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Remote e-learning model in the post COVID-19 era; building a resilient higher education strategy

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ABSTRACT

The research explored the pedagogic impacts of the virtual e-learning management platforms adopted at Chinhoyi University of Technology, as a COVID-19 pandemic resilience strategy. It established the link between students' e-learning adoption patterns and e-learning performance outcomes. Structural equation modelling was applied in analysing data from a sample of 70 undergraduate students. The results indicated that despite management's good intentions in mitigating the COVID-19 disaster on higher education, the performance of virtual e-learning system as a pandemic response strategy was curtailed by more inhibitors than accelerators. Factors such as unequal access to e-learning facilities, network connectivity challenges, internet access, unreliable electricity and unaffordability of compatible digital gadgets, constituted serious impediments to virtual e-learning adoption. Very few undergraduate students accessed the most versatile BigBlueButton e-learning platform, with very limited application of offline e-learning technologies like CD-ROM and flash disks. Instead, WhatsApp groups with the least e-learning interactive capabilities were most popular and highly subscribed. The implications are that universities' future e-learning pandemic resilience strategies should be supported by national level interventions that promote inclusivity and accessibility to e-learning facilities. The use of offline e-learning content material recorded in videos and flash disks should be promoted as low-cost e-learning management systems.

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Introduction and context of the study

The capacity of educational systems to respond to future pandemic via e-learning technological innovations is still highly questionable in developing countries. Following the global closure of schools, universities and colleges around the world during the COVID-19 pandemic era, universities and colleges adopted e-learning technological change (Dhawan, 2020; Huang et al., 2020) as one of the resilience strategy. The deployment of remote e-learning technology during pandemic served as a temporary measure to ensure 'learning never stops', despite the unprecedented disruptions caused by COVID-19 (Dhawan, 2020; UNESCO, 2020). Education was now being received from home (Mukute et al., 2020), as a measure to contain the spread of the disease, whilst enforcing WHO's social distancing guidelines in order to minimise persons contact and curb the contagious effect of the disease (Dhawan, 2020).

Enforcement of social distancing means attendance of physical lectures was impossible, hence the implementation of e-learning model (Kuwonu, 2020; Moyo-Nyede & Ndoma, 2020). Unfortunately, the effectiveness of the e-learning innovative change was seriously curtailed by structural constraints in the national technological environment. This triggers a very strong concern on high education disaster preparedness, in the event of another future pandemic. As a result, it is prudent to interrogate the e-learning preparedness of the higher education sector in absorb impact of any future pandemic in the

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post-COVID-19 era. Experience from the COVID-19 pandemic, tells us that, being caught unprepared is a highly risky and disruptive scenario to the smooth functioning of the higher educational system. Therefore, there is need to direct research effort towards assessing post-COVID-19 e-learning preparedness.

Background to the study

The virtual e-learning strategy rescued close to 1.58 billion learners, who were affected by the closure of schools and universities, from 192 countries; of which 297 million were from Africa and 4.13 million from Zimbabwe (ILO, 2020; Moyo-Nyede & Ndoma, 2020). Radios, televisions, the internet and social media were launched in primary and secondary education, while Moodle, Skype, e-mail, Zoom and Google Classroom were adopted in higher and tertiary education sector (Kuwonu, 2020; Moyo-Nyede & Ndoma, 2020). This guaranteed simultaneous social distancing and education progression, with minimum risk of the spread of COVID-19 pandemic (Maatuk et al., 2022; Mahyood, 2020).

Students and lecturers at CUT were introduced to BigBlueButton, an open-source learning management platform with diverse interactive learning capabilities that allows synchronous learning, with audio, videos and information chat capabilities. However, the platform has high data consumption rate and requires strong network connectivity as compared to WhatsApp, thereby making it quite demanding in terms of accessibility and implementation. Other online pedagogical instructional platforms like Google classroom, CUT Virtual Learning Environment (VLE), WhatsApp and Zoom were also used as alternatives. Surprisingly, WhatsApp one of the least recommended platforms became popular with students and lecturers. Learning instructions were conveyed through student WhatsApp groups, making the platforms more darling.

Sadly, remote e-learning was adopted by universities in Sub-Saharan Africa and Zimbabwe in particular in the absence of e-readiness, which defines the capability of e-learning users to apply e-learning resources and multimedia technologies (Matimaire, 2020; Rohayani & Kurniabudi, 2015). Structural constraints like inadequate electricity supply, low internet connectivity, high cost of data and rural-urban digital divide were prevalent with the potential to widen educational inequalities, depriving educational rights to the most disadvantaged students who could not accessible adequate e-learning resources (UN, 2020; UNESCO, 2020). E-readiness encompasses e-learning infrastructure accessibility, availability of computers, e-learning digital compatible devices, internet connectivity and relevant operating systems that support the e-learning program (Hale, 2006). Unequal e-readiness induces educational inequalities (Lizcano et al., 2020), thereby triggering disparities in educational accessibility.

