# The Factors Affecting the Adoption of Virtual Learning Environments (VLE) and Learner Management Systems (LMS) by Higher Education Students during and post-COVID-19 In Kenya

**Jimmy K.N. Macharia**
**United States International University – Africa**
**Email:** kmacharia@usiu.ac.ke

**Abstract**

Over the past three decades, researchers, academics, and technology innovators have been grappling with the problem of technology adoption and acceptance of the unintended phenomena of technology rejection and low utilization. COVID'19 pandemic has accelerated the need for the adoption of disruptive technologies, particularly in education worldwide. Prior researchers have posited that Higher education institutions (HEIs) globally and particularly in Kenya made an effort to transition to Virtual Learning Environments (VLEs) from March 2020 during the COVID'19 pandemic. Since VLEs were new to many HEIs and students and instructors, this paper is devoted to investigating the role of COVID'19 on the Adoption of Disruptive Remote Learning technology by Higher Education Students in Kenya. The study employed a descriptive research design, using a self-administered online cross-sectional survey questionnaire to a purposefully selected 136-university student's sample. Borrowing the technology acceptance model (TAM) from the academic environment, we apply it to the student VLEs context and extend it by incorporating the user, COVID'19 context, and technology factors to adopt VLEs. In academic settings, perceived Usefulness has been the predominant driver of technology adoption. Our empirical results show that while perceived use (a utilitarian aspect) contributes to students' adoption of virtual learning environments, what contributes, is the COVID'19 context. Furthermore, the results show that the COVID'19 lockdowns positively and significantly influences students' adoption of Virtual Learning Environments (VLEs).

**Keywords:** *Virtual Learning Environments (VLEs), COVID'19, Adoption, Disruptive Technology, Usefulness, Ease of Use, Subjective norm, Time-saving, Higher Education.*

## 1. Introduction

### 1.1 Adoption of VLEs in Higher Education

Prior studies have established that although Virtual Learning Environments (VLEs) in Higher Education have increased significantly in recent years. However, there is some teaching staff whose usage and adoption are minimal (McMahon, 2016). Moreover, van Raaij and Schepers, (2008) have argued that the success of a virtual learning environment (VLE) depends considerably on student acceptance and use of such an e-learning system. COVID'19 outbreak has caused a downward spiral in the world economy and caused a substantial impact on the higher education system. In early 2020, the COVID'19 (caused by the SARS-CoV-2 virus) pandemic shocked the world, almost bringing it to an unprecedented stop (Aristovnik et al. 2020). The sudden closure of campuses as a social distancing measure to prevent community transmission shifted face-to-face classes to Virtual Learning Environments (VLEs). This phenomenon shifted the focus on utilizing VLEs tools and platforms for effective student engagement. Unfortunately, prior researchers have posited that this largely unplanned and unprepared shift may have had limitations of accessibility and affordability for many students, which in turn may have influenced their adoption or lack of it (Rashid & Yadav, 2020). Current researchers argue that the pandemic has uncovered the shortcomings existing in the higher education system. They have established the need for more training of educators in digital technology to adapt to the world's rapidly changing education climate (Rashid & Yadav, 2020). In the post-pandemic situation, Virtual Learning Environments (VLEs) may become an integral part of the higher education system. For these reasons, prior researchers advocate for higher education institutions and universities to plan post-pandemic education and research strategies to ensure quality student learning outcomes (Rashid & Yadav, 2020). This paper attempts to answer that call by investigating the Role of COVID'19 on Disruptive Remote Learning Technology Adoption by Higher Education Students.

Prior studies define disruptive technologies as emerging technologies that result in a step change the cost of access to products or services or dramatically change how we gather information, make products, or interact. Disruptive technologies have increasingly been altering the development and delivery process paths of emerging markets and businesses operating in emerging markets (IFC, 2020). Disruptive technologies are far broader than digital services. Examples include artificial intelligence (AI), block chain, robotics, 3D printing, genomics, and distributed power systems. (IFC, 2020). According to Yadav (2019), in higher education, four technologies, namely Virtual Reality (VR), Collaboration Platforms, Augmented Reality (AR), and Artificial Intelligence (AI), will be disruptive. On the other hand, platforms that offer VLEs provide facilitators with tools and resources to support education delivery. Facilitators (including teachers) can design VLEs for multiple purposes and functions (McBurnie, 2020). During the immediate COVID'19 crisis, VLEs can provide out-of-school students with an alternative platform to access quality educational content and pursue institutional and national learning objectives. However, education planners should note that many students in low- and middle-income countries may not benefit from VLEs due to poor connectivity and a lack of technological hardware (McBurnie, 2020). This is then a strong motivation for this paper to study the Role of COVID'19 on Disruptive Remote Learning Technology Adoption by Higher Education Students in a developing country, Kenya.

### 1.2 Technology Adoption and Job Performance in Educational Settings

Numerous researchers have argued that Virtual learning environments (VLEs, Learner management systems (LMS), and other educational, supportive technologies such as the Internet, World Wide Web, and e-mail have become among the top concerns of learning institutions. These problems are acute in higher education during and after COVID'19 (De Giusti, 2020; Aristovnik et al. 2020). There has been widespread adoption of VLEs in higher learning institutions due to the emergence of COVID'19 in early March 2020. However, this phenomenon has failed to produce the fundamental changes in learning and teaching that many expected to the extent that many institutions and education systems are waiting to reduce COVID '19 community transmission to return to face-to-face learning. On the other hand, several researchers have posited that effective VLEs adoption, diffusion, and infusion are critical for universities' operation and activities, including education, teaching, research, communication, and management (Cosgrave et al., 2011). For example, the study by Jelinek et al. (2006) deployed a longitudinal methodology that produced evidence that sales technology tools improve job performance. Further, a recent empirical study by Baskaran et al. (2020) has established that technology adoption significantly influences employees' job performance .

The study of the barriers to the VLEs adoption in learning and teaching in the higher education sector has become an area of interest to researchers (Bowen et al., 2012; Cosgrave et al., 2011). Further, the rising need for Online, Distance, and E-learning (ODeL) education that is open, adaptable, equitable, flexible has increased. However, the question of "Why Don't All Lecturers Make Use of VLEs?" is still unanswered (Lingard, 2007). The issue is not only crucial for VLE vendors but also for higher education institutions, including universities. Finally, the emergence of COVID'19 and new types of education providers through VLEs has even begun to challenge traditional learning and teaching models that were adopted and put into practice throughout the world for centuries or decades and changing them forever (World Economic Forum, 2020).

### 1.3 VLE Adoption in Kenya

Prior researchers have agreed that the value of e-learning lies in its ability to train anyone, anytime, anywhere, and that implementing and sustaining e-learning programs require more than merely moving education and learning online (Tarus & Gichoya, 2015). Moreover, the learners and instructors need access to a stable internet, a smartphone, and a computer to participate effectively. Unfortunately, prior researchers report that Kenya's university students and lecturers face enormous challenges moving online (The Conversation, 2020). Some challenges include lecturers and students needing the technical skills to function in this new environment: sustained support before, during, and after delivery. The future of learning will likely become increasingly digital, regardless of the pandemic (The Conversation, 2020).

Further, besides lowering the cost of internet access and providing stable electricity, the challenge of inadequate investment in e-learning resources, both physical and human, is crucial. Finally, many universities need to enhance the VLEs, to have videoconferencing tools and proctored examination platforms. Each institution must also have an organizational structure, the necessary expertise through training on online delivery, and a dedicated budget to run these systems efficiently(The Conversation, 2020).

