Statistics and Mathematical Research Journal
ISSN: 2997-6898|
Volume 13 Issue 1, January-March, 2025
Journal Homepage: https://ethanpublication.com/articles/index.php/E33,
Official Journal of Ethan Publication

EVALUATING SMART LEARNING ENVIRONMENTS: A CONCEPTUAL MODEL APPROACH

Oluwaseun Adebayo Olatunji and Chika Ikenna Okafor
Department of Computer Science, Adamawa State University Mubi, Nigeria
DOI: https://doi.org/10.5281/zenodo.17375717

Abstract
This study examines the application of Bayesian Vector Autoregressive model in modeling Nigerian narrow money and quasi money as a guide for monetary policy, using monthly data from 2015 - 2022. The objectives include to; model and estimates the interaction between Nigerian narrow money and quasi money, determine the direction of causality, significance of the causality among the variables, and determine the fractions in each variable explained by the changes in the other variables. The data used for the study were narrow money and quasi money, extracted from the Central Bank of Nigeria online statistics bulletin. The model used in the study is Bayesian Vector Autoregressive models. The results of the descriptive statistics revealed that all the series are statistically significant at the 5 percent level of significance. Augmented Dickey Fuller (ADF) and Phillip Perron (PP) test were used to test for stationarity of the variables under investigation. The results of Johansen Cointegration test showed that there is no cointegration or long-run equilibrium relationship between narrow money and quasi money at a 0.05 significance level. The Adjusted R-square value indicates that 97.7% variation in future narrow money values is explained by first and second per-determined value of narrow money itself and quasi money. Th narrow money has a significant effect on quasi money during the studied period. The result of VAR model stability test (AR root circle) satisfied the stability condition, with all characteristic root lying inside the circle. The result of the impulse response function revealed that narrow money responded positively to quasi money. It was found that narrow money granger caused quasi money. This suggests that changes in the money supply have potential effect on economic activity through the narrow-money market, which may have implications for monetary policy decision. Therefore, it was recommended that there should be adequate monetary policy development measures to capture both short-run and long-run relationship between the study variables, including structural reforms to address issues related to shocks from one variable to the other.

Keywords: *Model, Narrow Money & Quasi-Money*

INTRODUCTION

The increasing developments in smart and mobile technologies such as artificial intelligence, machine learning, the Internet of Things (IoT), and wearable computing devices have continued to impact every sphere of life. It is now possible to compute anywhere using the superior power of mobile devices connected to the internet (Serba & Loan, 2020; Fakinlede et al., 2015). The educational institutions, as the center for research, innovation, and development, have continued to be more innovative due to these new technological developments.

The educational institutions are now called smart campuses, smart education, smart learning environments, smart classrooms, and smart learning processes as the results of the transformative power of smart and mobile technologies (Spector, 2016; Yot-Dominguez & Marcelo, 2019; Zhu et al., 2016). Educational institutions are taking these opportunities and, coupled with the infrastructure deficits, are now offering a blended pedagogical framework to meet the needs of on-campus and off-campus students and those on remote learning. This promotes the increasing deployment of skill-based courses in an online learning environment to meet skills gaps in the digital workforce (Rosmansyah et al., 2022; Hoel & Mason, 2017; Zhu et al., 2016; Zhu & He, 2012).

A smart learning environment is developing using smart and wearable technologies to support personalized experiences for inclusive learning experiences (Rosmansyah et al., 2022; Serba & Loan, 2020). This intelligent learning environment can support online learning experiences for interaction and engagement. Furthermore, the learning environment can support learners' diverse learning behaviors and needs. However, there is a lack of a well-defined and comprehensive evaluation model of a smart learning environment based on its characteristics and other contextual factors to support implementation and deployment decisions.

Thus, the research questions are: What are the factors influencing the use of a smart learning environment, and how can these factors be modeled and validated to provide a novel comprehensive model for evaluating a smart learning environment? Addressing these questions will provide insights into implementing and deploying a smart learning environment for an inclusive learning experience.