Evidence from Zimbabwe supports existence of e-readiness induced educational inequalities (Mukute et al., 2020). For instance Moyo-Nyede and Ndoma (2020) noted that although nine in every 10 households had cell phones, only 43% had access to the internet, 62% never used internet, with only 14% using internet every day. Given that e-learning platforms are HTML web applications that requires internet connectivity (Huang et al., 2020), lack of internet accessibility cripples 82% of learners in sub-Saharan Africa (Moyo-Nyede & Ndoma, 2020; UNESCO, 2020). The transformative capability of remote e-learning to usher a sustainable and a resilient education system that can mitigate, adapt to and recover from shocks or stresses during times of pandemics and disasters is derived from the strength of the internet and the World Wide Web (Maslov et al., 2021; Shivshanker & Weisenhorn, 2020). Internet guarantees learning continuity, as content and knowledge sharing among geographically dispersed learners can be made possible during and after pandemics (Alturki & Aldraiweesh, 2021; Cavus et al., 2021; Huang et al., 2020).

Now that COVID-19 pandemic was officially declared over by WHO (Rigby & Satija, 2023), educational policy makers, academics and researchers should interrogate the effectiveness of remote e-learning system as a future pandemic response strategy. While there are several researchers who looked at factors that influence the application of e-learning technological innovations in education (Alturki & Aldraiweesh, 2021; Cai et al., 2020; Crichton, 2015; Maatuk et al., 2022) and those who analysed e-learning adoption behaviour during the COVID-19 pandemic like Cavus et al. (2021), Dhawan (2020) Mukute et al. (2020) and Doyumğaç et al., 2021)none of these researchers focused on e-learning technology as a resilient strategy for future educational pandemic. This research addresses this gap by exploring remote e-learning innovations as a strategy for a resilient and sustainable higher educational system in future pandemics or disasters. This will help to build comprehensive strategies for universities to pursue the integration of remote e-learning into the curriculum instructional delivery system, not as an ancillary measure but as an integral educational stabilisation tool (Serdyukov, 2017; Shelton, 2011). This is the only way to build a resilient higher educational system during times of disasters and pandemics.

Literature review

Policies that develop a resilient higher education system during times of disaster and pandemic depends on the acceptance, adoption and usage of e-learning innovations as supported by the technology diffusion theories (Huang et al., 2020; Park & Choi, 2019; Rogers, 2003; Straub, 2009; Wang & Liu, 2005). The technology diffusion theories explain how different e-learning technologies and learning management systems can be accepted or adopted as learning tools (Cavus et al., 2021) based on individual, organisational, innovation-related and societal perspectives (Huang et al., 2020; Maslov et al., 2021). Individual traits are personal attributes like gender, age, experience, knowledge, attitude, behaviour and beliefs about the technological change, that shapes one's intentions to use a technological innovation and the subsequent adoption behaviour, which in turn, determines the success of any technological innovation (Bakkabulindi, 2014; Rogers, 2003). The attributes also incorporates learner's digital capabilities, access to e-learning infrastructure and connectivity level, that impact on the ability of an individual learner to embrace the e-learning technological changes (Chang & Tung, 2008; Hale, 2006).

The unified theory of acceptance and use of technology theory advanced by Venkatesh et al., (2003) and the Rogers' innovation diffusion theory maintains that personal attributes are shaped by the extent to which the individual interacts with change agents (Bakkabulindi, 2014). Change agents are individuals or groups of people who lead or help the digital transformation process, as they drive the innovative change (Solis, 2018). The more individuals interact with these change agents, the more they are likely to adopt technological innovations for productive e-learning transformation.

The process of digital e-learning transformation can therefore, be understood as a by-product of collaboration, coordination and convergence under the innovation eco-system (Carayannis et al., 2018) and the concern-based innovation framework (Olson et al., 2020). This implies that for e-learning technological innovation to develop more resilient higher educational system, it should concern all stakeholders and be centred on an innovation ecosystem that recognises the interactions among various actors, under the concept of value co-creation (Cai et al., 2020; Carayannis et al., 2018). The term 'concerns' refers to the various perceptions, motivations, attitudes, feelings and engagements by students and all stakeholders in relation to the forms or types of e-learning platforms (Serdyukov, 2017). Whereas, value co-creation means university e-learning innovations should be based on the active involvement and support from multiple actors like students, parents, lecturers, the community, private sector and government who forms an eco-system of dependency (Cai et al., 2020; Carayannis et al., 2018; Serdyukov, 2017). Implementing educational changes, whilst neglecting the learners, the teachers and the society, is futile (Serdyukov, 2017).

