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Adoption, use and enhancement of virtual learning during COVID-19

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Abstract

This study focuses on the uses of digital technology during teaching and learning. The preparedness, adoption, and use of virtual learning are inquired. Technology cannot enhance learning unless adopted, embraced, and effectively used. Three hundred and one (301) online questionnaires were administered to Higher and Tertiary institutions (HTEIs) students. The data were analyzed using the Structural Equation Model (SEM). Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) were confirmed to be positive predictors of the Behavioural Intention (BI) to use technology. Facilitating Conditions (FC) is a non-significant construct to BI to use technology. Thus, irrespective of the availability of Information Communication Technologies (ICT) infrastructure and support needed to use virtual learning, students are forced to use virtual technology due to COVID-19. Pandemics such as COVID-19 force students and lecturers to use virtual learning irrespective of factors surrounding them. Pandemics are an anchor for the full embracement of virtual learning. Pandemic 'like' elements applied in the education system foster education. Google Classroom and its features prove to improve the teaching and learning processes. Chatbots and contextualized virtual Educational Humanoid robots enhance learning through interactivity. Pandemics need to be tested if they are a perfect fit as a new Unified Theory of Acceptance and Use of Technology (UTAUT) model construct. In addition, a model for effective blended learning during and post COVID-19 must be developed.

Keywords COVID-19 · Improving virtual learning · UTAUT · Higher education · Pandemics

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1 Introduction and background

The novel coronavirus (COVID-19) disease created enormous challenges in the tertiary education sector. Globally, universities are expected to offer education to students despite the pandemic (Maheshwari, 2021). In April 2020, the peak of global lockdowns, the pandemic disturbed learning for over 1.6 billion students in about 190 countries (UNESCO et al., 2021). Thus COVID-19 has severe implications for the attainment of Sustainable Development Goal 4 (SDG4) since education is among the sectors that were strongly impacted by the pandemic (Shulla et al., 2021). Universities have adopted the blended learning model, which integrates the power of face-to-face and online learning. Learning Management Systems such as Google Classroom are a centre stone of learning during this era and in the future. There is scant literature on higher education students' preparedness in using digital learning during pandemics. The global novel coronavirus disease (COVID -19) has strong implications on the way of life and more so on physical meetings in general and the tertiary education sector in particular (Bragg et al., 2021). The World Health Organization (WHO) declared the disease a public health emergency globally on 30 January 2020 (Muhammad et al., 2020). Subsequently, it was classified under the rubric of pandemics on 11 March 2020 (Maier & Brockmann, 2020). Globally, as of 13 July 2021, the WHO had reported 188,058,728 confirmed cases of COVID-19, including 4,055,644 deaths (WHO, 2021; Worldometer, 2021). Under intensive lockdown stages, Higher and Tertiary Education Institutions (HTEIs) were by governments to close as a precaution to contain the spread of the COVID-19. This meant abandoning the blended physical and virtual learning and a turn to an exclusive virtual model of teaching and learning. Higher education students are more accustomed to the 'old school' way of learning as compared to the so-called 'new-normal' and their response to such surprises/shocks is not known (Vanslambrouck et al., 2019).

The COVID-19 pandemic brought many face-to-face activities to a hiatus, posing a major threat to the continuance of teaching and learning in the education sector. The crisis illuminates the urgent need for higher education systems to evolve in practice, theory, and research to absorb or overcome such shocks in the future. However, the pandemic, painful as it is, has brought in some major environmental benefits. Studies have shown a stagnant concentration of carbon dioxide in the atmosphere over the period March to April 2020 (You et al., 2021), and this can only be attributed to the global travel restrictions and shutting down of most businesses. Meanwhile, the air in large cities such as Beijing and New Delhi became purer while the skies blued something that had not been experienced in decades but accomplished by the COVID -19 pandemic in just less than half a year.

COVID-19 induced lockdown measures restricting travelling result in a substantial reduction in atmospheric carbon dioxide levels, although this might fall short of what is required to limit global warming to 1.5 °C. Virtual technology is applied in teaching and learning and in other sectors. It has facilitated the concept of work from home, virtual business meetings, summits, and conducting conferences in various sectors. A lot of travel accompanied these activities before

COVID-19, and virtual technology has reduced the risk of infection and spread of the virus associated with travelling. In the process of precaution, the number of flights and volume of traffic has been reduced, which ultimately reduced the atmospheric levels of carbon dioxide. Related pandemics might recur some years to come, implying that, where applicable, people are forced to remain virtual to ensure service provisions are at minimum risk of infection.