Following the proceeding challenges and gaps in policy, implementation, and deployment practices for VLEs, this paper investigates the factors affecting the adoption of Virtual Learning environments (VLEs) and Learner Management Systems (LMS) Adoption by Higher Education Students in During and post-COVID'19 in Kenya. The factors to be considered include cost and time saving, subjective norm, COVID'19 context, Perceived Usefulness, and Ease of Use of the VLEs.

## 2. Problem Statement

For over three decades, since Davis et al. (1989) introduced the Technology Acceptance Model (TAM), researchers have been grappling with technology's low utilization or ultimate rejection and failure (Murthy & Mani, 2013). Moreover, while all the world over, higher education embraces virtual learning environments (VLEs), worrying to note that contemporary researchers are asserting that Kenya isn't ready for VLEs (The Conversation, 2020). The researchers investigated 12 public and private universities in Kenya that offer open and distance learning programs. Their study revealed that students preferred face-to-face or blended methods of teaching and learning. However, according to The Conversation, (2020), only 19,000 (3.8%) out of 500,000 students, were enrolled for open and distance learning. They argue that due to the challenges students face in online or distance courses – they prefer to register in regular face-to-face programs (The Conversation, 2020). Further, less than half (about 45%) of students enrolled in distance learning programmes could access course materials through their university's online platforms; the rest either received them through email or in hard copy (The Conversation, 2020). It is evident from the preceding assertions, that even for universities that deployed VLEs, they are either under-utilized, or have not achieved their set objectives without COVID'19.

Further prior researchers (Bowen et al., 2012; Cosgrave et al., 2011) have called for further research into barriers to the VLEs adoption in learning and teaching in higher education. This study is indeed a response to meet this need by attempting to fill the knowledge gap. However, the failure of the deployed VLEs to achieve the students' intended utilization levels is also evidence of challenges in deployment practice (Lingard, 2007). Additionally, the lack of adequate funding indicates a policy gap (Tarus & Gichoya, 2015). According to World Economic Forum (2020), higher education has changed forever.

Consequently, there is an urgent need for Kenya universities to be ready now. This paper investigates the factors affecting the adoption of Virtual Learning environments (VLEs) and Learner Management Systems (LMS) Adoption by Higher Education Students in During and PostCOVID'19 in Kenya. Among the factors to be considered, include cost-saving, time-saving convenience, subjective norm, COVID'19 context, Perceived Usefulness, and Ease of Use of the VLEs.

## 3. Literature Review

### 3.1 Theoretical Background

The technology acceptance model (TAM) has extensively explained IT adoption and usage (Davis et al., 1989). Nevertheless, the model has criticism since investigations are focused on IT adoption and principally use the instrumental perspective (Agarwal & Karahanna, 2000), concentrating mainly on extrinsic or functional motivational factors such as ease-of-use and Usefulness (Bruner & Kumar, 2005). Although social norms are expected to play a critical role in student acceptance of VLEs, particularly in the COVID'19 era, other contextual factors such as cost (of access), time-saving, and COVID'19 lockdown in the illumination of student adoption, acceptance, and usage of VLEs. Rabaa'i (2016); and Huang et al. (2013) have pointed the importance of including Subjective norms in the investigation of the Extending the Technology Acceptance Model (TAM) to Assess Students' Behavioral Intentions to adopt an e-Learning System: The Case of Moodle as a Learning Tool. The COVID'19 era context is well advocated by many researchers and players in the education sector, including World Bank Group (2020) in their report " Remote Learning response to COVID'19 Knowledge Pack, " as the study by (Rizun & Strzelecki, 2020). Unfortunately, the antecedents of Time, Cost, and COVID'19 have not received enough attention from researchers; consequently, they have been included in the theorizing of this paper. Incorporating these factors into TAM may better explain and predict student adoption and usage of VLE.

### 3.2 Technology Acceptance Model

The theoretical foundation for this paper stems from the technology acceptance model (TAM)) (Davis et al. 1989) . The study has adopted it as the foundation for our framework to explain student adoption and usage of VLE. Rigorous TAM assessments and comparisons with other intention-based models such as the theory of planned behavior (TPB) and the idea of reasoned action (TRA) have established that TAM is theoretically tailored for the study of computer-technology acceptance.

Additionally, prior studies have posited that TAM has a high research significance in the Information systems domain(Todd & Shirley Taylor, 1995). Further, TAM is capable of explaining user behavior across a wide range of end-user computing technologies and user populations while at the same Time being both parsimonious and theoretically acceptable (Bruner & Kumar, 2005). In TAM, the usage of technology or user application is determined by behavioral intention, which in turn, is affected by the direct effects of perceived ease of use and perceived Usefulness (Davis et al., 1989). In models where Attitude is included, perceived ease of use and perceived Usefulness jointly affect Attitude, while perceived ease of use directly affects perceived Usefulness. TAM has been broadly used in IS research (Hasanah et al., 2019; Hubert et al. 2019).

### 3.3 Empirical Review

The central idea underlying TAM is that a person's behavioral intention (BI) to use a ''system'' (the new hardware, software, etc.) is determined primarily by two assessments: its Usefulness and its EOU (Davis et al. 1989). Perceived Usefulness has to do with the degree to which a person believes a specific system will perform a particular task. In contrast, EOU has to do with the extent to which a person thinks using a technology that will be relatively free of effort (Bruner & Kumar, 2005). TAM remains the most used and the most practical theory for researchers because even if TAM and TAM3 are the most used theories, TAM has an advantage that is the possibility of being combined with other theories without the risk of ending up with a very complex model (Chroqui et al. 2017). Figure 1 shows the model tested in this study (c-TAM). The theoretical rationale for each of the paths in c-TAM is given in the following sections.

#### 3.3.1 Perceived Usefulness (PU)

Prior research has established that Usefulness is typically the key driver of BIU (Davis et al. 1989). However, current literature has revealed several exceptions. One exception to this was the finding by Shawnice L. (2017) that the Usefulness → BI (or usage) path was non-significant. However, explanations for this phenomenon are due to the users' experience and confidence level with mobile devices. The researchers argue that the emphasis on perceived Usefulness of behavioral intent to utilize, or not, a particular technology may become irrelevant because mobile technology has become embedded in the higher education environment (Shawnice , L. 2017). They added their explanation that the differences could have arisen from the measures used in that study. The result revealed that the outcome was have driven by the fact that Usefulness was measured for the web's particular activity. This could explain their abnormal finding and suggest that the notion that perceived usefulness impacts usage is still valuable. (Shawnice ,L. 2017). Due to this contradiction and un-validated explanations, this study found it noble to investigate PU influence on BIU. Given that strong theoretical and empirical support for Perceived Usefulness (PU), we make the following propositions:

H1. : Perceived Usefulness (PU) has a positive influence on the behavioural Intention (BIU) of users towards adopting Virtual Learning Environments (VLE)

### 3.2.2 Perceived Ease of Use (PEOU)

Although the original TAM posited and found EOU affected the Usefulness of a system in workplace environments, studies in the student domain contradict findings. For example, Coşkunçay et al. (2018) have established that Perceived Ease of Use (PEOU) has a direct, positive, and significant influence on the Perceived Usefulness (PU) of Learning Management System (LMS) by students. On the other hand, (2000) has established that PEOU does not significantly influence PU in adopting the Learning Management System (LMS). Consequently, to illuminate this contradiction, this study has investigated the relationship between PEOU and PU. It is expected that as students believe that VLE is more comfortable to use, they are likely to perceive it helpful as they can spend their Time doing other things rather than figuring out how to use the technology (Bruner & Kumar, 2005).