Successful e-learning adoption model should recognise the importance of a social system. The role of social systems in shaping technological artifacts and the acceptance of technological innovations has been reinforced by the social construction theory of technology and the technology-organisation-environment theory (Park & Choi, 2019; Shields, 2012). These theories emphasises on a mutual deterministic relationship between the social structure and digital technology (Cai et al., 2020; Park & Choi, 2019; Rafael, 2013). Social structures and social systems shape the organization's and society's preparedness to harness new innovations (Bakkabulindi 2014; Rafael, 2013). Modern social structures are more ready to adopt and accept e-learning technological innovation than conservative traditional social systems (Cai et al., 2020; Findik-Coskuncay et al., 2018).

It is the technological readiness that determines whether the university have a good culture to accept e-learning technological change (Huang et al., 2020). To that effect, the impact of e-learning on higher education increases when the e-learning system is well integrated into the cultural norms of the social system (Findik-Coskuncay et al., 2018). The cultural norms influence individual perceptions or beliefs towards an innovation. These beliefs influence users' attitude and behaviour towards accepting or rejecting a technological application (Abdullah & Toycan, 2017; Bakkabulindi, 2014; Wang & Liu, 2005).

The Rogers' innovation diffusion theory and Davis et al.'s (1989) technology acceptance model summarised these perceptions based on the perceived ease of use and perceived usefulness beliefs. Individual perceptions about the innovation characteristics like the innovation's relative advantage, compatibility, user friendliness or complexity, trialability and observability (Huang et al., 2020) shapes the use behaviour. It is this actual technological system usage that generates direct impacts on education system (Crichton, 2015; Wang & Liu, 2005). The more users are willing to use a system, the more they are likely to benefit during or after a pandemic. In turn, increased use of a learning management system influences both the system's perceived usefulness and perceived ease of use (Taylor & Todd, 1995).

Perceived usefulness is the potential user's subjective probability that using certain technology can enhance work performance (Davis et al., 1989). Perceived usefulness increases with use rate. Whereas perceived ease of use is the degree at which the prospective users expect the technology to be free of effort. Free of effort means, the extent to which a technology can be used without complexities. If a technological application is perceived to be easy to use, it is also more likely to be accepted (Davis et al., 1989; Maslov et al., 2021). Users' attitude and acceptance of an information technology determines the system's net benefits (Wang & Liu, 2005).

Recent studies reveals that, during the COVID-19 pandemic era, the adoption, diffusion and utilization of the innovative e-learning technology in the higher education sector, has been generally met with resistance and was at a very slow pace (Cavus et al., 2021). There is abundant evidence pointing to a very low student acceptance of open source e-learning platforms (Huang et al., 2020). Evidence from Mahyood (2020) on Saudi Arabian university, Huang et al. (2020) from Taiwanese technical university and Matar et al., (2011) from Arad universities indicates that adoption and acceptance of e-learning technologies was very low, as the switching process from classroom based mode to online model during the COVID-19 pandemic was met with numerous technial, academic and communication challenges. As such, the size of adoption costs prolongs the adoption lag (Comin & Hobijn, 2010).

Methodology

A survey of 475 students who were registered between 2020 and 2021 was used. These students were exposed to blended learning mode during the COVID-19 pandemic era. The data included the total number of courses attempted by each student, number of passes attained by each student per each semester from the total number of courses attempted. Passes were categories as number of distinctions attained by the students per semester, the number of passes with at least a B pass, and number of passes below a B grade, number of course failed. The first two passes were very competitive passes whereas passes below B are considered weak and uncompetitive on the job market.

A comprehensive questionnaire was developed to solicit for student perceptions and opinions about e-learning ease of use and perceived usefulness using a 4-point Likert scale. Learners were asked to rate their opinions on e-learning usefulness based on whether it is not useful, not sure, useful and very useful. In terms of ease of use they were to indicate whether it was: not ease, not sure, ease and very ease. Different questions were also asked to solicit for students' opinions and feelings about different e-learning platforms. A 5-point Likert scale was used to rate different students' opinions about their experiences with different e-learning platforms. Rating these statements helped to determine the students' different opinion based on their experience with BigBlueButton as compared to other platforms.

The questionnaire also covered learner's demographic characteristics that affect e-learning adoption capabilities. These factors include gender, average family income, family size, students' family responsibility, family locational factors, accessibility to digital networks and availability of compatible digital learning tools. It also captured student locational factors, like whether the student is from the rural, urban or peri-urban set-up, accessibility of the area to network connectivity, accessibility of electricity. Each geographical area confers different e-learning technological resources and capabilities. Income differential implies differentials in adoption capacity given that e-learning adoption demands investment in digitally compatible gadgets, which may cost money. Similarly, the cost of data may also be an e-learning barrier to students from low-income families.