Universities, which are rich grounds for technology inventions and expediting the transfer of technology, have at least three critical roles to play during and after the pandemic. Firstly, they should continue with human capital development to provide services during and after the pandemic. Secondly, in the process of the first role, they have to impart skills in the use of virtual technologies (VTs) to the graduates. Thirdly, they should help identify challenges in the transfer of online technologies. In addition, universities need to lead from the front through sustained adoption of these VTs in teaching and research. This is only possible if universities are ready to respond effectively to the pandemic threats through the transfer, adoption and use of virtual learning. However, there is still vigorous debate on the level of preparedness of higher education students on the use of digital learning (Rapanta et al., 2020; Reyes-Chua et al., 2020). Hindrances to student preparedness and full embracing of VTs include the cost of ICT infrastructure and services, efficiency and effectiveness of supporting systems like data, power, gadgets, and network coverage (Kaisara & Bwalya, 2021). The Coronavirus pandemic pushed universities to abruptly transit to online teaching and learning but the readiness of students remains a black box. Tang et al. (2021) focused on the subject and mainly centred on student characteristics such as gender, qualification level, and implementation of different virtual learning activities. Other researche focused on the acceptance of virtual technology by instructors (Blackwell et al., 2013; Hoareau et al., 2021; Samuel et al., 2018). Chen (2011) postulated that educational compatibility and technological expectancy are important determinants of e-learning acceptance by students in their order of significance. Given the limitation of the UTAUT model and other Technology Adoption Models, this research seeks to answer; what determines the use of technology during pandemics. Unlike other constructs in extant technological adoption and usage models, which seem to be pulling in nature and volition-driven (see Sections 2.1; 2.3; and Fig. 1.), the recommended construct 'pandemic' is pushing in nature since it pushes learners to embrace it against their own volition due to lack of alternative learning option. In this research, it's zrecognized that the extant UTAUT model(s) are limited, as they do not factor in shocks or crises situation such as the current COVID-19 pandemic. We argue that crises and shocks significantly determine the use, acceptance, and adoption of technology particularly the elimination of a normal transition time. The concept of crises has been coined as emergency remote teaching and the authors proffered solutions for future crises. Furthermore, emergency remote teaching was distinguished not to be an atom with online learning (Barbour et al., 2020). As influenced by a crisis, the deviation from the norm sets in motion a new trajectory of technology use. Thus there is increasing pressure for considering the implications of pandemics in technology transfer and adoption. Therefore, the paper seeks to make a theoretical and

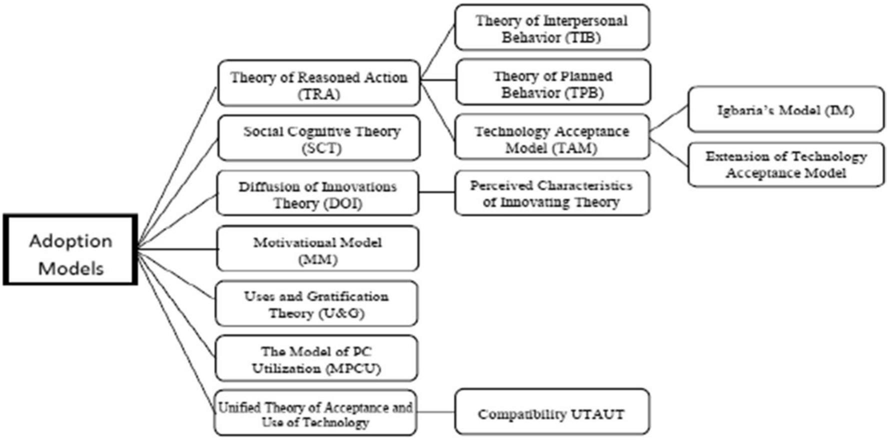

Fig. 1 An overview of Adoption / Acceptance Models. *Source:* (Taherdoost, 2018)

methodological contribution to the use of technology scholarship by recommending a new UTAUT construct that determines the use of technology in turbulent or crises times.

The hypotheses applied in this research are:

1. H_1: Performance Expectancy (PE) significantly influences Behavioural Intention (BI) to use and ultimately the usage of virtual learning during COVID-19.
2. H_1: Effort Expectancy (EE) significantly influence BI to use and ultimate usage of virtual learning during COVID-19.
3. H_1: Facilitating Conditions (FC) significantly influence BI and ultimate usage of virtual learning during COVID-19.
4. H_1: Social Influence (SI) significantly influence BI to use and ultimate usage of virtual learning during COVID-19.

The objective that relates to the hypotheses is: How does the UTAUT model inform the acceptance, adoption, and usage of virtual technology in Higher Education during COVID-19 to enhance education? Furthermore, the research addresses how Google Classroom is enhanced to inform further teaching and learning? The concepts are essential since technology cannot enhance learning unless adopted, embraced, and effectively used. The research further informs new trends of pedagogical uses of digital technology using Google Classroom. The aforementioned concepts further the technology body of literature particularly under crisis environments and propose an alternative model and explanatory concept that can be used in research, teaching and learning under crisis environments.

2 Related work

There is a large body of literature, which focuses mainly on the challenges and opportunities in the adoption of virtual technologies in Higher and Tertiary Education Institutions (HTEIs), and the applicability of the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Hoi, 2020; Nikou & Economides, 2017). One glaring assumption in most models particularly the UTAUT is that the adoption process takes place under a typical or 'normal' environment thus, it is expected to proceed mainly on a volition trajectory (Efiloğlu Kurt & Tingöy, 2017; Radovan & Kristl, 2017). This construct neglects adoption, embracing, and usage of Virtual Technologies (VTs) in times of crises and non-volition trajectory. Therefore, there is a dearth of literature in this area and we seek to modify the existing theories and models to include non-volition constructs like pandemics.

2.1 Theoretical framework

An overview of the most popular theories and models of technology acceptance, adoption, and usage is a necessary entry point to this research (Fig. 1.). Technological adoption and acceptance models originate from a diversity of theories such as Diffusion of Innovation theory (DOI) which was borrowed from sociology. Many psychosocial theories, for example, the Theory of Interpersonal Behaviour (TIB), Theory of Planned Behaviour (TPB), Social Cognitive Theory (SCT) have their origins in the Theory of Reasoned Action (TRA), which was derived from social psychology (Fishbein & Ajzen, 1975; Taherdoost, 2018). These theories have proven to effectively explain and forecast various human behaviours in different situations. However, TPB and TRA differ from DOI in that TRA and TPB emphasize explaining individuals' behaviour whilst DIO concentrates on adoption decisions in which the zorganizational characteristics play a pivotal and not the individual. TAM (Davis, 1989), TPB, and DOI use a unidirectional viewpoint towards the causal relationship, where environmental constructs affect cognitive beliefs, which affect attitudes and behaviours. In this study, the most relevant conceptual model for HTEIs student technology acceptance, adoption, and effective usage is applied using the UTAUT (detailed discussion of UTAUT is presented in Section 2.3).