BACKGROUND AND RELATED WORKS

Smart Learning Environment

Smart, mobile, and wearable computing advancements are transforming how people compute and interact daily. These technologies are transforming learning environments into smart learning environments capable of providing personalization for inclusive learning experiences. According to Hwang (2014), a smart learning environment is "the technology-supported learning environment that adapts and provides appropriate support (feedback, guidance, hint, or tool) in the right place and right time based on the individual needs that might be determined by analyzing the behavior and performance of the learner." A smart learning environment takes into account the characteristics of learner, makes available individualized educational materials and user-friendly interactive technologies, records and analyzes the learning process in its entirety, and offers feedback on the learner's progress (Rosmansyah et al., 2022; Hoel & Mason, 2017; Zhu et al., 2016).

The smart learning environment and the smart devices can interact with a learner and make decisions depending on the learner's actions. The use of data analytics may serve to promote learners' success by monitoring their progress, and teachers can utilize it to deliver helpful feedback by visualizing learning data. Learners are provided with digital materials, interaction, essential learning assistance, supportive tools, and learning ideas at the appropriate time, location, and format (Egielewa et al., 2021; Zhu et al., 2016).

A smart learning environment can provide a hybrid learning system that provides learners and other stakeholders with a motivational learning process while simultaneously achieving learning outcomes due to the employment of intelligent tools and techniques (Rosmansyah et al., 2022). It comprises contextual awareness, location awareness, real-world scenarios, recommendation systems, numerous engagement channels, assistance, personalization, and adaption (Hwang, 2014). Learners are more motivated to attain their goals when these features support inclusive learning experiences (Egielewa et al., 2021; Serba & Loan, 2020).

Related Works

The success or failure of technology implementation and adoption depends on user's level of acceptance (Mohammadi & Garibaldi, 2010; Hua et al., 2014). Several models or frameworks have been developed to evaluate learning environments. For example, Akour et al. (2021) developed an extended technology acceptance model (TAM) and theory of planned behavior (TPB) to analyze university adoption of mobile learning platforms for accessing course materials, searching the web for information related to their disciplines, sharing knowledge, and submitting assignments during the COVID-19 pandemic. Although the model-integrated constructs form well-known behavioral models, they lack contextual factors that might influence the evaluation of mobile learning. Moreover, the model was not qualitatively validated to explore other intrinsic factors that might influence the adoption of mobile learning.

Hamid et al. (2020) explored factors influencing students' acceptance of learning management systems by extending the Technology Acceptance Model (TAM) using system design, system accessibility, technical support, and subjective norm as external variables. The study revealed that all the constructs of the TAM, including the extended ones, support the student's intention to use the learning management system. Similarly, Abubakar et al. (2021) used an extended unified theory of acceptance and use of technology (UTAUT) by including training, impact on the instructors' attitude, and computer self-efficacy towards the attitude to use a learning management system. The findings show that instructors' attitudes impact students' behavior toward using the learning management system. In addition, Mailizar & Maulina (2021) used extended TAM to explore factors influencing students' behavioral intention to use e-learning during COVID-19. The extension used system quality and experiences as external constructs. The findings show that all the constructs supported behavioral intention to use e-learning and thus recommended exploring e-learning qualities and support mechanisms. However, these models lack the intrinsic characteristics of the smart learning environment and thus require integration with another robust model to evaluate the smart learning environment.

Ramayana & Bali (2015) developed the integrated Fit Model for evaluating the success and acceptance of e-learning by integrating human-technology-organization (HOT) fit (Yusof et al. 2006), IS success (DeLone & McLean, 2003), & unified technology acceptance and use of technology (UTAUT) (Venkatesh et al. 2012). This is an excellent framework for evaluating user satisfaction in a learning environment that is segmented into three dimensions. However, the constructs within each dimension still need further investigations to have a comprehensive and specific measure to address evaluation issues. The dynamic characteristics of smart technologies called for a new approach to evaluation constructs and dimensions.