Data analysis

Given that the BigBlueButton platform was the most recommended e-learning management platform at CUT due to its impressive e-learning interactive capabilities, understanding factors that determine its adoption was therefore critical. Using the SEM, the study analysed these factors as a complex interconnection between learner's perceptions towards using the BigBlueButton e-learning management system and the adoption patterns, which in turn affects the learners' performance outcomes. This relationship was complex in that e-learning enhanced performance will also influence learners' perceptions and e-learning adoption patterns. Such a complex ecosystem of interdependencies cannot be easily estimated using the Ordinary Least Square technique or other regression analysis that do not factor in the path analysis component of the SEM. Therefore, a combination of confirmatory factor analysis and path analysis were used to give a complete picture of the interdependencies among the latent variables. The SEM technique as a multivariate approach was selected due to its capabilities to evaluate complex networks of causal relationships in an ecosystem of interdependency among interacting variables (Fan et al., 2016).

Confirmatory factor analysis has the capabilities to estimate the latent psychological traits, such as attitude, perception and satisfaction (Prudon, 2015) by learners towards the use of BigBlueButton when compared to other online learning management systems. Whereas the path analysis component estimated the direct and indirect causal effects among the e-learning technology adoption variables like perception, adoption patterns and students' performance outcomes (Prudon, 2015). Previous technology impact studies like Park and Choi (2019) used the path analysis to analyse the path link between digital innovation and economic growth of nations. The approach can address the mediation effect, the complex direct and indirect causal relationships among the technology success variables. For instance, both perceived usefulness of a technology and its perceived ease of use, indirectly affect user satisfaction through influencing attitude towards use, which in turn influences behavioural intention to use and the actual technology use, leads to user satisfaction and the realised performance outcomes. This complex relationship generates a complex path analysis problem that cannot be resolved by regression analyses, but by a full structural equation model, which combines the confirmatory factor analysis and the path analysis, whilst simultaneously accounting for measurement error and capturing the latent effect of the mediating variables (Weston & Gore, 2006)

We first estimated the measurement model, and then estimating the full structural equation model. The measurement model emphasises on the latent or composite variables. It helps to determine model fit related to the latent portion of the model. The full structural equation model addressed the relationships among variables based on the path analysis. The data were analysed using the Lavaan package developed by Rosseel (2012).

Model specification and the variables

Three latent variables were created based on perception, adoption or use and performance. This was done by estimating a system of simultaneous Equations 1 to 3 using the SEM technique for the latent variables of perception ($Perc$), adoption (Ado) and performance (Pef) of the e-learning system.

$$Pef = \beta_{11}Ado + \beta_{12}Perc + \beta_{13}Gender + \beta_{14}Loc + \beta_{15}Resp + \varepsilon_{11} \tag{1}$$

$$Ado = \gamma_{21}Perc + \varepsilon_{21} \tag{2}$$

$$Perc = \varphi_{31}Ado + \varepsilon_{31} \tag{3}$$

A system of simultaneous Equations 1 to 3 provides a clear path analysis of the causal relationships among e-learning technology adoption, learners' perception and the e-learning adoption pattern. E-learning adoption pattern was broadly defined as the learner's status regarding the use and interest or motivation in the application of the BigBlueButton learning management system. This state was such that, learners either adopted BigBlueButton or did not adopt it. Based on the model, learners' performance was assumed to be positively influenced by both adoption pattern (Ado) and the learners' perceptions ($Perc$) about the usefulness of a particular learning management system. In that regard, if a learner adopted BigBlueButton learning management system for lecture, expectations were that performance will be high. Conversely, if a learner never adopted BigBlueButton performance was expected to be lower. Adoption (*Ado*) in Equation 2 was assumed to be influenced by perception (*Perc*). If perceptions about the e-learning technology are positive, learners were more likely to adopt the e-learning technology. If they have a negative perception, then adoption was likely to be slow and at time unlikely.

Latent variables used and their validity

A latent variable is a variable that is not directly observed but can be inferred from a set of observable variables. The three latent variables adoption, perception and performance were developed using the marker variable approach as applied by Weston and Gore (2006) to control for the effect of common method variance which is associated with Likert scale data. The common method variance arises when there is systematic covariation in the construct used to measures the observed scores during the variable measurement. It threatens the validity of the cross-sectional researches that do not use multiple methods (Malhotra et al., 2006).