2.2 Virtual learning

Virtual learning is defined as an online learning environment composed of the elements pedagogical functions, appropriate technologies, and social zorganization of education (Barajas, 2003). The virtual learning context in this research is based on the use of Google Classroom and institutional Electronic Learning (eLearning) platforms. Virtual learning in institutions of Higher Learning has become a necessity in times of lockdowns and social distancing enforced by governments and the World Health Organisation in an attempt to curb the spread of the highly infectious and contagious pandemic of COVID-19 and other related respiratory diseases (Bao, 2020). Information Communication Technologies (ICTs) have become of great value to transform the education system during and post crises such as pandemics and disasters. The adoption and use of virtual learning are premised upon having basic ICT Infrastructure by both staff and learners; training of staff and learners to effectively use the ICT tools; continuous monitoring and support of the stakeholders in virtual learning processes. Learners and instructors are faced with time and resource constraints.

The transition from classroom lectures to virtual lectures has been coupled with several pros and cons to both students and staff. Opportunities include availability, convenience, and recording of lectures for future use. The lecturers coin an average increase in working hours due to virtualization. Processes that used to take less time like marking result in exponential time increase as a result of factors like internet connectivity, power outages, the versatility of the laptop or gadgets being used, and expertise in the use of ICTs. Learners' challenges also include lack of good Internet connectivity (even cost – lack of funds and or supporting and or unavailability of funds), lack of ICT gadgets (including compatible, poor, or inadequate infrastructure), and other necessary resources that support virtual learnings (Adnan & Anwar, 2020; Alkhawaja & Halim, 2019; Chitanana, 2008; Mutisya & Makokha, 2016).

In addition, the challenges in the online component of blended learning include insufficient self-regulation by students and inadequate tech-savvy skills and resources/infrastructure, support such as training for the use of learning technology (Rasheed et al., 2020). These elements relate to the technology acceptance models which determine factors affecting the adoption and use of technology. However, there is a paucity of information on this concept using the UTAUT model during the COVID-19 era.

2.3 Conceptual model: The unified theory of acceptance and use of technology (UTAUT) model

van Raaij & Schepers (2008) applied the Unified Theory of Acceptance and Usage of Technology (UTAUT) and built a conceptual model to explain the differences between individual students in the level of acceptance and use of virtual learning. The adoption and use of technology are determined by technological and organizational conditions such as training, scheduling the implementation procedures and involving users, and provision of necessary resources such as infrastructure (Almusawi et al., 2021). This research focuses on the use of the UTAUT model to see the preparedness, adoption, and use of virtual learning. Efiloğlu Kurt & Tingöy (2017) applied the model using the case studies of Turkey and the UK and concluded that the behavioural intention and use behaviour in virtual learning differs according to country, and all UTAUT models constructs are valid in virtual learning. The UK students had a higher level of intention to use virtual learning than the Turkish students. There are more than 9 technology adoption models; among them, the UTAUT model was used since it merges specifically both the elements of the behavioural intention of adoption and use of technology (Alshehri et al., 2012). The Unified Theory of Acceptance and Use of Technology (UTAUT) model can be used to assess the adoption and use of technology in Higher Institutions of Learning since it focuses on the major variables (acceptance and use) (Venkatesh et al., 2016). The model has four main constructs, namely performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) (Venkatesh et al., 2012, 2016).

The Unified Theory of Acceptance and Use of Technology (UTAUT) model is behavioural factors centric and focuses on four constructs mentioned above that represent the behavioural intention to use or user behaviour. The concepts are shown in Fig. 2.

The three constructs PE, EE, and SI are zcategorized as direct determinants of behavioural intention (BI) to use technology. BI and FC have been coined as direct determinants of technology use. The theory moderating constructs are gender, age, experience, and voluntariness of use (Alshehri et al., 2012).

The four UTAUT model constructs have been defined and zcontextualized with virtual learning PE is the extent to which using virtual learning will provide benefits to lecturers in their work processes and the learning of students. EE is viewed as the degree of ease of use of technologies such as virtual learning by lecturers and students (Han et al., 2021). SI is the extent to which lecturers and staff perceive that local university authorities, government officials in ministries responsible for higher and tertiary education, and other stakeholders believe and expect they should use online learning. FC refers to lecturers' and students' perceptions of the resources (ICT infrastructure) and applications such as learning analytics dashboards and support needed and available to use virtual learning (Han et al., 2021; Venkatesh et al., 2003). The effects of the four constructs on the intention to use virtual learning are explored, whilst moderating constructs have been excluded since the test is being conducted under the 'new norm' of COVID-19.

Technology acceptance is affected by the BI to use technology. Using the structural equation modelling (SEM) it was concluded that there is a statistically significant relation to technology acceptance (Scherer et al., 2020). FC and PE were observed to be positively associated with the perceived usefulness of technology (Hanham et al., 2021). PE, EE, and SI are positive predictors of the BI to use technology (Hanham et al., 2021). The existing UTAUT model versions seem not compatible with current learning conditions where no virtual learning alternatives are in place since they do not include a new non-volition construct that informs the use of virtual learning in universities during pandemics like the COVID-19 (Tang et al., 2021). The UTAUT-2 model was not focused on since it focuses on the additional constructs, PV=Price Value, HM = Hedonic Motivation, and TR = Trust, which are directly linked to consumer goods and services and not virtual learning (Venkatesh et al., 2012). This research recommends a new construct, 'pandemics'.