Although there is consensus on the importance of EOU in predicting technology adoption, there is some inconsistency in the literature on how this variable affects BI (Bruner & Kumar, 2005). The POEU → BI path is significant in some studies and not important in others. In the study on the impact of cognitive absorption on perceived Usefulness and perceived ease of use in online learning, Saadé, and Bahli (2005) found that Perceived Ease of Use (PEOU) has a direct, positive, and significant influence on the Behavioral Intention to Use online learning. On the other hand (Purnomo & Lee, 2013), in their study on E-learning adoption in Indonesia's banking workplace, the relationship between perceived ease of use and behavioral intention is not supported. Although a few researchers have attempted to explain that this contradiction is attributed to the inclusion of utilitarian and hedonic variables or lack of it (Bruner & Kumar, 2005). However, their justification is questionable because, in the study by Purnomo and Lee (2013) on E-learning adoption in the banking workplace in Indonesia, the hedonic variable Attitude was not included. Yet, the established that that Perceived Ease of Use (PEOU) does not direct, positive, and significant influence on the Behavioral Intention to Use online learning. In this paper, it was postulated that as students believe VLE is easier to use, they are likely to also going to increase their behavioral intention to use it. Based on the support theoretical and empirical research for PEOU influences on the adoption of VLE, we make the following propositions:

H2a. : Perceived Ease of Use (PEOU) has a positive influence on the Behavioural Intention to use Virtual Learning Environments (VLE)

H2b: Perceived Ease of Use (PEOU) has a positive influence on the Usefulness of Virtual Learning Environments (VLE)

### 3.2.3 COVID'19

The COVID'19 pandemic has forced schools and colleges to shut down temporarily. This has caused havoc in the education system. According to a UNESCO report, more than 157 crore students across 191 countries were severely impacted by the closure of educational institutions due to coronavirus (Husain, 2020). The issue of the COVID'19 and its impact on higher education is an emergent focus of debate worldwide. Closing universities and canceling classes have become a COVID'19 reality in many countries globally, leading to enormous anxiety and uncertainty (Husain, 2020). Even before COVID'19, there was already high growth and adoption in education technology, with global tech investments reaching US$18.66 billion in 2019 and the overall market for online education projected to reach $350 Billion by 2025. Whether it is language apps, virtual tutoring, video conferencing tools, or online learning software, there has been a significant surge in usage since COVID'19 (World Economic Forum, 2020). However, there has been no adequate research on the influence of adopting or using Educational Technology such as VLEs. Therefore, this paper postulated da relationship between COVID'19 and PEOU (COVID'19 --> PEOU). Further, we shall explore the link COVID'19 → BIU. A few researchers have pointed this as an area of interest in research (Alqahtani & Rajkhan, 2020; Surkhali & Garbuja, 2020). Given the existing gap in both theoretical and empirical research for COVID'19 influences on the adoption of VLE, this paper makes the following propositions:

H3a. COVID'19 Lockdown positively influences the perceived ease of use (PEOU) of Virtual Learning Environments (VLE).

H3b: COVID'19 Lockdown has a positive influence on users' behavioural Intention (BIU) towards adopting Virtual Learning Environments (VLE).

**3.2.4 Social Norm**

Davis et al. (1989) found social norms (SN) an essential determinant of behavior intended to be weak. The technology acceptance model (TAM) does not take in social norms (SN) as a factor of behavior intention (BIU). It is a crucial determinant, theorized by the Theory of Reasoned Action TRA and Theory of Planned Behavior (TPB) (Lai, 2017). Due to these inconsistencies, this paper found it noble to include Social Norm in its investigation. This is justified since students are generally in the same age group, are involved in similar activities, and are likely to significantly influence each other's behavior, habits, and even adoption of technology like virtual learning environments.

Given that solid theoretical and empirical support for social influence, we make the following propositions:

H4. : Interpersonal influence has a positive effect on the behavioural Intention (BIU) of users towards adopting Virtual Learning Environments (VLE)

**3.2.5 Time**

Time-saving is associated with the Usefulness of a system land leads to more favorable attitudes toward using a system and a greater inclination to adopt it (Rogers, 1995). Rogers (1995) asserts that Time is the third element that influences diffusion and states that it is involved in diffusion in the innovation-decision process, innovativeness, and innovation's adoption rate. The innovation-decision process is how an individual passes from first knowledge of an invention to forming an attitude toward adopting the innovation t(Rogers, 1995). Moreover, since a student has adequate Time to be on the computer for his/her learning, in a few weeks, he/she will be familiar with the VLE interface, features, functionality and therefore find it easy to use. This paper investigates the effects of" time-saving" as an antecedent of PU. As a result, we propose the propositions that follow:

H5a: Time saving and convenience of VLEs has a positive influence on the Attitude of users towards the Usefulness of Virtual Learning Environments (VLE)

H5b: The Time saving and convenience of VLEs has a positive influence on the Attitude of users towards the ease of use of Virtual Learning Environments (VLE)

H5c: The Time saving and convenience of VLEs have a positive influence on the Attitude of users towards conforming to the social norm.

**3.2.6 Cost Saving**

Ordinarily, in the absence of COVID’19 lockdowns and restrictions, students PA an equivalent of $100 per semester for private bus company transport from Nairobi city to the campus, which is about 10 Kilometres from the central business district. Additional cost saving is made on the transport from CBD to their parent's residence in the city's suburbs. Furthermore, a similar amount or more is required for lunch in the cafeteria in any given semester. Consequently, even if the students spent 20% of the total amount, they will save $250 per semester. More important. In the context of COVID’19 lockdowns, the travel time from home to campus and back, which primarily can be estimated to 4 hours because of traffic jams is a significant saving. Consequently, we expect a strong relationship between cost saving and time-saving. As a result, we propose the propositions as follow:

H6: Cost saving has a positive influence on the Attitude of VLE users towards Time Saving due to Virtual Learning Environments (VLE)

**3.2.7 Research Model and Hypotheses**

A critical review of TAM by several researchers, including (Legris et al. 2003; Marangunić & Granić, 2015), has revealed that it is essential to include other components to provide a broader view of a better explanation of IT adoption. Specifically, factors related to developing world context (Musa, 2006). Figure 1 depicts the research model used in this study. This model integrates the COVID’19 lockdowns perspective into the original TAM and includes timesaving and cost saving as a salient determinant of student intention to use VLE.