Evaluating technology-enhanced learning provides insights to educational stakeholders about why learning technology fails or succeeds and how best it can be implemented for effective pedagogical delivery. Thus, technology-enhanced learning and evaluation of system implementation is an important endeavor, evident through many publications (Guerra et al., 2016; Nussbaumer et al., 2015; Mohammed & Garibaldi, 2010). A smart learning environment, as an emerging learning environment, is a hybrid learning system that provides learners and other stakeholders with a motivational learning process while achieving learning outcomes due to the employment of intelligent tools and techniques (Rosmansyah et al., 2022). It is characterized by context awareness, location awareness, real-world scenarios, recommendation systems, multiple channels of interactions, support, personalization, adaptation, etc. (Hwang, 2014). These characteristics support inclusive learning experiences and motivate learners to achieve goals (Egielewa et al., 2021; Serba & Loan, 2020). Several models or frameworks have been previously developed to evaluate learning environments. However, most of them were not validated to understand the perception and experiences of the learners in enriching the constructs of the model. Furthermore, there is a scarcity of a model that includes the characteristics of a smart learning environment to make informed decisions regarding the implementation and deployment.

METHODOLOGY FOR DEVELOPMENT OF THEORETICAL MODEL

Several integrated models have been used to evaluate the learning environment; however, most models were not validated qualitatively to understand other behavioral and contextual factors impacting the use of a learning environment. Furthermore, because of their characteristics, most models were limited in scope to evaluate smart learning environments. For example, Akour et al. (2021) developed an extended TAM and TPB to analyze university adoption of mobile learning. Although the model-integrated constructs are from well-known behavioral models, they lack contextual factors to evaluate smart learning environments. Moreover, the model was not validated to explore other contextual factors that might influence the adoption of mobile learning.

This study extended the integration of TAM and TPB to understand other behavioral and contextual factors influencing the use of a smart learning environment. TAM and TPB have been used to explain or predict individual adoption from the user's perspective (Venkatesh & Davis, 2000). TPB complements TAM constructs and adds or enhances explanatory and predictive powers (Premkumar & Roberts, 1999; Venkatesh & Davis, 2000). TAM with TPB constructs allows for predicting users' acceptance of technology for both volitional and non-volitional conditions (Thong, Yap & Raman, 2012). This research integrates TPB constructs and cannot use TPB as a sole model because it lacks strong explanatory power and cannot stand independently (Awa et al., 2015). Furthermore, each model lacks comprehensive constructs to evaluate a smart learning environment.

Technology acceptance model (TAM): This model is derived from the concept that "perceived usefulness and ease of use" influence technology adoption. It hinges on a belief that perceived usefulness is the extent to which an individual believes that using a particular technology will enhance their job performance. Perceived ease of use is the extent to which one believes using a particular technology will make their work easier (Venkatesh & Davis, 2000). This model further explains that perceived usefulness and ease of use drive users to adopt new technology. This model proved to be one of the widely accepted models. The constructs of TAM are perceived ease of use, perceived usefulness, attitude towards use, and actual usage.

Theory of Planned Behavior (TPB**):** This model was guided by three types of thoughts: behavioral belief, normative belief, and control belief (Armitage & Conner, 2000). This theory is believed to be effective in validating users' innovation acceptance. The three (3) antecedents (attitude towards behavior, subjective norms, and perceived behavioral control) directly or indirectly predict individual behaviors and intentions for new technology.

The integration of these constructs served as the initial model for evaluating the smart learning environment, as shown in Table 1.

Table 1: The categorization of the constructs of TAM and TPB

Theory	Constructs
Technology Acceptance Model (TAM)	Perceived ease of use (PEOU), Perceived Usefulness (PU), Actual Usage (AU)
Theory of Planned Behavior (TPB)	Attitude Towards Use (ATB), Subjective Norms (SN), Perceived Behavioral Control (PBC), Behavioral Intention (BI),

However, integrating these constructs is limited to providing factors influencing the use of a smart learning environment. It lacks contextual factors and the characteristics of a smart learning environment to understand issues around implementing and deploying a smart learning environment. Hence, there is a need to validate the model among experts and potential users to understand factors influencing the use of a smart learning environment to develop a welldocumented comprehensive model for evaluating a smart learning environment.

Validating the Integrated Model

Given the scarcity of theoretical models for evaluating a smart-based learning environment that considered its' characteristics and other personal factors, this study was considered exploratory, and therefore, a case study approach was considered appropriate (Yin, 2003; Marshall & Rossman, 1989). A case study is useful for exploring areas where existing knowledge is limited (Eisenhardt, 1989) and is also valuable in understanding a particular situation (Yin, 2003). A single qualitative case study strategy was adopted to understand experts' and potential users' perceptions of factors influencing the use of smart learning environments.