Adoption pattern was created by using learner's BigBlueButton status (BBB_{status}) as a marker variable in Equation (1). Learner's BigBlueButton use status was a binary choice that assumed a value 1 if the learner used BigBlueButton and a 0 if the learner never used. Adoption was generated from a set of observed variables as according to Equation (4)

$$Ado = \sim 1{*}BBB_{status} + difficulties_{CUTVLE} + Better_{WhatsApp} + No_{interest} \tag{1}$$

The marker variable was given a coefficient of 1 and was followed by three other observed variables that were generated using a 5-point Likert scale measure. According to the Likert scale, 1 described strongly disagree status, 2 disagree, 3 neutral, 4 agree and 5 strongly agree. The three observed variables were created from three different statements that described the BigBlueButton adoption pattern. This variable ($difficulties_{CUTVLE}$) asked learners to strongly agree or agree with the statement; 'I faced more difficulties in using BigBlueButton than CUT VLE'. The variable $Better_{WhatsApp}$ asked the learners to state their position regarding to the statement: 'It is better to use WhatsApp than BigBlueButton'. The variable $No_{interest}$ where learners were asked to state their position regarding the statement; 'I have no interest in using BigBlueButton'.

The latent variable learner's perception on BigBlueButton (*Perc*) was created using three observed variables which were also derived from a 5-point Likert scale. The learners were to respond to the following set of statements; 'I tried BigBlueButton but I failed to adopt it', 'BigBlueButton has unnecessary high cost' and 'I need more time to learn BigBlueButton'.

$$Perc = \sim 1{*}Not_{useful} + More_{time} + High_{costs} \tag{5}$$

Using a 5-point Likert scale, learners were to agree or strongly agree with the statement that 'BigBlueButton is not very useful', the observed variable Not_{useful} was created to capture the perceived usefulness of the platform. This variable entered as a marker variable in creation of the latent variable for perception (*perc*). The other variable $More_{time}$ 'I need more time to learn BigBlueButton', captured the perception on easier to use of the e-learning management system. More time to learn is needed if the platform is difficult and the adoption rate is slow. The latent variable perception also included users' perception on affordability. With learners asked to provide their perception on the statement 'BigBlueButton has unnecessary high costs'.

The latent variable performance was constructed using courses failed as a marker variable. A binary choice variable show whether a student failed a course during the semesters assessed. If the learner failed at least a course, a 1 was assigned, if no course was failed a 0 was assigned.

$$Perf = \sim 1{*}\mathrm{Failed}_{\mathrm{course}} + B_{passes} + D_{passes} \tag{5}$$

The variable B_{passes} measured the change in the ratio of the number of at least a B pass attained by the student to the total number of passes attained by the student between the semesters August to December 2020 and March to June 2021. The ratio of at least a B pass reflects an above average performance, which can get the student into a merit pass. If the change in ratio is positive it shows an increase in the number of B passes and negative change shows a decrease in the number of B passes.

Similarly, D_{passes} represents the change in the ratio of the number of distinctions attained by the students during the semester to the number of total courses passed during the semester. A positive or negative change in this ratio carries the same connotation as for the Bs.

Mediating effects variables

Equation 1 included the mediating variables like gender of the student, home location (*Loc*) of the student and fees responsibilities (*Resp*). The mediating effect arises because the relationship among e-learning adoption patterns, perception and educational performance was assumed to be directly or indirectly influenced by gender, location and fees responsibility factors (Prudon, 2015). The gender variable was entered into the model as a dummy variable with values of 1 if the learner is a male and 2 if the learner is a female. Learners' performance was expected to decrease with the female attributes and increase with male attributes because female learners were assumed to be overburdened by increased stress from household chores, high rates of forced marriages, early pregnancies and higher chances of university dropouts, than their male counterparts (MIET Africa, 2021; Mukute et al., 2020).

Learners' home location also affects e-learning technology adoption and learners' performance. Learners whose homes are located in the urban areas and growth points were more likely to enjoy good access to electricity and network coverage, than those in rural areas and peri-urban areas, therefore better resourced to perform and adopt technology. Location was captured using a 4-point measure. If the home was located in urban areas, they were assigned a 1, if in growth point was assigned a 2, peri-urban was assigned a 3 and 4 if they were in rural areas. The variable responsibilities indicate the person who was responsible for fees and general upkeep. If the student was self-funding a 1 was assigned, and a zero otherwise

Results

Distribution of lecture attendance by virtual e-learning platforms

Table 1 shows the distribution of lecture attendances on different virtual e-learning platforms. Evidence indicates poor performance of BigBlueButton, Google Classroom and CUT VLE lectures, with average attendances of 16%, 21%, and 12% respectively. The three virtual e-learning, platforms performed badly compared to WhatsApp which scored an average attendance rate of 78% for the two classes used in this study.