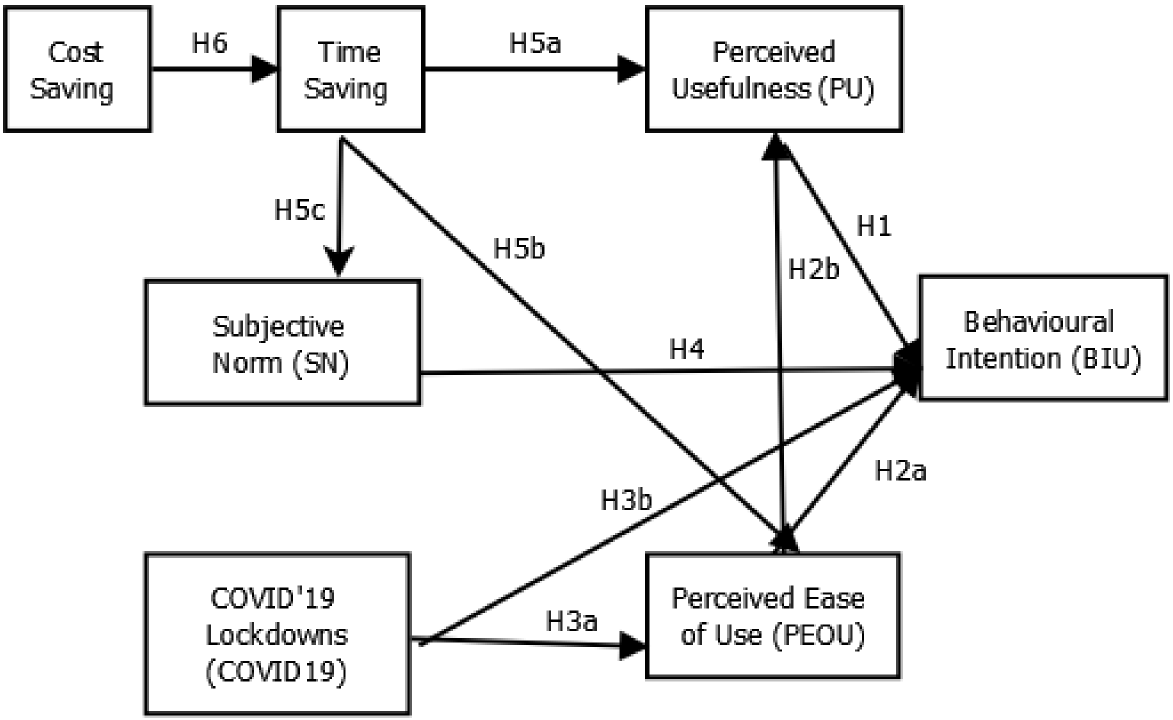



**Figure 1: Proposed Adoption model of VLE**

## 4. Methodology

### 4.1 Research Design

The study adopted a descriptive research design using a cross-sectional survey strategy with a self-administered online questionnaire. The survey was conducted at a large taking the Digital Literacy class where all activities, including practical and examinations, were performed using the Virtual Learning Environment (VLE) Blackboard LMS platform. The study was founded on the positivist paradigm. The inclusion criteria for participation was a willingness to take part in the study. Students who were not reachable by email at the time of data collection were excluded from the data collection.

### 4.2 Data Collection

The minimum sample was calculated using an online calculator for structural equation modeling (Soper, 2021).The study aimed at investigating students' adoption of the VLE. The VLE had all features, including video conferencing provided on a single Blackboard learning management system (LMS) interface. Additionally, students could form WhatsApp groups or use email and phone calls to help deck or instructors. The Blackboard Learning portal-containing lecture notes, chat room facilities, and streaming videos of lectures to provide out-of-classroom support to students beyond the classroom. Students could download lecture materials, including a course outline, slide notes, case studies, and video recordings of past classes that were made available to students. Students could raise their hands during the class sessions, ask questions, or show their case studies, problem solutions, in-class activities, group discussions, and problem-solving answers. The student could also discuss the material with their classmates and instructors using the online chat room and discussion forums. The majority were first-year undergraduate students who did not have any prior knowledge of this VLE. At the end of the semester, one hundred and thirty six (136) usable data records were obtained from the online questionnaire.

**4.3 Measures**

This research's measures were adapted from prior studies where modifications were done to fit the specific context of the Virtual Learning Environments. Measurements for perceived Usefulness (PU) perceived ease of use (EOU), Subjective (SN). However, we introduced measures for COVID'19 lockdowns (COVID'19), Time Saving (TIME), and Cost Saving (COST) that were not available from prior studies. (CS) Behavioral intention (BIU) was phrased on a seven-point Likert scale, from 1 = strongly disagree to 7 = strongly agree.

**4.3 Data Analysis**

In the analysis of the data, the assessment of both psychometric properties and model testing was done using the IBM AMOS 23 framework, one of the most widely used structural equation modeling (SEM) techniques in information systems. Chin, (1998), posits that if SEM is precisely applied, it can surpass first-generation techniques such as principal components analysis, factor analysis, discriminant analysis, or multiple regression. TAM provides superior flexibility in estimating associations among many predictors and criterion variables and permits modeling with unobservable latent variables. Further, it makes assessments of the model uncontaminated with measurement errors (Lee et al. 2005b). Statistical Package for Social Sciences (SPSS) Version 23 was used for factor analysis,

**4.4 Reliability, Validity, and Fit Indices**

**4.4.1 Reliability**

Generally, reliability is how reliable the study measurement model is in measuring the envisioned underlying constructs (Munir, 2018). The Reliability of the measurement model is assessed based on the criteria detailed in Table 1. Prior research has revealed that there are three benchmarks for the assessment of Reliability for a measurement model:

**Table 1. Reliability**

| **Reliability** | **Criteria** |
|---|---|
| Internal Reliability | Internal Reliability is achieved when the Cronbach's Alpha value is 0.6 or higher (Ahmad et al. 2016) |
| **Composite reliability/** Construct Reliability | The measure of Reliability and internal consistency of the measured variables represents a latent construct. To achieve the construct reliability, also known as **composite Reliability**, a value of CR $\geq 0.6$ is required (Ahmad et al. 2016). |
| Average Variance Extracted | Average Variance Extracted (AVE) is the average percentage of variation explained by the items in a construct. An AVE $\geq 0.5$ is required (Ahmad et al. 2016). |

The formula to calculate the value of Construct Reliability (CR) and Average Variance Extracted (AVE) are shown in Table 2 below.

**Table 2. Formula**

| | Formula | Notes |
|---|---|---|
| CR | $(\Sigma\kappa)^2 / [(\Sigma\kappa)^2 + (\Sigma 1 - \kappa^2)]$ | K = factor loading of every item n = number of items in a model |
| AVE | $\Sigma\, \kappa^2 / n$ | |

### 4.4.2 Validity

Validity is the ability of an instrument to measure what is supposed to be measured for a construct (Jian et al., 2020). The validity of the measurement model is assessed based on the requirements stated in Table 3. There are three types of validity required for each measurement model:

**Table 3. Validity**

| Validity | Requirements |
|---|---|
| Convergent validity | The convergent validity is achieved when all items in a measurement model are statistically significant. This validity could also be verified through Average Variance Extracted (AVE). The value of AVE should be greater or equal to 0.5 to achieve this validity(Taherdoost, 2016) |
| Construct validity | The construct validity is achieved when the Fitness Indexes achieve the level of acceptance. |
| Discriminant validity | The discriminant validity is achieved when the measurement model is free from redundant items. Another requirement for discriminant validity is the correlation between each pair of the latent exogenous construct should be less than 0.85. Other than that, the square root of AVE for the construct should be higher than the correlation between the respective constructs (Awang, 2015) |

### 4.4.3 Fit Indices

The data was analyzed by Structural Equation Modeling (SEM) (Bekesiene et al., 2017) using IBM AMOS 26.0 software (Arbuckle, 2019). SEM is a multivariate technique, which estimates a series of inter-related dependence relationships simultaneously. The hypothesized model can be tested statistically in simultaneous analysis of the entire system of variables to determine the extent to which it is consistent with the data (Ahmad et al., 2016). Several Fitness Indexes in SEM reflect how to fit the model to the data. It is recommended that the use of at least one fitness index from each category of model fit (Taherdoost, 2018). The information concerning the model fit category, their level of acceptance, and literature are presented in Table 4.