This study adopted an exploratory qualitative case study to explore factors influencing user behavior to use a smart learning environment in the Faculty of Science, Adamawa State University Mubi-Nigeria. The study was conducted using nine focus group discussions, with each group having six participants. Lecturers, students, and experts from the eLearning team of the university. The qualitative sample size of six groups was sufficient to validate the population, and this is based on the literature, which states that the average sample size for qualitative research can vary from 5 to 50 for a large population and from 2 to 30 for a small population. In this case, the six-sample size was sufficient to validate the population (Fugard

& Potts, 2015; Guest et al., 2017). The research participants were chosen on purpose to obtain the information needed.

Data was collected using face-to-face focused group discussions, a technique well suited to exploratory research because it allows expansive discussions to illuminate factors of importance (Yin, 2003). The focused group discussions lasted between 20 and 35 minutes. The open-ended questions allowed respondents to express their experiences and views and the socially complex contexts underpinning learning technology adoption (Oppenheim, 2000; Yin, 2003).

The data collected were analyzed using thematic approaches, i.e., familiarization with datasets, generation of initial codes, theme search, theme examination, and refining themes (Braun & Clarke, 2006). The results of the themes analyzed were provided to the respondents to eliminate the study's bias and offset the effects of different realities (Kaplan & Duchon, 1988). All the collected data were recorded with each participant's consent and transcribed, proofread, and annotated by the researcher and then coded using NVivo. Also, venting was used, whereby results and interpretations were discussed with professional colleagues and the interviewees to avoid the problem of multiple realities (Kaplan & Duchon, 1988).

Findings and Discussions

The factors from the study were grouped into themes guided by the initial factors of the integrated model in Table 1. Thus, based on the theme analysis, five contextual factors— perceived quality, perceived support, perceived technology resources, perceived personalized adaptation, and perceived experiences—were the new constructs identified from the study. The perceived quality, perceived support, and perceived technology resources are the external variables that impact the behavioral factors to influence the intention and actual usage of a smart learning environment. Thus, the external factors are perceived quality, perceived support, and perceived technology resources. The behavioral factor is perceived ease of use, usefulness, attitude towards use, attitude towards behavior, subjective norms, perceived personalized adaptation, perceived behavioral control, perceived personal experiences, intention, and actual usage, as shown in Figure 1.

Thus, integrating these factors informs the novel model for evaluating a smart learning environment. This model can be used to evaluate both the intention and actual usage of a smart learning environment and can support decisions and policy-making on implementing and deploying a smart learning environment in a contextual setting.

