 14*(10), 6203. https://doi.org/10.3390/su14106203

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Nuraziza, N., Oktaviani, L., & Sari, F. M. (2021). EFL Learners' Perceptions on ZOOM Application in the Online Classes. *Jambura Journal of English Teaching and Literature, 2*(1), 41-51. https://doi.org/10.37905/jetl.v2i1.7318

Onaolapo, S., & Oyewole, O. (2018). Performance expectancy, effort expectancy, and facilitating conditions as factors influencing smart phones use for mobile learning by postgraduate students of the University of Ibadan, Nigeria. *Interdisciplinary Journal of E-Skills and Lifelong Learning, 14,* 95 - 115. https://doi.org/10.28945/4085

Pedroso, C. B., Silva, A. L., & Tate, W. L. (2016). Sales and Operations Planning (S&OP): insights from a multi-case study of Brazilian organizations. *International Journal of Production Economics, 182,* 213-229. http://dx.doi.org/10.1016/j.ijpe.2016.08.035.

Raja, R., & Nagasubramani, P. C. (2018). Impact of modern technology in education. *Journal of Applied and Advanced Research, 3*(1), 33-35. https://doi.org/10.21839/jaar.2018.v3is1.165

Rashid, A., Rasheed, R., Amirah, N. A., Yusof, Y., Khan, S., & Agha, A. A. (2021). A Quantitative Perspective of Systematic Research: Easy and Step-by-Step Initial Guidelines. *Turkish Online Journal of Qualitative Inquiry, 12*(9), 2874-2883.

Ratheeswari, K. (2018). Information Communication Technology in Education. *Journal of Applied and Advanced Research, 3*(1), 45-47. https://doi.org/10.21839/jaar.2018.v3is1.169

Rizun, M., & Strzelecki, A. (2020). Students' Acceptance of the COVID-19 Impact on Shifting Higher Education to Distance Learning in Poland. *International Journal of Environmental Research and Public Health, 17*(18), 6468. https://doi.org/10.3390/ijerph17186468

Sabas, J., & Kiwango, T. A. (2021). Evaluating the Influence of Performance Expectancy on the Adoption of Students' Information System in Higher Learning Institutions. *Accountancy and Business Review, 13*(2), 39-50. https://doi.org/10.59645/abr.v13i2.23

Sair, S. A., & Danish, R. Q. (2018). Effect of Performance Expectancy and Effort Expectancy on the Mobile Commerce Adoption Intention through Personal Innovativeness among Pakistani Consumers. *Pakistan Journal of Commerce and Social Sciences, 12*(2), 501-520.

Salloum, S. A., & Al-Emran, M. (2018). Factors affecting the adoption of e-payment systems by university students: extending the TAM with trust. *International Journal of Electronic Business, 14*(4), 371-390. https://doi.org/10.1504/ijeb.2018.098130

Saraswat, S., Jain, R., & Awasthi, S. (2021). Outlook of Consumers towards Online Pharmacies: Roles of Performance Expectancy, Effort Expectancy and Adoption. *Effulgence, 19*(1), 16-26. https://doi.org/10.33601/effulgence.rdias/v19/i1/2021/16-26

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-edge psychological tests and testing research* (pp. 27-50). Nova Science

Sitar-Taut, D.-A. (2021). Mobile learning acceptance in social distancing during the COVID-19 outbreak: The mediation effect of hedonic motivation. *Human Behavior and Emerging Technologies, 3*(3), 366-378.

Solano, L., Cabrera, P., Ulehlova, E., & Espinoza, V. (2017). Exploring The Use of Educational Technology in EFL Teaching: A case study of Primary Education in the South Region of Ecuador. *Teaching English with Technology, 17*(2), 77-86.

Tahar, A., Riyadh, H. A., Sofyani, H., & Purnomo, W. E. (2020). Perceived Ease of Use, Perceived Usefulness, Perceived Security and Intention to Use E-Filing: The Role of Technology Readiness. Journal of Asian Finance, *Economics and Business, 7*(9), 537-547. https://doi.org/10.13106/jafeb.2020.vol7.no9.537

Tan, P. J. (2013). Applying the UTAUT to Understand Factors Affecting the Use of English E-Learning Websites in Taiwan. *SAGE Open, 3*(4), 215824401350383. https://doi.org/10.1177/2158244013503837

Teo, T., & Noyes, J. (2011). An assessment of the influence of perceived enjoyment and attitude on the intention to use technology among pre-service teachers: A structural equation modeling approach. *Computers & Education, 57*(2), 1645-1653. https://doi.org/10.1016/j.compedu.2011.03.002

Torrentira, M. C. (2020). Online Data Collection as Adaptation in Conducting Quantitative and Qualitative Research During the Covid-19 Pandemic. *European Journal of Education Studies, 7*(11), 78-87. https://doi.org/10.46827/ejes.v7i11.3336

Tusyanah, T., Wahyudin, A., & Khafid, M. (2021). Analyzing Factors Affecting the Behavioral Intention to Use e-Wallet with the UTAUT Model with Experience as Moderating Variable. *Journal of Economic Education, 10*(2), 113-123.

Udang, L. N. (2022). UTAUT Factors Influencing Perception & Behavioral Intention of Learners & Lecturers Towards Adoption of Online Classes During COVID-19 Pandemic. *Research Square, 2*(3), 1-27. https://doi.org/10.21203/rs.3.rs-2124853/v

Ukut, I. I., & Krairit, D. (2019). Justifying students' performance, A comparative study of both ICT students' and instructors' perspective. *Interactive Technology and Smart Education, 16*(1), 18-35.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly, 36*(1), 157-178. https://doi.org/10.2307/41410412

Villena-Taranilla, R., Tirado-Olivares, S., Cozar-Gutierrez, R., & Gonzalez-Calero, J. A. (2022). Effects of virtual reality on learning outcomes in K-6 education: A meta-analysis. *Educational Research Review, 35,* 100434. https://doi.org/10.1016/j.edurev.2022.100434

Wijaya, T. T., Cao, Y., Weinhand, R., Yusron, E., & Lavicza, Z. (2022). Applying the UTAUT Model to Understand Factors Affecting Micro-Lecture Usage by Mathematics Teachers in China. *Mathematics, 10*(7), 1008. https://doi.org/10.3390/math10071008

Wilson, N., Keni, K., & Pattyranie Tan, P. H. (2021). The Role of Perceived Usefulness and Perceived Ease-of-Use Toward Satisfaction and Trust which Influence Computer Consumers' Loyalty in China. *Gadjah Mada International Journal of Business, 23*(3), 262-294. https://doi.org/10.22146/gamaijb.32106

Winata, S., & Tjokrosaputro, M. (2021). The Roles of Effort Expectancy, Attitude, and Service Quality in Mobile Payment Users Continuance Intention. *Advances in Economics, Business and Management Research, 653,* 121-126. https://doi.org/10.2991/aebmr.k.220501.020

Yee, M. L., & Abdullah, M. S. (2021). A Review of UTAUT and Extended Model as a Conceptual Framework in Education Research. *Jurnal Pendidikan Sains Dan Matematik Malaysia, 11,* 1-20.

Zardari, B. A., Hussain, Z., Arain, A. A., Rizvi, W. H., & Vighio, M. S. (2021). Development and Validation of User Experience-Based E-Learning Acceptance Model for Sustainable Higher Education. *Sustainability, 13*(11), 6201. https://doi.org/10.3390/su13116201