**Table 4. Fitness indexes**

| Name of category | Name of index | Index name | Level of acceptance | Literature |
|---|---|---|---|---|
| Absolute Fit | Chisq | Discrepancy chi square | $p \leq 0.05$ | (Wheaton, 1987) |
| | RMSEA | Root Mean Square of Error Approximation | $\leq 0.08$ | (Browne & Cudeck, 1992) |
| | GFI | The goodness of Fit Index | $\geq 0.90$ | (Jöreskog et al. 2016) |
| Incremental Fit | AGFI | Adjusted Goodness of Fit | $\leq 0.90$ | (Tanaka & Huba, 1985) |
| | CFI | Comparative Fit Index | $\geq 0.90$ | (Bentler & Hu, 1998) |
| | TLI | Tucker-Lewis Index | $\geq 0.90$ | (Bentler & Hu, 1998) |
| | NFI | Normed Fit Index | $\geq 0.90$ | (Bollen, 1989) |
| Parsimonious Fit | Chisq/df | Chi Square/Degree of freedom | $\leq 5.0$ | (Marsh & Hocevar, 1985) |

## 5. Results

This paper's results were obtained using the two-step analytical procedures established by Hair et al. (2010). First step established the measurement model while in the second step the structural model was affirmed. This two-step approach is justified to guarantee the conclusion on the structural relationships which were established from the set of measurement constructs with appropriate psychometric properties (Lee et al. 2005a).

### 5.1 The Measurement Model

In this paper, confirmatory factor analysis was used to assess the psychometric properties of the multi-item 7-point scales used to collect the data. After conducting factor reanalysis, the factor loadings for further analysis were established. Reliability of the constructs was assessed using Cronbach Alpha, Composite Reliability (CR), and average Variance extracted (AVE) as shown in Table 5. Additionally, the correlations between the different constructs were obtained as shown in Table 6. Further, to assess the validity of the construct, both convergent and discriminant validity was assessed. Discriminant validity was measured using the squared root of the average Variance extracted (AVE) and the results indicated in Table 2.

#### 5.1.1 Reliability

The results shown in Table 5 show that internal Reliability was achieved because the Cronbach's Alpha value is greater than the threshold value of 0.6 (Ahmad et al. 2016). Composite Reliability, which is also known as Construct reliability in this paper, is the measure of Reliability and internal consistency of the measured variables representing a latent construct. From the results of Table 5, composite Reliability has achieved the construct since all values of CR $\geq 0.6$, which is recommended by prior researchers (Ahmad et al. 2016).

**Table 5: Instrument Reliability**

| **Measuring Construct** | **Number of Items** | **Cronbach Alpha** | **Composite Reliability (CR)** | **AVE** |
|---|---|---|---|---|
| Perceived Usefulness (PU) | 4 | 0.927 | 0.881 | 0.651 |
| Perceived Ease of Use (EOU) | 4 | 0.891 | 0.844 | 0.575 |
| Subjective Norm (SN) | 4 | 0.853 | 0.799 | 0.501 |
| COVID'19 Lockdowns (COVID'19) | 5 | 0.967 | 0.941 | 0.872 |
| Time Saving (TS) | 4 | 0.936 | 0.868 | 0.623 |
| Cost Saving (CS) | 3 | 0.903 | 0.808 | 0.764 |
| Behavioral Intention (BIU) | 4 | 0.893 | 0.833 | 0.556 |

Further, Average Variance Extracted (AVE), which is the average percentage of variation explained by the items in a construct, has been satisfied since all values of AVE ≥ 0.5 as required (Ahmad et al. 2016).

### 5.1.2 Convergent Validity

Taherdoost, ( 2018) posts that convergent validity, refers to the degree to which two measures of constructs that theoretically should be related are related. Prior studies assert that composite Reliability of 0.70 or above and average variance extracted of more than 0.50 are deemed acceptable (Lee et al. 2005a). All the measures of composite Reliability (CR) and average Variance extracted (AVE) fulfill the recommended thresholds, where the composite Reliability ranges from 0.808 to 0.941 and the average Variance extracted ranges from 0.501 to 0.872

### 5.1.3 Discriminant Validity

According to Taherdoost, ( 2018), Discriminant validity (or divergent validity) tests that constructs that should have no relationship do, in fact, not have any relationship. Discriminant validity is the degree to which the measure measures what it is intended for, and hence it is not a reflection of some other variable. In research, discriminant validity is assessed by low correlations between the measures of study variables and other variables' measures. Prior studies assert that evidence about discriminant validity of the measures is verified with the squared root of the average Variance extracted (AVE) for each variable being higher than the correlations between it and all other variables (Bagozzi, 1986). Table 3 summarizes the results of the discriminant analysis of this paper. It can be seen that the square root of average Variance extracted for each construct inserted in the diagonal of the table is greater than the correlations between the constructs and all other constructs. These results advocate an adequate discriminant validity of the measurements.

**Table 6: Discriminant validity using Correlation Matrix of the Constructs and SQRT (AVE)**

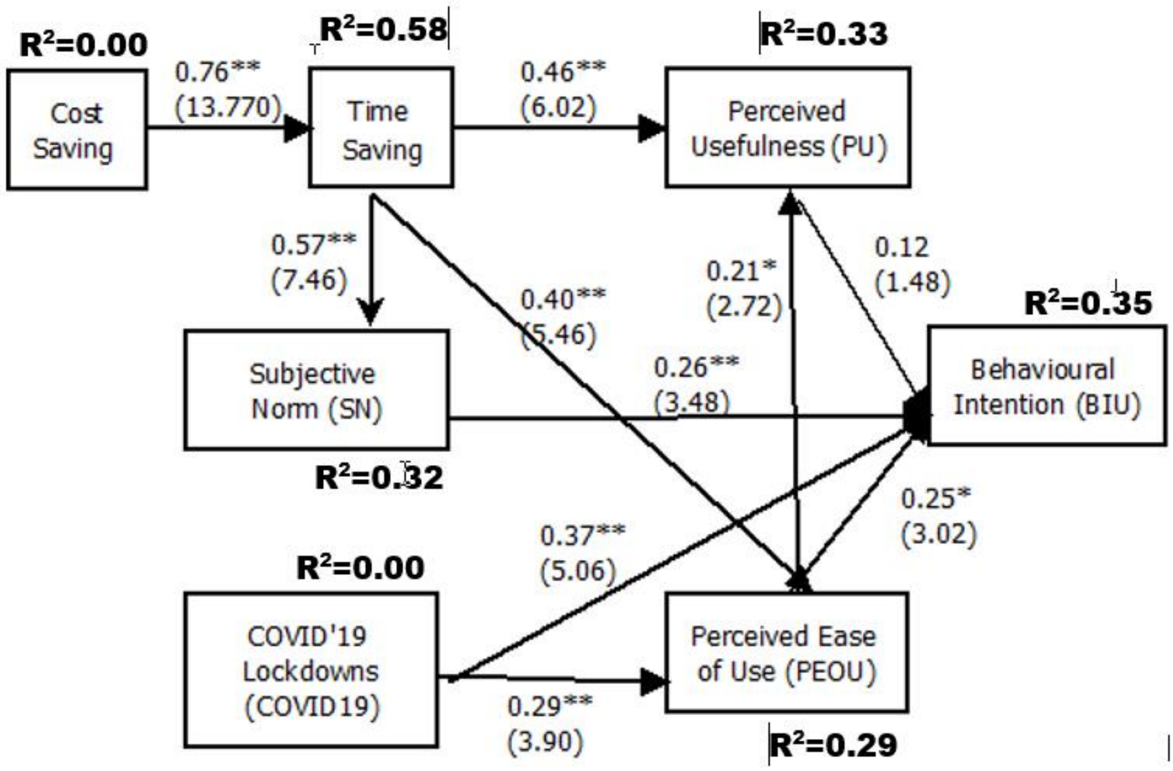
| | PU | PEOU | SN | COVID19 | TIME | COST | BIU |
|---|---|---|---|---|---|---|---|
| PU | **0.807** | | | | | | |
| PEOU | .432** | **0.758** | | | | | |
| SN | .453** | .402** | **0.708** | | | | |
| COVID19 | .331** | .458** | .307** | **0.934** | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| TIME | .558** | .478** | .566** | .278** | **0.789** | | |
| COST | .504** | .432** | .555** | .333** | .763** | **0.874** | |
| BIU | .419** | .512** | .494** | .477** | .392** | .451** | **0.746** |