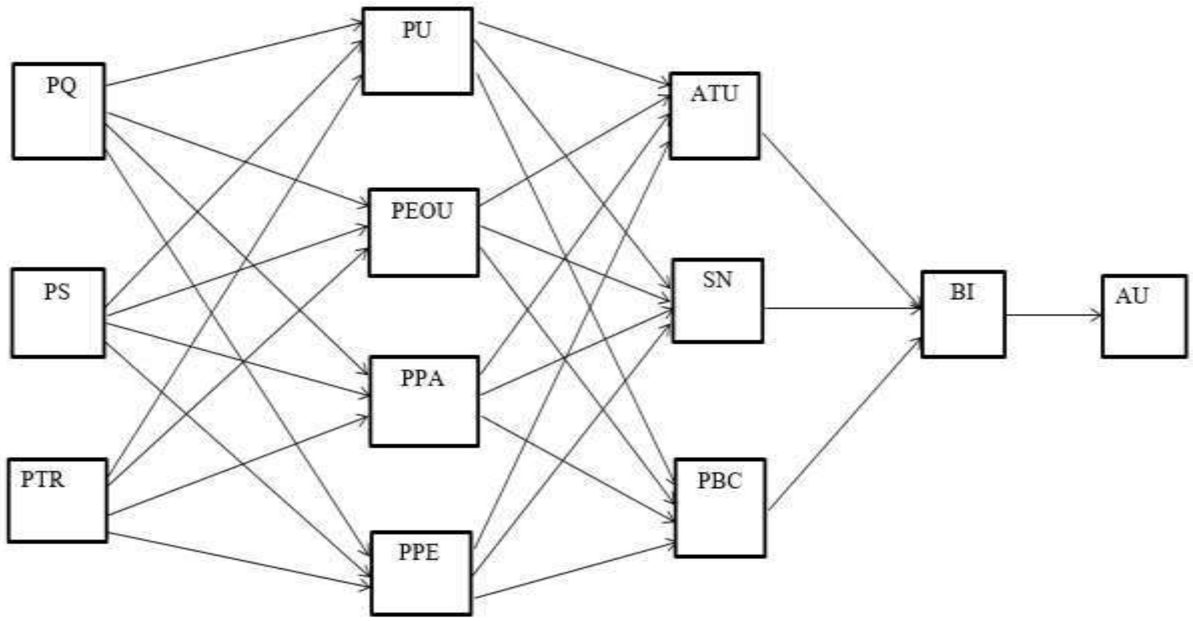

Figure 1: Model for Evaluating Smart Learning Environment

Thus, the constructs of the model are discussed as follows:

Perceived Quality (PQ): This is the extent of the benefits that can be delivered to the user regarding processing time, availability, and support. The responsiveness and efficiency of the smart learning environment are the qualities that are important to users. The previous studies show the quality of service has a favorable association with user intention to use learning technology (Awang et al., 2019; Bembenutty et al., 2016; Mohammadi, 2015).

Perceived Support (PS): Several studies on implementing information systems have examined the role and value of learning support. Given how important information systems are and how they serve as a resource for an organization, support from management, teachers, and other stakeholders is key to getting people to use the technology. Learning support from teachers and top management is the degree to which the teacher or top management understands the importance of the information system functions and is involved in information system activities (Mailizar & Maulina, 2021).

Perceived technology resources (PTR): These are computer hardware, software, and internet connectivity that can support users. The constructs include help desks, hotlines, online support services, machine-readable support knowledge bases, faxes, automated telephone voice response systems, remote control software, and other facilities (Zogheib et al., 2015). The perceived availability of technology resources affects how useful and easy to use technology is. Without technical resources and help, smart learning environments can't work effectively and efficiently (Abbad et al., 2009).

Perceived ease of use (PEOU): Perceived Ease of Use (PEU) in the context of smart learning environments is the degree to which users think that using a smart learning environment will be easy (Lin et al., 2010). Previous research has shown that how easy something is to use has a big effect on how useful it is thought to be (Binyamin et al., 2019; Joo et al., 2018). Also, studies have shown that how easy learning environments are thought to be to use is a strong predictor of how people feel about using them (Uyouko & Wong, 2015; Zogheib et al., 2015).

Perceived Usefulness (PU): Perceived usefulness (PU) is how users think a smart learning environment can help them reach their teaching and learning goals. Studies in the past showed that PU had the most impact on attitude (Martinho et al., 2018; Uyouko & Wong, 2015; Zogheib et al., 2015). PU also greatly affected how people planned to act toward a smart learning environment (Al-Sayyed & Abdalhag, 2016; Uyouko & Wong, 2015).

Perceived personalized adaption (PPA): Advanced technology-based smart learning environments enable personalized learning. It offers an efficient learning option. Students can choose content based on their current situation at any time and wherever on campus. Personalized adaptive learning is unimpeded. Individual learners choose learning resources and services (Hwang, 2014). Personal learning environments are created by learners using varied materials and resources. Smart learning environments can manage text, audio, and video as learning resources. Since learners have diverse needs, knowledge levels, backgrounds, and interests, this lets them choose the best learning path (Zhu et al., 2016).

Perceived Experience (PE): Both Agarwal & Karahanna (2000) and Saadé & Bahli (2005) noted that experience is a psychological concept that can be thought of as a natural drive that includes fun and satisfaction. Previous research shows that when perceived experience is combined with TAM, its research revealed that people with a lot of experience value using technology, focusing on on-time experience, which can strongly predict how useful and easy to use something will be seen to be. So, a user may think that technology is easy to use because they think that if it's easy to use, they can use it without much thought or work. This situation can happen when people who are good with technology use it often, making the environment feel comfortable and friendly.

Subjective Norms (SN): Subjective norm is a social impact variable that relates to an individual's opinion that influential people around them think that the conduct in issue should or should not be done (Fishbein & Ajzen, 1977). According to studies, SN can directly or indirectly alter an individual's intention to utilize the system (Ataran & Nami, 2011; Venkatesh & Davis, 2000). Park et al. (2014) and Sabah (2016) found that SN affects PU system use intention.