The sample evidence suggests that, on average a Bsc Supply Chain Management (BSCM) class with 385 registered students had an attendance rate of 14% on BigBlueButton, 18% on Google class and just 12% on CUT VLE. WhatsApp platform had the highest attendance rate for both classes with 78% attendance for BSCM and 80% attendance for Bsc International Marketing (BSIM). Similarly, BSIM class had lower attendance on BigBlueButton, Google classroom and CUT VLE, with 22%, 33% and 10%, respectively. The distribution confirms that e-learning platforms like BigBlueButton, Google classroom and CUT VLE were less popular than WhatsApp platform. This bias towards WhatsApp, was explained by students on the basis data affordability. Students pointed out that other e-learning management platforms, like the BigBlueButton have high costs of data and therefore, not affordable. However, Google classroom and CUT VLE do not consume as much data as BigBlueButton, yet their use or adoption rate was still very low. This lower utilisation rate may raises the question pertaining to the virtual e-learning preference structures.

Table 1. Distribution of average lecture attendance (%) by virtual e-learning platform.

Class	n	BigBlueButton	WhatsApp	Google classroom	CUT VLE
BSCM	385	14	78	18	12
BSIM	90	22	80	33	10
Total	475	16	78	21	12

Source: Electronic attendance records (BigBlueButton, WhatsApp, Google Class, CUT VLE).

The preference structures

Table 2 shows the virtual e-learning management systems preference structures. WhatsApp had the highest proportion of respondents who had more preference on it, with 48% of the 41 students who responded to the question indicating more preference and 32% preferred it. Only 3.2% indicated that they do not prefer WhatsApp e-learning instructional system. Google Class had almost 21.4% of the 27 respondents indicating more preference, with another 21.4% were in the preferred rating, and 14.3% did not prefer it. CUT VLE had 32% of the 32 respondents indicating more preference and 24% rating it in the preferred category, 20% did not prefer it. BigBlueButton had 16.7% of the 70 respondents choosing more preferred options and 33.3% selecting preferred, 14.3% did not prefer it. Zoom had 13 learners who responded to it, with only 7% of this number utilised it for learning, 20% of the respondent strongly preferred it, 60% weakly preferred it and 20% did not prefer it.

Table 3 indicates respondents' perception on the perceived usefulness of the digital platform.

Usefulness of digital e-learning platforms

Of the 32 learners who responded on CUT VLE, 35.7% and 39.3% rated it very useful and useful respectively. Surprisingly, only 43% utilised this platform as compared to 67% of the 70 students who responded on BigBlueButton and 59% of 41 learners who responded on WhatsApp. BigBlueButton had 70 learners who responded to the question on usefulness, with 26.7% indicated that it was very useful, and another 26.7% also indicated that it was useful, with 67% indicated that they used it. BigBlueButton had 53% of the respondents who rated it either useful or very useful.

E-learning platforms ease of use

Table 4 indicates responses from e-learning platform's ease of use. The degree at which a platform is used depends on its ease of use, also known as 'free from effort' (Davis et al., 1989). As shown in Table 4, the general perceptions based on students' ratings present WhatsApp as the easiest e-learning platform to use with 70% of the respondents supporting the cause. CUT VLE was second with 65% of the respondents supporting the argument. BigBlueButton had 45% of the respondents concurring that it is either ease or very easy to use. Google class is the list rated.

Therefore, factors such as cost and learning capabilities are equally important in determining the platform usage rate (Lizcano et al., 2020). A platform that meets all the three tests is more likely to be adopted that a platform that meets one and fail the other test. The poor utilisation of Google Class and CUT VLE even after indications that the platforms were useful, may suggest absence of strong learning

Table 2. Digital e-learning platforms preference structure.

	Response frequency	Prop used %	Not preferred %	Weakly preferred %	Preferred %	Strongly preferred %
BigBlueButton	70	67	14.3	33.3	33.3	16.7
CUT VLE	32	43	20.0	24.0	24.0	32.0
Google class	27	23	14.3	28.6	21.4	21.4
WhatsApp	41	59	3.2	16.1	32.3	48.4
Zoom	13	7	20.0	60.0	–	20.0
CD-ROM	3	100	–	15.0	65.0	20.0
Flash Disk	8	100	–	–	80.0	20.0

Table 3. Usefulness of digital e-learning platforms.

	Response frequency	Prop used %	Not useful %	Fairly useful %	Useful %	Very useful %
BigBlueButton	70	67	8.9	33.3	26.7	26.7
CUT VLE	32	43	–	25.0	39.3	35.7
Google Class	27	23	5.9	23.5	11.8	41.2
WhatsApp	41	59	18.4	7.9	26.3	47.4
Zoom	13	7	–	66.7	–	16.7
CD-ROM	2	100	–	–	50.0	50.0
Flash-Disk	8	100	–	–	44.0	56.0

Table 4. Perceptions on e-learning platforms ease of use.