**5.2 The Structural Model**

The structural model was estimated using the maximum likelihood method. Figure 2 represents fit statistics, general explanatory power, estimated path coefficients where all paths are indicated with an asterisk to indicate 95% confidence interval, and 2 asterisks at 99% confidence interval. The associated t-value of the paths is indicated inside the brackets. The model's overall fit was assessed using the typical statistics, both incremental (NFI, IFI, and CFI), absolute fit indices, which comprised of model fit summary, and parsimony adjusted measures. The incremental fit indices (NFI=0.91, IFI=0.93, CFI=0.93) were all >0.90. In the absolute fit indices, the Model Fit Summary measurer's results: Chi-Square=37.80, Degrees of Freedom=11, CMINDF= 3.436, and Probability=0.000, indicate a very good fit of the model to the data. Additionally, Parsimony-Adjusted Measures used are RMSEA=0.134, PLOSE=0.002, although RMSEA value is greater than 1, the alternative measure of PLOSE=0.002<0.05 and hence satisfactory. Consequently, the structural model analysis results suggest an excellent fit of the proposed model to the data (Lee et al. 2005a; Arbuckle, 2017).

The fit statistics in Figure 2 on next page indicate that the research model provides a good fit to the data ($x^2_{11}$ = 37.80, p = 0.000; AGFI = 0.80; RMSEA = 0.13, PCLOSE=0.002). This $x^2$ is significant, and all other statistics are within the range that suggests a good model fit. Arbuckle (2017) stated that an acceptable fit exists where AGFI ≥ 0.80 and RMSEA < 0.10 or significant PLCOSE ≤ 0.05, particularly when degrees of freedom are small (Kenny et al. 2015). Besides, the model accounts for 33% of the Variance in perceived Usefulness (PU), 29% of the Variance in perceived ease of use. (PEOU), 32% of the Variance in subjective norm (SN), 58% of the Variance in time-saving (TIME), and 35% of the Variance in behavioral intention (BI). The findings indicated that COVID'19 lockdowns exhibited equally strong impacts on students' perceived ease of fuse (PEOU) and behavioral intention (BIU) to use Virtual learning environments (VLE).




**Chi-Square=37.80, Degrees of Freedom=11, CMINDF= 3.44**
**Probability=0.000, RMSEA=0.13, TLI=0.90, CFI=0.93,**
**NFI=0.91, GFI=0.92, AGFI=0.80, IFI=0.93, PLOSE=0.002**

**Figure 2: Result of the proposed research model.**

### 5.3. Path Coefficients

Perceived usefulness posited a non-significant direct effect on behavioral intention (b = 0.12, t = 1.49, p=0.14), whereas perceived ease of use had a substantially moderate effect on usefulness (b = 0.21, t = 2.72, p=0.01) and behavioral intention (b = 0.25, t = 3.02, p=0.00). COVID'19 lockdown posited a significant direct effect on perceived ease of use (b = 0.29, t = 3.90, p=0.000), and on behavioral intention (b = 0.37, t = 5.06, p=0.000). On the other hand, time saving had a substantially strong effect on usefulness (b = 0.46, t = 6.02, p=0.000), perceived ease of use (b = 0.40, t = 5.46, p=0.000) and subjective norm (b=0.57, t=7.97, p =0.000. Subjective norm had a significant direct effect on behavioral intention (b = 0.26, t = 3.448, p=0.000), whereas Cost saving had very high direct effect on time saving (b=0.76, t=13.70, p=0.000).The result supported the entire hypothesis except hypothesis 1. Usefulness on the other hand, did not have any significant impact on students' behavioral intention (BIU) to use virtual-learning environments. Thus, the model as hypothesized in Figure 1 and all of the hypothesized paths therein were supported except the first one as shown in Table 7.

**Table 7: Results of Hypotheses**

| Hypothesis | Variable | Path | Variable | Estimate | S.E. | C.R. | P | Hypothesis States |
|---|---|---|---|---|---|---|---|---|
| **$H_1$** | PU | → | BIU | **0.12** | **0.06** | **1.49** | **0.14** | Not Supported |
| **$H_{2a}$** | PEOU | → | BIU | **0.25** | **0.07** | **3.02** | **0.00** | Supported |
| **$H_{2b}$** | PEOU | → | PU | **0.21** | **0.09** | **2.72** | **0.01** | Supported |
| **$H_{3a}$** | COVID19 | → | PEOU | **0.29** | **0.07** | **3.90** | *** | Supported |
| **$H_{3b}$** | COVID19 | → | BIU | **0.37** | **0.07** | **5.06** | *** | Supported |
| **$H_4$** | NORM | → | BIU | **0.26** | **0.06** | **3.48** | *** | Supported |
| **$H_{5a}$** | TIME | → | PU | **0.46** | **0.07** | **6.02** | *** | Supported |
| **$H_{5b}$** | TIME | → | PEOU | **0.40** | **0.06** | **5.46** | *** | Supported |
| **$H_{5c}$** | TIME | → | NORM | **0.57** | **0.05** | **7.97** | *** | Supported |
| **$H_6$** | COST | → | TIME | **0.76** | **0.05** | **13.70** | *** | Supported |

## 6. Discussion

This study has deployed TAM to investigate COVID'19 lockdown, Cost Saving, and Cost Saving in the adoption of virtual learning environments. Motivated by a need to understand the fundamental drivers of student adoption of virtual learning environments, this paper's research incorporated a COVID'19 lockdown perspective into TAM. They postulated that the COVID'19 lockdown factor influences both perceived ease of use and behavioral intention to use VLE. Additionally, due to students saving travel time and costs and the cost of meals, the study found it noble to include Time and cost savings as factors that have a role in students' adoption of VLE.

The measurement model confirms adequate Cronbach's Alpha, Composite Reliability, Average Extracted Variance, and convergent and discriminant validity. The structural model provided an excellent fit to the data, and all path coefficients in the research model were found statistically significant (except the path from Usefulness to behavioral intention). The results showed that both the COVID'19 lockdowns factor and perceived ease of use played an essential role in affecting students' intention to use VLE. COVID'19 lockdowns factor depicts a significant impact on students' perceived ease of use to VLE. Surprisingly, perceived Usefulness did not have a significant impact on student behavioral intention to use VLE. These findings concur with those by finding by Shawnice L. (2017) that the Usefulness → BIU (or usage) path was non-significant. According to (Rogers, 1995) the third element that influences the diffusion is "Time" involved in diffusion in the innovation-decision process, innovativeness, and innovation's adoption rate. Davis et al. (1989) found social norms (SN) as an important determinant of behavior intended to be weak. The technology acceptance model (TAM), concurs with the findings of this study. The results in this study on Perceived Ease of Use agree with those of Coşkunçay et al. (2018), which established that Perceived Ease of Use (PEOU) has a direct, positive, and significant influence on the Perceived Usefulness (PU) of Learning Management System (LMS) by students. The lack of support of H1 in this study findings could need a larger sample to verify the same.