Perceived Behavioral Control (PBC): This depends on how easy or hard a person thinks it is to do the behavior of interest. Situations and actions affect how behavioral control is seen, so a person's view of behavioral control can change depending on the situation. People's perceptions of how easy or hard it is to do the behavior of interest are what PBC measures (Ajzen, 1991). Previous studies have shown that PBC greatly affects whether people plan to use learning technology platforms (Al-Emran et al. 2020; Cheon et al. 2012).

Behavioral Intention (BI): The Theory of Planned Behavior says that a person's behavior can be explained by their behavioral intention, which is the decision to act in a certain way in the future (Al-Sayyed & Abdalhag, 2016). This model aligns with the adoption theory; behavior intention and use will greatly affect

Statistics and Mathematical Research Journal
ISSN: 2997-6898|
Volume 13 Issue 1, January-March, 2025
Journal Homepage: https://ethanpublication.com/articles/index.php/E33,
Official Journal of Ethan Publication

how people use smart learning environments. BI is the most important aspect that plays a role in determining whether or not a system is successful (Al-Sayyed & Abdalhag, 2016; Chang et al., 2017).

Actual Usage (AU): Actual system use is how people act when using a system. Davis (1989) opined that actual system usage is a type of external psychomotor response that can be measured by someone who uses the system. Lo et al. (2015) said that usage is measured by the time spent using the technology or how often it is used. This also means using a system more than once can change how users accept it (Andy et al., 2021).

CONCLUSION AND FURTHER WORKS

The advancement in smart, mobile, and wearable computing is transforming how people compute and interact every day. These technologies are transforming the learning environment into a smart learning environment capable of providing personalization for inclusive learning experiences. Several evaluation frameworks were proposed to evaluate the learning environment. However, a well-explored model that considers the characteristics of a smart learning environment and personal factors is lacking.

This study explored the literature and developed an integrated model for evaluating a smart learning environment. The study further validated the model based on the strengths and limitations of the technology acceptance model (TAM) and theory of planned behavior (TPB). This study contributed to harnessing different evaluation studies in both learning technologies and IS literature to provide a comprehensive understanding of the issues and the need for a smart learning environment evaluation study that advanced the existing knowledge in user technology evaluation. Furthermore, this model unified different constructs into defined and measurable dimensions from learning technology models and evaluation.

The study identified five new factors: perceived quality, perceived support, perceived technology resources, perceived personalized adaption, and perceived experiences that can influence a smart learning environment. Although the proposed model focuses on educational settings, its evaluation study will be useful for stakeholders measuring the adoption and deployment of learning technology or other IS applications in educational and related organizations. As part of further research, this model will be used to evaluate a smart learning environment to understand if the new constructs can influence user satisfaction in using a smart learning environment.

References

Abbad, M.M., Morris, D., & Nahlik, C.D. (2009). Looking under the Bonnet: Factors Affecting Student Adoption of E-Learning Systems in Jordan. International Review of Research in Open and Distance Learning, 10(2), 1-25.

Al-Sayyed, F., & Abdalhaq, B. (2016). Interventional Factors Affecting Instructors Adoption of E-Learning Systems: A Case Study of Palestine. Journal of Theoretical and Applied Information Technology, 10(1).

Awa, H. O., Ojiabo, O. U., & Emecheta, B. C. (2015). Integrating TAM, TPB and TOE frameworks and expanding their characteristic constructs for e-commerce adoption by SMEs. Journal of Science & Technology Policy Management, 6(1), 76-94.

Armitage, C. J., & Conner, M. (2000). Social cognition models and health behavior: A structured review. Psychology and health, 15(2), 173-189.

Ajzen I. The theory of planned behaviour. Organ Behav Hum Decis Process 1991 Dec; 50(2):179-211. [doi:10.1016/0749-5978(91)90020-t]

Akour I, Alshurideh M, Al Kurdi B, Al Ali A, Salloum S Using Machine Learning Algorithms to

Predict People's Intention to Use Mobile Learning Platforms During the COVID-19 Pandemic: Machine Learning Approach JMIR Med Educ 2021;7(1): e24032

Ataran, A., & Nami, K. (2011). Examining acceptance of information technology: A longitudinal Study of Iranian high school teachers. International Conference on Information and Financial Engineering, 12(2011), 190-195.