	Response frequency	Prop used%	Not easy %	Fairly easy %	Easy %	Very easy %
BigBlueButton	70	67	11.9	38.1	23.8	21.4
Google classroom	27	23	6.7	40.0	13.3	26.7
CUT VLE	32	43	7.7	26.9	23.1	42.3
WhatsApp	41	59	16.2	13.5	13.5	56.8
Zoom	13	7	20.0	60.0		20.0
CD-ROM	2	100′	–	–	50.0	50.0
Flash Disk	8	100	–	–	–	100

Table 5. Structural equation modelling statistics.

	Measurement model	Full model
Comparative fit index (CFI)	0.891	0.871
Tucker-Lewis index (TLI)	0.847	0.836
Root mean square error approximation		0.055
Akaike information criterion (AIC)	1031.862	1030.156
Bayesian information criterion (BIC)	1080.412	1085.039
Sample-size adjusted Bayesian information criterion (BIC)	1008.059	1003.249
Chi-square	40.353, df 32, $p = 0.148$	60.841, df 59, $p = 0.158$
Performance		
Failed at least a coursed	1.00	1.00
Ratio of at least a B pass to total courses passed	0.224* (0.761)	2.323* (1.473)
Ratio of distinctions to total courses passed	0.014* (0.066)	0.196* (0.245)
Use/adoption		
I used BigBlueButton for e-learning	1.00	1.00
I faced more difficulties in using BigBlueButton than CUT VLE	1.400*** (0.360)	1.479*** (0.392)
It is better to use WhatsApp than BigBlueButton	0.618** (0.256)	0.582** (0.259)
I have no interest in using BigBlueButton	0.114** (0.139)	0.075** (0.141)
Perceptions		
BigBlueButton is not very useful	1.00	1.00
BigBlueButton has unnecessary High cost	0.577*** (0.198)	0.558*** (0.192)
I need more time to learn BigBlueButton	1.061*** (0.259)	1.032*** (0.248)

Standard errors are shown in parenthesis ().
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

capability factor as an explanation for low adoption rate. Lower adoption of Google class and BigBlueButton might be partly due to the perceptions by students on the 'ease of use or free from effort' (Davis et al., 1989) aspects of the platforms. The perceived ease of use is the degree to which learners believe the two systems to be free from effort.

Failure to address these sentiments will constitute serious impediments to a successful application of virtual digital e-learning technology as the best option to circumvent the negative impacts of future pandemics like COVID-19 on higher education performance. Whilst, lack of training, high-cost data, problems related to 'ease of use', and weak digital e-learning platform capabilities are some of the important factors that influenced the adoption pattern, other factors like network connectivity were highlighted as major impediments that derailed the performance impacts of every digital e-learning platforms.

There is also a disturbing fact about very limited application of offline e-learning technologies. Only 2% of the sampled students indicated that they used CD-ROM for e-learning purposes, with 11% concurring that they used flash disk for the e-learning purposes. The low utilisation rate of these offline e-learning technologies is a serious issue that need to be attended to. Unless students realise the importance of offline technologies, they will continue to complain about internet challenges without any immediate solution. It is very important to encourage students to utilise these offline e-learning technologies.

Structural equation modelling results

Table 5 presents the econometric output from both the confirmatory factor analysis. Although the comparative fit index (CFI) and Tucker-Lewis index (TLI) failed to meet the expected fit level of above 0.9 with the reported values of 0.891 and 0.847 respectively for the measurement model, the insignificant χ^2 as an absolute fit suggests that the model fits the data well. According to Roos, (2022), the CFI and

Table 6. Full model regressions.

	Adoption	Perceptions	Performance
Perceptions	3.353** (4.124)		−0.029** (0.027)
Adoption		0.659*** (0.204)	0.025** (0.027)
Gender			−0.025* (0.027)
Location			0.032 (0.020)
Responsibilities			−0.009 (0.007)

Standard errors are shown in parenthesis ().
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

LTI suffers from sample size effect, they require larger sample to provide good measures of fit; hence they cannot be relied on for small samples.

All observed variables were found to be significant as they loaded to the three latent variables: 'performance', 'use/adoption' and perceptions. The coefficient for all the marker variables were 1. These findings imply absents of any likelihood of model misspecification (Weston & Gore, 2006). As such, there were strong basis to proceed with the full model estimation to determine the relationships among the hypothesised latent variables.