3 Methods

A cross-sectional questionnaire survey was used to investigate the factors affecting the adoption and use of virtual learning using the UTAUT model. Opportunities and challenges in using virtual technologies in the delivery of lectures in Higher and

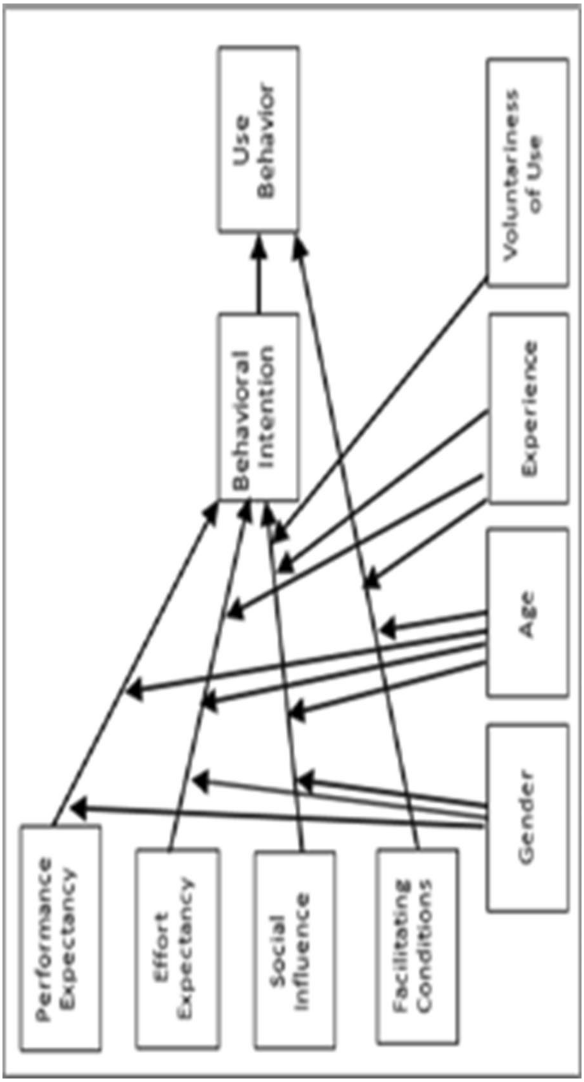

Fig. 2 Original UTAUT model. *Source:* (Venkatesh et al., 2003)

Tertiary Education Institutions (HTEIs) were also identified through the instrument, open-ended questions and literature review. The study was undertaken in Gweru, targeting students in HTEIs who are domiciled in Zimbabwe, and a total of 301 responded. The students were accessed via HTEIs platforms and they are exposed to an almost uniform environment of accessibility to technology irrespective of their location in Zimbabwe. R-Statistical Package and Stata Version 16 were used for data analysis and Cronbach's α test was done to test the reliability of the items. The modelling of data was done by two internal statisticians and an external (expert), and the results matched since the same software and procedures were applied. Inferential statistics were applied to explore the four constructs concerning behavioural intention and, ultimately use of virtual learning in HTEIs using the Structural Equation Modelling (SEM) technique (Scherer et al., 2020). The hypotheses in Section 1 have been applied. A structural equation model for the relationship between four constructs (PE, EE, SI, and FC) and the direct relationship Behavioural intention to use (BIU) as well as the indirect relationship Technology use (Tuse) was constructed. The five stages, namely, model specification; identification; estimation; evaluation; and modification as described by Teo, Tsai, & Yang (2013) were adopted and are generally accepted by many other scholars during model building (Byrne, 2016). Beginning with separate models, where zero covariance was assumed amongst the constructs, three separate models were constructed, each going through the five stages stated above. The final and adopted model was chosen on the one assumption of a non-zero covariance amongst the constructs. The hypotheses in Section 1 were tested in the current work.

4 Results and discussion

The respondents consisted of more males (64.5%) than females (33.9%). The margin is high since most students in most higher learning institutions where generally more males are pursuing higher education compared to females. Most of the students were from urban areas (70.8%). Only 16.6% reside in rural areas, reflecting the unequal accessibility of virtual platforms between the rural and urban dwellers. Most of the respondents were below 29 years of age (83.4%) at the level of undergraduate studies (91.7%) (Table 1).

The results of the application of the UTAUT model on the adoption and use of virtual learning, and the assessment in the use of virtual learning environment (Google Classroom) and its features, the context of use, and user experience and interaction by students are presented in this section. The values matched the minimum Cronbach Alpha coefficient of 0.7 recommended (Griethuijsen et al., 2014), as shown in Table 2.

With a total of 6 constructs containing varied test items totalling 25 a reliability analysis was performed before model building. Performance Expectancy (PE) items had good internal consistency with a Cronbach Alpha coefficient of 0.919, so was the Effort Expectancy (EE), Cronbach Alpha coefficient of 0.882. The rest of the constructs had at least one test item negatively correlated with the rest of the other items; hence, a Cronbach Alpha value below the recommended minimum

Table 1 Distribution of respondents by selected socio-demographic characteristics

Socio-demographic variables	Variable categories	n	%
Gender	Female	102	33.89
	Male	194	64.45
	Prefer not to answer	5	1.66
Location	High density suburb	1	0.33
	Medium suburb	2	0.66
	Peri-Urban	35	11.63
	Rural Area	50	16.61
	Urban Area	213	70.77
Age	18–20	124	41.20
	21–29	127	42.19
	30–39	40	13.29
	40–49	9	2.99
	50–59	1	0.33
Level of study	Undergraduate	276	91.70
	Master's	24	7.97
	PhD	1	0.33

$N = 301$

Table 2 Reliability Analysis for questionnaire test items used in the study

Construct	No. of test Items	Cronbach's α for all test items	Cronbach's α after reverse scale
Performance Expectancy	3	0.919	0.919
Effort expectancy	4	0.882	0.882
Social Influence	2	0.606	0.702
Facilitating conditions	4	0.612	0.821
Behavioural Intention	12	0.426	0.941

threshold of 0.7. After performing a reverse scale by removing at least one of the items, we achieved good internal consistency for Social Influence (SI), Cronbach Alpha = 0.702, Facilitating Conditions, Cronbach Alpha = 0.821, and Behavioural Intention (BI), Cronbach Alpha = 0.941.