**7. Conclusions and Recommendations**

Time and cost savings of transport outweighs the cost of the internet. Students can therefore study and do other work. This advantage may continue to influence students to like and demand VLE even after COVID'19. Student affects each other on the use of VLE mainly due to saving cost and time features. To encourage more and influence interaction, instructors may use online chat rooms and discussion boards to foster student collaboration and a sense of community (Lee et al. 2005a). Students may be inherently motivated to feel connected to others within a virtual environment. Creating a virtual community of student users is therefore likely to be socially influenced towards adopting and using VLE.

In short, a successful VLE should include the components of utility and ease of use, create community groups for collaboration socially and academically. VLE developers and implementers should pay special attention to collaboration features in designing and implementing VLE. The influence of COVID'19 lockdowns will have created habits and adoption of VLE that will be difficult for students to change overnight or quickly. Consequently, universities and other higher education institutions need to prepare their operations and VLE to continue uninterrupted well beyond COVID'19. Our research model explains 35% of the variances of behavioral intention. The findings imply that other significant factors abound in affecting students' adoption decisions towards VLE. Further research recommends that to cater to too many institutions, many regions, and a larger sample. Additionally, other fundamental variables may be required to raise the variance explained.

**References**

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly: Management Information Systems*, *24*(4), 665–694. https://doi.org/10.2307/3250951

Ahmad, S., Zulkurnain, N., & Khairushalimi, F. (2016). Assessing the Validity and Reliability of a Measurement Model in Structural Equation Modeling (SEM). *British Journal of Mathematics & Computer Science*, *15*(3), 1–8. https://doi.org/10.9734/bjmcs/2016/25183

Alqahtani, A. Y., & Rajkhan, A. A. (2020). E-learning critical success factors during the COVID'19 pandemic: A comprehensive analysis of e-learning managerial perspectives. *Education Sciences*, *10*(9), 1–16. https://doi.org/10.3390/educsci10090216

Arbuckle, J. L. (2017). Amos 25 User's Guide. *IBM SPSS Amos 25 User's Guide*, 693.

Arbuckle, J. L. (2019). *IBM® SPSS® User's Guide Amos™ 26*. https://www.ibm.com/docs/en/SSLVMB_26.0.0/pdf/amos/IBM_SPSS_Amos_User_Guide.pdf

Aristovnik, A., Keržič, D., Ravšelj, D., Tomaževič, N., & Umek, L. (2020). Impacts of the COVID'19 pandemic on life of higher education students: A global perspective. *Sustainability (Switzerland)*, *12*(20), 1–34. https://doi.org/10.3390/su12208438

Awang, Z. (2015). *SEM made simple: A gentle approach to learning structutal equation modeling*.

Bagozzi, R. P. (1986). *Evaluating structural equation models with unobservable variables and measure ...*

Baskaran, S., Lay, H. S., Ming, B. S., & Mahadi, N. (2020). Technology Adoption and Employee's Job Performance: An Empirical Investigation. *International Journal of Academic Research in Economics and Management Sciences*, *9*(1). https://doi.org/10.6007/ijarems/v9-i1/7443

Bekesiene, S., Hoskova-Mayerova, S., & Diliunas, P. (2017). Structural equation modeling using the amos and regression of effective organizational commitment indicators in lithuanian military forces. *16th Conference on Applied Mathematics, APLIMAT 2017 - Proceedings*, 91–102.

Bentler, P. M., & Hu, L. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods, 3*(4), 424–453.

Bollen, K. A. (1989). A New Incremental Fit Index for General Structural Equation Models. *Sociological Methods & Research*, *17*(3), 303–316. https://doi.org/10.1177/0049124189017003004

Bowen, W. G., Guthrie, K. M., & Lack, K. a. (2012). Barriers to Adoption of Online Learning Systems in U . S . Higher Education. *Higher Education*, 1–33.

Browne, M. W., & Cudeck, R. (1992). Alternative Ways of Assessing Model Fit. *Sociological Methods & Research*, *21*(2), 230–258. https://doi.org/10.1177/0049124192021002005

Bruner, G. C., & Kumar, A. (2005). Explaining consumer acceptance of handheld Internet devices. *Journal of Business Research*, *58*(5), 553–558. https://doi.org/10.1016/j.jbusres.2003.08.002

Chin, W. W. (1998). Issues and opinion on structural equation modeling. *MIS Quarterly: Management Information Systems*, *22*(1).

Chroqui, R., Okar, C., Talea, M., & Ouiddad, A. (2017). Adoption of information systems throught innovation diffusion theory and technology acceptance model : Systematic literature review. *SMALO Research Strategy Management Logistic*, *July*, 0–7.

Cosgrave, R., Rísquez, A., Logan-phelan, T., Farrelly, T., Costello, E., & Palmer, M. (2011). Usage and Uptake of Virtual Learning Environments in Ireland: Findings from a Multi Institutional Study. *Aishe-J*, *3*(1), 1–14.

Coşkunçay, D. F., Alkış, N., & Yıldırım, S. Ö.-. (2018). International Forum of Educational Technology & Society A Structural Equation Model for ICT Usage in Higher Education Published by : International Forum of Educational Technology & Society Linked references are available on JSTOR for this article : A Stru. *Educational Technology & Society*, *21*(2), 13–27.

Davis, F. D., Bagozi, R. p, & Warshaw, P. R. (1989). *User Acceptance of Computer Technology : A Comparison of Two Theoretical Models User Acceptance Of Computer Technology : A Comparison Of Two Theoretial Models*. *September 2016*. https://doi.org/10.1287/mnsc.35.8.982

De Giusti, A. (2020). Policy Brief: Education during COVID'19 and beyond. *Revista Iberoamericana de Tecnología En Educación y Educación En Tecnología*, *26*, e12. https://doi.org/10.24215/18509959.26.e12

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

Hasanah, R. L., Wati, F. F., & Riana, D. (2019). TAM Analysis on The Factors Affecting Admission of Students for Ruangguru Application. *Jurnal Sistem Informasi*, *15*(2), 1–14. https://doi.org/10.21609/jsi.v15i2.778

Huang, C.-C., Wang, Y.-M., Wu, T.-W., & Wang, P.-A. (2013). An Empirical Analysis of the Antecedents and Performance Consequences of Using the Moodle Platform. *International Journal of Information and Education Technology*, *3*(2), 217–221. https://doi.org/10.7763/ijiet.2013.v3.267

Hubert, M., Blut, M., Brock, C., Zhang, R. W., Koch, V., & Riedl, R. (2019). The influence of acceptance and adoption drivers on smart home usage. *European Journal of*