Awang, H., Mat Aji, Z., Sheik Osman, W. R., Abdul Nasir, A., Mat Deli, M., & Wan Hamat, W.Y. (2019). Virtual Learning Environment (VLE) implementation strategy: An analysis of practicality for Google Classroom implementation in Malaysian schools. Journal of Educational Research &Indigenous Studies, 2(1), 1–16.

Abubakar, A. A., Jazim, F., Al-Mamary, Y. H., Abdulrab, M., Abdalraheem, S. G., Siddiqui, M. A & Alquhaif, A. (2021). Factors influencing students' intention to use learning management system at Saudi Universities: A structural equation modelling approach.

Human Systems Management, (Preprint), 1-14.

Andy, R., Dewi, A. C., & As'adi, M. (2021, May). An Empirical Study to Validate The Technology Acceptance Model (TAM) In Evaluating "Desa Digital" Applications. In

IOP Conference Series: Materials Science and Engineering (Vol. 1125, No. 1, p. 012055). IOP Publishing.

Agarwal, R. & Karahanna, E. (2000). Cognitive absorption, and beliefs about information technology usage. MIS Q. **2000**, 24, 665–694. Al-Emran M, Arpaci I, & Salloum SA. An empirical examination of continuous intention to use m-learning: An integrated model. Educ Inf Technol (Dordr) 2020 Jan 04; 25:2899-2918

Bembenutty, H., White, M., & DiBenedetto, M. (2016). Applying Social Cognitive Theory in the Development of Self-Regulated Competencies throughout K-12 Grades. Springer International Publishing Switzerland. The Springer Series on Human Exceptionality. https:// doi. org/ 10. 1007/ 978-3- 319-28606-8_ 9,215- 239

Binyamin, S., Rutter, M., & Smith, S. (2019). Extending the technology acceptance model to understand students' use of learning management systems in Saudi higher education.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101. https:// doi. org/ 10. 1191/ 14780 88706 qp063oa

Chang, Y, Chen, S., Yu, K, Chu, Y. and Chien, Y. (2015). Effects of Cloud-Based M- MLearning on Students' Creative Performance in Engineering Design. British Journal of Educational Technology, 2-5. Doi:10.1111/bjet.12343

Cheon J, Lee S, & Crooks SM, Song J. (2012). An investigation of mobile learning readiness in higher education based on the theory of planned behaviour. Comput Educ 2012 Nov;59(3):1054-1064. [doi: 10.1016/j.compedu.2012.04.015]

Davis, F.D. 1989." Perceived Usefulness, Ease of Use, and User Acceptance of Information Technology." MIS Quarterly. Vol. 13.

DeLone, W. and McLean, E. (2003). The DeLone and McLean Model of Information Systems Success: A Ten Year Update. Journal of Management Information Systems, 19(4), 9–30.

Egielewa, P., Idogho, P. O., Iyalomhe, F. O., & Cirella, G. T. (2021). COVID-19 and digitized education: Analysis of online learning in Nigerian higher education. E-Learning and Digital Media, 19(1), 19-35

Eisenhardt, K. M. (1989). Making fast strategic decisions in high-velocity environments.

Academy of Management Journal, 32(3), 543-576.

Fakinlede, C, Yusuf, M., Mejabi, O., & Adegbija, V. (2015). Readiness for Online Learning in Higher Education: A Mixed-Methods Assessment of Students at a Nigerian University. Malaysian Journal of Distance Education 16(1), 37–57.

Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behaviour: An introduction to theory and research.

Fugard, A. J., & Potts, H. W. (2015). Supporting thinking on sample sizes for thematic analyses: A quantitative tool. International Journal of Social Research Methodology, 18(6), 669684.