4.1 Variable reduction using factor analysis

The 25 items of the 6 constructs were subjected to principal component analysis (PCA) using the R-statistics package. A correlation matrix was used to assess the suitability of the data for factor analysis. Several values with Pearson's correlation coefficient above 0.3 were observed, showing the suitability of the data for factor analysis. The Kaizer-Meyer-Olkin value was 0.89 exceeding the recommended value of 0.6 and Bartlett's Test for Sphericity was statistically significant (P < .001), implying the factorability of the correlation matrix.

PCA showed 7 components with Eigenvalues above 1 explaining 63.3% of the variability. The scree plot reveals a break after the second component. However, after performing parallel analysis, 6 components had eigenvalues exceeding 1; hence 6 components were retained for building the SEM. The 6 components explained over 50.6% of the variability. The interpretation of the components provided more insights into the Unified Theory of Acceptance and Use of Technology Model (UTAUT).

The measurement model, which specifies the relationship between observed variables and latent variables is depicted in Fig. 3. In this case, one latent factor (PE) was estimated by three observed variables, namely PE1, PE2, and PE3. The estimated effect of the observed variables was each found to be statistically significant (Table 3) $p < 0.001$, SE for PE1, PE2, and PE3 respectively equal to constrained (for PE1), 0.045 and 0.049, with respective estimates 1, 1.044, and 0.997 (Figs. 4 and 5).

The structural model was used to test the hypothesized relationship that the construct PE as measured by the three observed variables (PE1, PE2, and PE3) significantly affects the behavioural intention to use technology (BIU) which in turn significantly influences Tuse (Hanham et al., 2021) (Section 2.3). In other words, the construct PE significantly affects Tuse whilst being mediated by BIU. The test of the mediation hypothesis is shown in Table 3. Both the direct and indirect relationships were statistically significant with p values, 0.008 and < 0.001, respectively. The higher the PE, the higher the BIU and subsequently Tuse. In fact, there is a 0.663 increase in BIU for every unit increase in PE, resulting in a 0.043-unit increase in Tuse (Tables 4 and 5).

To explore the relationship depicted by a Path Model diagram in (Fig. 6.), estimates for the Structural Equation Model (SEM) were computed. Performance Expectancy was found to be a positive predictor of the Behavioural Intention to use technology (Table 6) ($b = 0.261$, $s.e = 0.060$, and p value <0.001), so was Effort

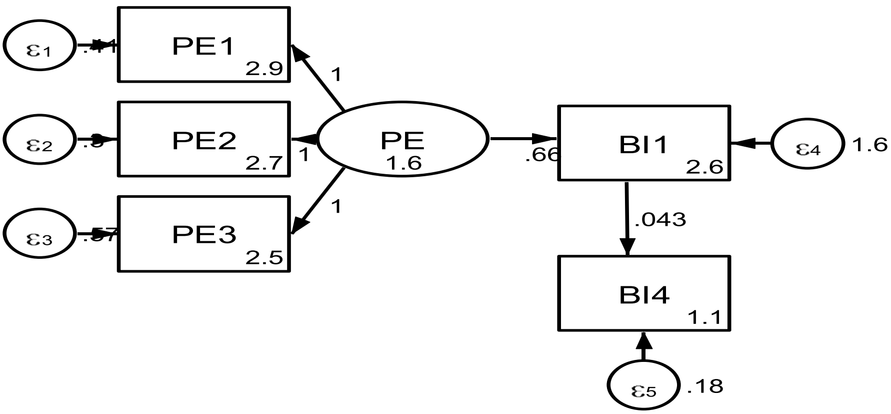

Fig. 3 Performance Expectancy influence on behavioural intention to use and ultimate use of virtual technology

Table 3 Relationship between the exogenous (Performance Expectancy) and the endogenous variables Behavioural Intention to use technology (BIU) and indirectly Technology use (Tuse)

Response variables	**Structural model**	Estimate	SE	z	*p* value
BIU	PE	0.663	0.064	10.30	<0.001***
	Constant	2.621	0.087	29.98	<0.001***
Tuse	BIU	0.043	0.016	2.63	0.008***
	Constant	1.140	0.049	23.06	<0.001***
	Measurement				
PE1	PE	1	(Constrained)		
	Constant	2.864	0.081	35.270	<0.001***
PE2	PE	1.044	0.045	23.080	<0.001***
	Constant	2.684	0.082	32.800	<0.001***
PE3	PE	0.997	0.049	20.390	<0.001***
	Constant	2.505	0.084	29.780	<0.001***

The relationship is depicted by the path diagram (Fig. 6)