Full structural equation model results

Table 6 shows the results for the full structural equation model. The results for three models are shown by three columns labelled adoption, perception and performance. According to the results, adoption status was positively influenced by perceptions, with the coefficient of 3.353 being significant at $p < 0.05$. This is in conformity with theoretical expectations, that positive perception can increase adoption rate. The results for perception model indicate that adoption status have a positive effect in shaping one' perception. The coefficient for adoption was 0.659 and was significant at $p < 0.01$. This implies that for students who adopted either voluntarily or involuntarily their perception about the platform's usefulness or ease of use will always change with adoption.

Finally, opinions on student performance outcome were found to be positively influenced by the adoption of BigBlueButton e-learning technology. The coefficient for adoption was found to be positive and significant, though at $p < 0.05$ level. The same performance variable was found to be negatively influenced by student perceptions about the technology's ease of use and usefulness. These findings imply that to enhance impact of e-learning technology on educational performance perception about the technological capabilities of e-learning had to be improved so that adoption rate or use rate improves. The findings support Findik-Coskuncay et al. (2018) that perception strongly affects performance. As students continue to realise more benefits from the application of a particular e-learning technology they are likely to change their perception towards it. Surprisingly gender was found to be significant but with a negative sign. Implying that male student tended to have a negative perception towards the e-learning performance than their female counterparts.

Discussion of the findings

Despite evidence that all the digital e-learning management platform positively impacted on students' final examination results, there is evidence of varied learning performance impact of the different digital learning platforms, when considered from the students' adoption or utilisation rate. The students' digital e-learning platforms preference structure was skewed in favour of WhatsApp platform. The university's most recommended BigBlueButton although very versatile and more interactive than the other e-learning management platforms it failed to attract more students, mainly due to students perception problems. Students had a wrong perception that the system is a costly heavy data platform, hence it had lower attendance rate. Although some students faced network and digital compatibility problems, the BigBlueButton platform holds enormous potential to transform the e-learning model.

The fact that BigBlueButton has been facing adoption challenges as a disaster mitigatory tool as compared to WhatsApp platform does not relegate it to lower end. Those who utilised it enjoyed its strong e-learning capabilities, with interactive features that are effective for synchronous learning. Other platforms like CUT VLE and Google Class do not provide synchronous learning environments. Synchronous learning happens when an effective real-time feedback between the lecturer and the student is guaranteed. WhatsApp and BigBlueButton provide effective real-time interactive learning environment; hence they should be given more consideration when learning is to be conducted virtually.

Whilst negative perception has affected BigBlueButton adoption rate, WhatsApp emerged the preferred platform due to its convenience, low costs and compatibility with many mobile smart phones. Platforms like CUT VLE and Google Classroom failed to attract more students, due to internet connectivity challenges, and their interactive learning capability levels. The differentiated adoption of the e-learning management platforms implies that dependency on a single e-learning platform will not effectively improve the learning outcomes. Students should be exposed to a variety of these virtual digital learning management platforms, so that they can have the leeways to select the most convenient learning platform. The application of multiple digital learning platforms will reduce the unequal access to learning content that may results from students' differences in e-readiness.

The results also concurs with the previous findings that the application of online learning may expose the vulnerable and compromised equal access to education, thereby creating a wide disparity with regards to learners' right to quality, safe and inclusive education based on social engagement with peers and educators (Mukute et al., 2020). A cross examination of the learning performance effect of the BigBlueButton learning management system, indicated that despite the systems' learning capabilities, students were unable to meet adjustment cost when it comes to adoption decisions. These adjustment costs include the cost of purchasing compatible electronic gadgets, purchasing data, training in the use of the different Learning Management Systems and accessing internet connectivity, as well as accessing guaranteed electric power.

Limitations

This research largely relied on quantitative data analysis techniques, thereby giving limited scope to qualitative comments. As such, future researchers on e-learning can utilise some of the most recently emerging methodological approaches like the online photovoice as applied by (Tanhan & Strack, 2020), or the community based participatory research approach . These approaches offer the participants room to express their own experience with little manipulations compared to traditional quantitative methods.

Conclusion

The findings from this research prove that virtual e-learning model can produce fantastic results on student performance if measures that empower the students to adopt the e-learning technology are implemented. Policies that guarantee student access to data and stable network are necessary. However, such policies require interventions that are beyond CUT's purview. Given that the problem of data and network connectivity problems are nationwide with potential to affect all universities in Zimbabwe, CUT can join effort with other universities to push for government policies to recognise the importance of digital e-learning model, as a panacea to pandemic inflicted damages to higher education. The skewed distribution in attendance is evidence to suggest that the COVID-19 induced e-learning model can improve higher educational performance if barriers inhibiting students' equal access to e-learning platforms are addressed. The general sentiments from the students that the university should train them on how to use the different online platforms means that information gap is still wide and more training workshops need to be organised.

Disclosure statement

No potential conflict of interest was reported by the authors.

About the author

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