*Marketing*, *53*(6), 1073–1098. https://doi.org/10.1108/EJM-12-2016-0794
Husain, N. (2020). *Impact of COVID'19 on Higher Education: Challenges, Opportunities and Road Ahead*. *May*.
IFC. (2020). The Impact of COVID'19 on Disruptive Technology Adoption in Emerging Markets. *International Finance Corporation*, 1–17. https://www.ifc.org/wps/wcm/connect/537b9b66-a35c-40cf-bed8-6f618c4f63d8/202009-COVID'19 -Impact-Disruptive-Tech-EM.pdf?MOD=AJPERES&CVID=njn5xG90
Jelinek, R., Ahearne, M., Mathieu, J., & Schillewaert, N. (2006). A longitudinal examination of individual, organizational, and contextual factors on sales technology adoption and job performance. *Journal of Marketing Theory and Practice*, *14*(1), 7–23. https://doi.org/10.2753/MTP1069-6679140101
Jian, O. Z., Yin, K. Y., & Awang, M. (2020). Developing And Validating the Measurement Model for Employee Engagement Construct Using Confirmatory Factor Analysis. *International Journal of Academic Research in Business and Social Sciences*, *10*(8), 924–941. https://doi.org/10.6007/ijarbss/v10-i8/7662
Jöreskog, K. G., Olsson, U. H., & Y. Wallentin, F. (2016). Multivariate Analysis with LISREL. In *Iranian Studies* (Vol. 34, Issues 1–4). Springer International Publishing. https://doi.org/10.1007/978-3-319-33153-9
Kenny, D. A., Kaniskan, B., & McCoach, D. B. (2015). The Performance of RMSEA in Models With Small Degrees of Freedom. *Sociological Methods and Research*, *44*(3), 486–507. https://doi.org/10.1177/0049124114543236
Lai, P. (2017). The Literature Review of Technology Adoption Models and Theories for the Novelty Technology. *Journal of Information Systems and Technology Management*, *14*(1), 21–38. https://doi.org/10.4301/s1807-17752017000100002
Lee, M. K. O., Cheung, C. M. K., & Chen, Z. (2005a). *Acceptance of Internet-based learning medium : the role of extrinsic and intrinsic motivation*. *42*, 1095–1104. https://doi.org/10.1016/j.im.2003.10.007
Lee, M. K. O., Cheung, C. M. K., & Chen, Z. (2005b). Acceptance of Internet-based learning medium: The role of extrinsic and intrinsic motivation. *Information and Management*, *42*(8), 1095–1104. https://doi.org/10.1016/j.im.2003.10.007
Legris, P., Ingham, J., & Collerette, P. (2003). *Why do people use information technology ? A critical review of the technology acceptance model*. *40*, 191–204.
Lingard, M. (2007). *Why Don't all Lecturers Make use of VLEs?: What Can the so-called "Laggards" tell us?* 1–58.
Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81–95. https://doi.org/10.1007/s10209-014-0348-1
Marsh, H. W., & Hocevar, D. (1985). *<Application_of_confirmatory_factor_analysis_to_the_study_of_self-concept_First-_and_higher_order_fac1.pdf>*. *97*(3), 562–582.
McBurnie, C. (2020). *The use of virtual learning environments and learning management systems during the COVID'19 pandemic*. https://doi.org/10.5281/zenodo.3805843.
McMahon, M. J. (2016). The Adoption of a Virtual Learning Environment Among " Digital Immigrant " Engineering Lecturers : a Case Study. *Irish Journal of Academic Practice*, *5*(1), 0–22. https://doi.org/10.21427/D78B04
Munir, F. F. A. (2018). Reliability and Validity Analysis on the Relationship between Learning Space, Studentâ€ ™s Satisfaction and Perceived Performance Using SMART-

PLS. *International Journal of Academic Research in Business and Social Sciences*, *8*(1), 775–786. https://doi.org/10.6007/ijarbss/v8-i1/3847

Murthy, S. R., & Mani, M. (2013). Discerning rejection of technology. *SAGE Open*, *3*(2), 1–10. https://doi.org/10.1177/2158244013485248

Musa, P. F. (2006). *Making a Case for Modifying the Technology Acceptance Model to Account for Limited Accessibility in Developing Countries*. *12*(3), 213–224. https://doi.org/10.1002/itdj

Purnomo, S. H., & Lee, Y. H. (2013). E-learning adoption in the banking workplace in Indonesia: An empirical study. *Information Development*, *29*(2), 138–153. https://doi.org/10.1177/0266666912448258

Rabaa'i, A. A. (2016). Extending the Technology Acceptance Model (TAM) to assess Students' Behavioural Intentions to adopt an e-Learning System: The Case of Moodle as a Learning Tool. *Journal of Emerging Trends in Engineering and Applied Sciences*, *7*(1), 13–30.

Rashid, S., & Yadav, S. S. (2020). Impact of COVID'19 Pandemic on Higher Education and Research. *Indian Journal of Human Development*, *14*(2), 340–343. https://doi.org/10.1177/0973703020946700

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), 1–19. https://doi.org/10.3390/ijerph17186468

Rogers, E. M. (1995). *Diffusion of innovations*. http://library1.nida.ac.th/termpaper6/sd/2554/19755.pdf

Saadé, R., & Bahli, B. (2005). The impact of cognitive absorption on perceived usefulness and perceived ease of use in on-line learning: An extension of the technology acceptance model. *Information and Management*, *42*(2), 317–327. https://doi.org/10.1016/j.im.2003.12.013

Shawnice ,L., A. (2017). *Acceptance of integration of mobile technology in the higher education environment: instructors' perception* [Northern Illinois University De Kalb, Illinois]. http://library1.nida.ac.th/termpaper6/sd/2554/19755.pdf

Soper, D. (2021). *Calculator: a-priori sample size for structural equation models*. https://www.danielsoper.com/statcalc/calculator.aspx?id=89

Surkhali, B., & Garbuja, K. (2020). Virtual Learning during COVID'19 Pandemic : Pros and Cons. *Journal of Lumbini Medical College*, *8*(1), 19–20. https://doi.org/https://doi.org/10.22502/jlmc.v8i1.345

Taherdoost, H. (2016). Validity and Reliability of the Research Instrument ; How to Test the Validation of a Questionnaire / Survey in a Research Hamed Taherdoost To cite this version : HAL Id : hal-02546799 Validity and Reliability of the Research Instrument ; How to Test the. *International Journal of Academic Research in Management*, *5*(3), 28–36.

Taherdoost, H. (2018). Validity and Reliability of the Research Instrument; How to Test the Validation of a Questionnaire/Survey in a Research. *SSRN Electronic Journal*, *January 2016*. https://doi.org/10.2139/ssrn.3205040

Tanaka, J. S., & Huba, G. J. (1985). A fit index for covariance structure models under arbitrary GLS estimation. *British Journal of Mathematical and Statistical Psychology*, *38*(2), 197–201. https://doi.org/10.1111/j.2044-8317.1985.tb00834.x

Tarus, J. K., & Gichoya, D. (2015). E-learning in Kenyan universities: Preconditions for successful implementation. *Electronic Journal of Information Systems in Developing*

*Countries*, *66*(1). https://doi.org/10.1002/j.1681-4835.2015.tb00474.x

The Conversation. (2020). *Kenya's university students and lecturers face huge challenges moving online*. https://theconversation.com/kenyas-university-students-and-lecturers-face-huge-challenges-moving-online-136682

Todd, P. A., & Shirley Taylor. (1995). Understanding Information Technology Usage : A Test of Competing Models. *Information Systems Research*, *6*(2), 144–176. http://pubsonline.informs.org/doi/abs/10.1287/isre.6.2.144?journalCode=isre%5Cnhttp://www.researchgate.net/publication/220079739_Understanding_Information_Technology_Usage_A_Test_of_Competing_Models

van Raaij, E. M., & Schepers, J. J. L. (2008). The acceptance and use of a virtual learning environment in China. *Computers and Education*, *50*(3), 838–852. https://doi.org/10.1016/j.compedu.2006.09.001

Wheaton, B. (1987). Assessment of Fit in Overidentified Models with Latent Variables. *Sociological Methods & Research*, *16*(1), 118–154. https://doi.org/10.1177/0049124187016001005

World Bank Grroup. (2020). *Remote Learning and COVID'19 EdTech Knowledge Pack on Remote Learning response to COVID'19* . 16.

World Economic Forum. (2020). *The COVID'19 pandemic has changed education forever. This is how*. https://www.weforum.org/agenda/2020/04/coronavirus-education-global-covid19-online-digital-learning/

Yadav, K. (2019). Disruptive innovative technologies in higher education. *International Journal of Advanced Education and Research International*, *4*(1), 43–54. https://doi.org/10.5281/zenodo.3805843