Note: *$p<0.1$; **$p<0.05$ and ***$p<0.01$

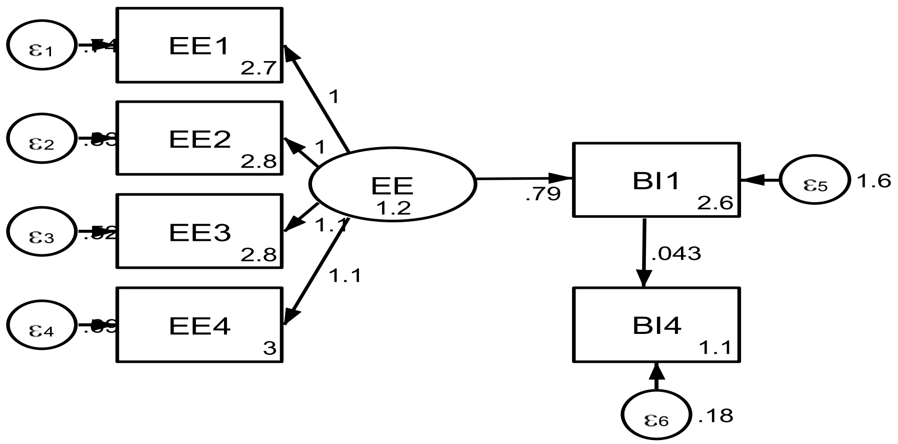

Fig. 4 Effort Expectancy influence on behavioural Intention to use and ultimate use of Virtual Technology

Expectancy ($b=0.204$, $s.e=0.061$, and p value <0.001) and finally Social Facilitation ($b=0.265$, $s.e=0.593$, and p value <0.001). To the contrary, Facilitating Conditions (FC) was found to be a non-significant construct of Behavioural Intention to use technology ($b=0.073$, $s.e=0.053$, and p value$=0.170$.

PE, EE, and SI had positive effects on the use of technology and is in tandem with previous researches and almost 99.99% of researchers agree on this notion (Efiloğlu Kurt & Tingöy, 2017; Venkatesh et al., 2003). The constructs are valid in virtual learning (Section 2.3). FC have no direct effect on learners' usage of virtual

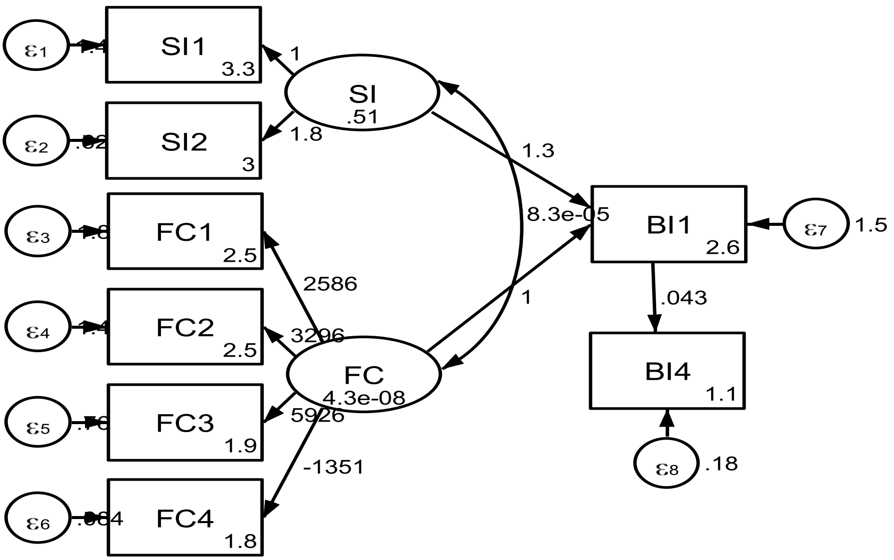

Fig. 5 Combined effect of Social Influence (SI) and Facilitating Conditions (FC) on behavioural Intention to use and ultimate use of Virtual Technology

Table 4 Relationship between the exogenous (Performance Expectancy) and the endogenous variables Behavioural Intention to use technology (BIU) and indirectly Technology use (Tuse) based on path diagram (Fig. 6)

Response variables	**Structural model**	Estimate	SE	Z	*p* value
BIU	EE	0.786	0.082	9.60	<0.001***
	Constant	2.621	0.087	29.98	<0.001***
Tuse	BIU	0.043	0.016	2.63	<0.001***
	Constant	1.140	0.049	23.06	<0.001***
	Measurement				
EE1	EE	1	(Constrained)		
	Constant	2.734	0.079	34.450	<0.001***
EE2	EE	1.001	0.072	13.910	<0.001***
	Constant	2.831	0.813	34.830	<0.001***
EE3	EE	1.138	0.074	15.290	<0.001***
	Constant	2.827	0.082	34.480	<0.001***
EE4	EE	1.111	0.753	14.750	<0.001***
	Constant	3.007	0.084	35.830	<0.001***

learning, which objects from the literature (Hoi, 2020; Tosuntaş et al., 2015). This resulted in our call for a more pressing factor that captures threats posed by pandemics. Thelack of alternative options ultimately forces learners to use virtual learning technologies against their own volition contradicting mainstream extant literature's

Table 5 Relationship between the main and interactive effects of Social Influence and Facilitating condition on the endogenous variables Behavioural Intention to use technology (BIU) and indirectly Technology use (Tuse) based on path diagram in (Fig. 6)

Response variables	**Structural model**	Estimate	SE	Z	*p* value
BIU	SI	1.265	0.184	6.86	<0.001***
	FC	1	(Constrained)	29.98	
	Constant	2.621	0.087	2.63	<0.001***
Tuse	BIU	0.043	0.016	23.06	<0.001***
	Constant	1.140	0.049	23.06	<0.001***
	Measurement				
SI1	SI	1	(Constrained)		
	Constant	3.306	0.079	41.530	<0.001***
SI2	SI	1.814	0.266	6.830	<0.001***
	Constant	3.003	0.087	34.440	<0.001***
FC1	FC	2585.954	7531.122	0.340	0.731
	Constant	2.488	0.084	29.580	<0.001***
FC2	FC	3295.662	9585.984	0.340	0.731
	Constant	2.492	0.078	31.830	<0.001***
FC3	FC	5925.652	17,222.930	0.340	0.731
	Constant	1.947	0.086	22.520	<0.001***
FC4	FC	−1351.247	3927.733	−0.340	1.731
	Constant	1.797	0.023	77.58	<0.001***
	Cov (SI,FC)	0.000	0.000	0.340	<0.001***

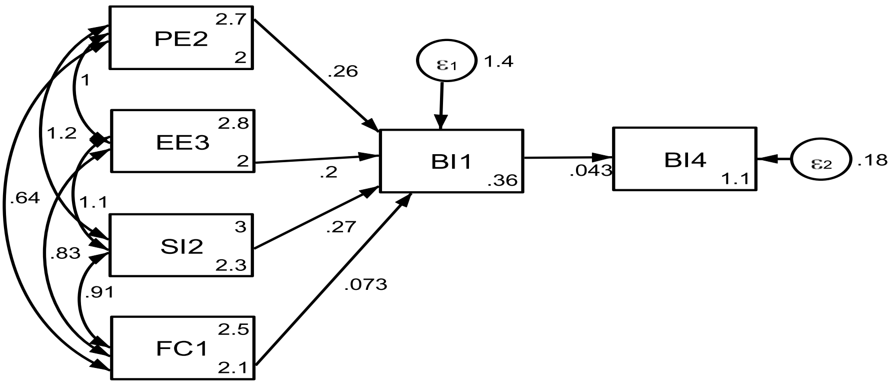

Fig. 6 Path Analysis (PA) model for the relationship between the exogenous – Performance Expectancy, Effort Expectancy, Social influence Facilitating condition and endogenous variables Behavioural Intention to use technology (BI1) and finally Technology use (BI4)

assertion that FC is essential (Almaiah et al., 2019). Table 6 contains all diagnostic fit statistics for all the models above as the basis for arguing and recommending the best model.

Table 6 Relationship between the exogenous (Performance Expectancy, Effort Expectancy, Social influence and Facilitating conditions) and the endogenous variables Behavioural Intention to use technology (BI1) and finally Technology use (BI4)

Response variables	Structural model	Estimate	SE	Z	*p* value
BI 1	Performance Expectancy (PE)	0.261	0.060	4.320	<0.001***
	Effort Expectancy (EE)	0.204	0.061	3.340	0.001***
	Social Influence (SI)	0.265	0.593	4.470	<0.001***
	Facilitating Conditions (FC)	0.073	0.053	1.370	0.170n.s
	Constant	0.364	0.184	1.980	0.048*
BI4	BI4	0.043	0.016	2.630	0.008***
	Constant	1.140	0.049	23.060	<0.001***
	Mean (PE)	2.684	0.082	32.800	<0.001***
	Mean (EE)	2.827	0.082	34.480	<0.001***
	Mean (SI)	3.003	0.087	34.440	<0.001***
	Mean (FC)	2.488	0.084	29.580	<0.001***
	Cov (PE, EE)	1.000	0.130	7.710	<0.001***
	Cov (PE, SI)	1.150	0.140	8.190	<0.001***
	Cov (PE, FC)	0.639	0.125	5.110	<0.001***
	Cov (EE, SI)	1.127	0.140	8.050	<0.001***
	Cov (EE, FC)	0.829	0.129	6.430	<0.001***
	Cov (SI, FC)	0.909	0.138	6.600	<0.001***

The opportunities and challenges discussed in this section on the adoption and use of virtual technology tandems with results in Section 2 except that FC is a cornerstone for adoption and use of VTs (Adnan & Anwar, 2020; Alkhawaja & Halim, 2019; Chitanana, 2008; Mutisya & Makokha, 2016). The Learning Management System used by respondents is Google Classroom. It's lightweight in data usage befits economically underperforming economies. In addition, the students regarded the virtual learning platform as a simple system for use, even for non-technical users.

Comments and notifications are automatically submitted during assignments submissions and other processes. The stream panel allows interactive interaction with the lecturer.

During the online test sessions, non-technical users write the tests with no challenges. Students with Internet connectivity challenges are the only ones who can face challenges and those lacking basic technical skills; hence it is essential to provide these services. For instance, the concept of infrastructure sharing in the form of drowning controlled satellites or mobile modems is provided, and training is given to students with no computer use background. This can include reaching the marginalized populations in the rural areas and other peri-urban areas, and even urban communities.

Videos posted in the Google Classroom might be difficult to download for non-technical students; hence refresher courses are essential or activation of direct download buttons or copy link options. Posted texts (books in pdf or word), PowerPoint, etc., should default to the file extension used by the poster instead of many file formats as it confuses other non-technical students when turning in assignments you can't load multiple files unless you first pull down the primary one and this is confusing. The Google Classroom platform should allow multiple file attachments, for example, during the submission of assignments. The platform is light on resources such as network, memory compared to other video conferencing platforms, and so on. Another advantage is it allows students to automatically save files to your Google Drive for easy access. However, there is a need for the Internet to access files unless they are downloaded to a personal computer hence there is a need to support offline automatic storage of learning materials and sessions. In addition, virtual learning platforms using Unstructured Supplementary Service Data can be rolled out to support all cell phone users and those without Internet access.

However, the system does not send automatic reminders for overdue work unless you log in, and this can be integrated as personal e-mail alerts and SMS. This calls for chabots and the use of contextualized virtual Educational Humanoid robots to enhance learning and interactivity. The artefacts are built using machine learning applied on live and archived data sets. Google meetings have Artificial Intelligence (AI) features like automatically lowering the hand after participating or giving a warning when the microphone is switched off whilst contributing. Generally, AI features supports engagement and make students remain focused during lectures hence more AI and machine learning (ML) features must be added regularly to LMS via plugins. Machine learning supports student-centric learning by creating content in areas students are not good in or suggesting learning groups according to specific traits. The concept of video conferencing supports versatility and live engagement. In summary, 95% of the students voted 5 stars (scale of 1 to 5) for aspects of the Google Classroom such as its features, functions, user interaction and experience, and impact on learning during COVID-19. In addition, the students appraised how the institutional electronic learning management system is seamlessly integrated with the Google Classroom, making it is so easy to work in and also with the support of learning brochures.

5 Limitations

The current study has limitations. Firstly, the researchers did not explore the moderating elements, namely gender, age, experience, and voluntariness of use, since, during lockdowns, students ultimately use virtual learning. Therefore, future research that explores the moderating impacts of the socio-demographic variables is recommended. Secondly, the study did not assess lecturers' views on the use of virtual learning and Google Classroom. This could enrich the understanding of the challenges and opportunities of using virtual platforms. Finally, the results from HTEIs are zgeneralized to represent the entire community and globally.

6 Conclusions

The deviation from the norm as influenced by a crisis sets in motion a new trajectory of technology use. The research made a theoretical and methodological contribution to the use of technology scholarship by proposing a new UTAUT construct that determines the use of technology in turbulent or crises times. Furthermore, it informed how Google Classroom can be improved to enhance teaching and learning using machine learning models which are institutional and or student-centric. COVID-19 and other life-threatening pandemics and or crises result in the acceptance and use of virtual learning against one's volition hence it can be coined that threatening pandemics results in forced use of technology. The sense of survival forces acceptance and use of technology hence zcontextualizing penalties as 'threats' in a rewarding notion that can be applied in HTEIs curriculum to improve the virtual teaching and learning processes. In a nutshell, the major common drawback observed from proposed constructs of almost all extant technological acceptance, adoption, and usage models summarised in Fig. 1. are pulling in nature since they are volition driven. In contrast, the recommended construct -pandemic- is pushing in nature since it pushes learners to embrace VTs against their own volition. The push factor emanates from the lack of alternative learning options due to COVID-19 lockdown restrictions and adherence to World Health Organization (WHO) guidelines to reduce the spread of the virus. Over and above the identification of the drivers of VTs acceptance, adoption, and usage, the proposed extension provides unique and insightful literature and methodological contribution to the technological usage arena.

Technologies eliminate everyday challenges; hence it needs to be harnessed, and research must be done to come up with more rewarding technological innovations; hence there is a need for partnership among various stakeholders such as governments, academics, students and HTEIs authorities in developing, deployment and maintenance of virtual learning platforms. An appraisal of the Google Classroom was made and included economic resources utilization, being user friendly (user interaction and experience), engaging the user, and supporting non-technical users. This encourages HTEIs to adopt an existing Learning Management System such as Google Classroom or institutional customized application that suits Google Classroom since it enhances the learning process. Strategies to reach marginalized populations who do not have Internet access are proposed such as using USSD applications and deployment of the Internet using drone-powered satellites. Offline access and Internet provision enhance inclusive education. Successful implementation of virtual learning will ultimately result in students learning effectively and applying skills adopted in the broader context. In addition, virtual learning has other positive attributes like reduction in paper usage and carbon dioxide-managed climate.

The majority of previous studies on UTAT models endorse the importance of facilitating conditions (FC). The results that FC has no effect, are somewhat counterintuitive and point to a non-volition influence – the Covid-19 pandemic Pandemics are deemed as life-threatening; thus, COVID-19 is viewed as a threat

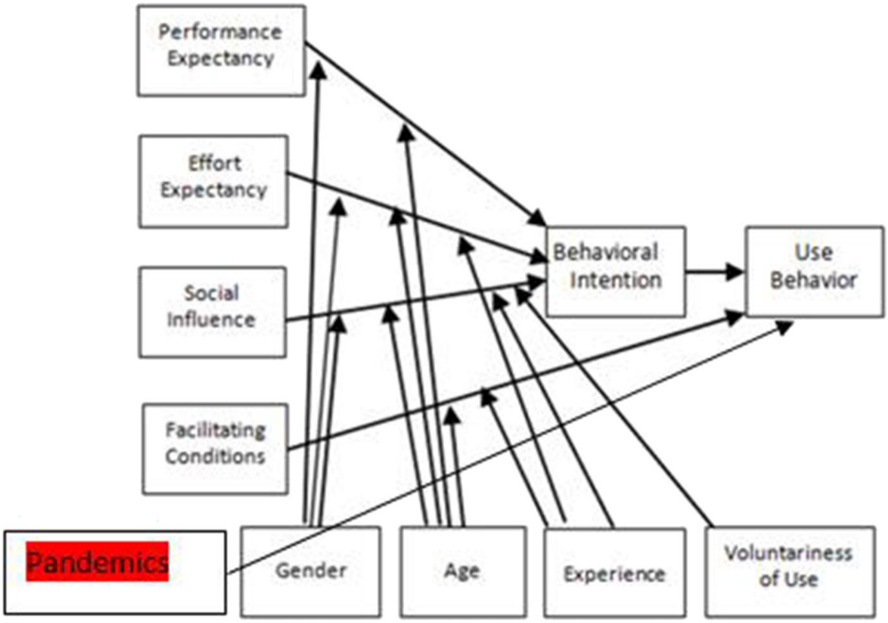

Fig. 7 Recommended UTAUT model

that forces students to use virtual learning irrespective of their background and volition. We recommend a new UTAT construct with pandemic as an essential variable (Fig. 7). Furthermore, this recommended new construct requires testing and thus, future research can use the model in Fig. 7 as an entry point to evaluate and develop models for effective blended learning during and post Covid-19. z.

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