Guerra, J., Hosseini, R., Somyurek, S., & Brusilovsky, P. (2016). An intelligent interface for learning content: Combining an open learner model and social comparison to support self-regulated learning and engagement. In Proceedings of the 21st International Conference on Intelligent User Interfaces pp. 152–163https:// doi. org/ 10. 1145/ 28567 67. 28567 84

Guest, G., Namey, E., & McKenna, K. (2017). How many focus groups are enough? Building an evidence base for nonprobability sample sizes. Field Methods, 29(1), 3–22. https:// doi. org/ 10. 1177/ 15258 22X16 639015

Hoel, T., & Mason, J. (2017). Standards for smart education – towards a development framework. Smart Learning Environments, 5, 3. https:// doi. org/ 10. 1186/ s40561- 018- 0052-3

Hwang, G. J. (2014). Definition, framework, and research issues of smart learning environments context-aware ubiquitous learning perspective. Smart Learning Environments, 1(1), 1-14

Joo, Y. J., Park, S., & Lim, E. (2018). Factors influencing pre-service teachers' intention to use technology: TPACK, teacher self-efficacy, and technology acceptance model. Journal of Educational Technology & Society, 21(3), 48-59.

Hamid, M. A., Salleh, S., & Laxman, K. (2020). A Study on the Factors Influencing Students

Acceptance of Learning Management Systems (LMS): A Brunei Case Study. International Journal of Technology in Education and Science, 4(3), 203-217.

Hua, Y., Amm, L., and Chan, I. (2014). Culture Dynamics of Information and Communication Technology (ICT) adoption in construction companies: The Engineering Project Organization Conference. http://hdl.handle.net/10722/201815

Kaplan, B., & Duchon, D. (1988). Combining qualitative and quantitative methods in information system research: A case study. MIS Quarterly, 12(4), 571–586. https:// doi. org/ 10. 2307/ 249133

Lo, M. C., Ramayah, T., & Mohamad, A. A. (2015). Does intention lead to the actual use of technology? A study of an E-learning system among university students in Malaysia. Croatian Journal of Education, 17(3), 835-863.

Mailizar, M., Burg, D., & Maulina, S. (2021). Examining university students' behavioural intention to use e-learning during the COVID-19 pandemic: An extended TAM model. Education and Information Technologies, 26(6), 7057-7077.

Mohamadali, S., and Garibaldi, M. (2010). A Novel Evaluation Model of User Acceptance of Software Technology in Healthcare Sector in Proceedings of the Third International Conference on Health Informatics. SciTePress, 392-393.

Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and I.S. success model. Computers in Human Behavior, 45, 359–374. https:// doi. org/ 10. 1016/j. ChB. 2014. 07.044.

Marshall C and Rossman GB. Designing Qualitative Research 1989 Newbury Park, CA Sage

Martinho, D., Santos, E., Miguel, I., & Cordeiro, D. (2018). Factors that influence the adoption of postgraduate online courses. International Journal of Emerging Technologies in Learning, 13(12).

Nussbaumer, A., Hillemann, E., Gütl, C., & Albert, D. (2015). A competence-based service for supporting self-regulated learning in virtual environments. Journal of Learning Analytics, 2(1), 101–133 https:// files. eric. ed. gov/ fullt ext/ EJ112 6954. pdf. Accessed 4 June 2022

Oppenheim, A. N. (2000). Questionnaire design, interviewing and attitude measurement. Bloomsbury Publishing.

Park, Eunil, and Ki Joon Kim (2014): An Integrated Adoption Model of Mobile Cloud Services: Exploration of Key Determinants and Extension of Technology Acceptance Model: Telematics and Informatics (31)3.

Premkumar, G., & Roberts, M. (1999). Adoption of new information technologies in rural Small businesses. Omega, 27(4), 467-484.

Rosmansyah, Y., Putro, B. L., Putri, A., Utomo, N. B., & Suhardi. (2022). A simple model of smart learning environment. Interactive Learning Environments, 1-22.

Ramayasa, I., and Bali, D., (2015). Evaluation Model of Success and Acceptance of E-Learning. Journal of Theoretical and Applied Information Technology, 82(3), 462-465.

Saadé, R. & Bahli, B. (2005). The impact of cognitive absorption on perceived usefulness and ease of use in online learning: An extension of the technology acceptance model. Inf. Manag. 2005, 42, 317–327

Saadé, R., & Bahli, B. (2005). The impact of cognitive absorption on perceived usefulness and perceived ease of use in online learning: an extension of the technology acceptance model. Information & Management, 42(2), 317-327.

Serba, C & Loan, L. (2020). QLearn: Towards a framework for smart learning environments. 24th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems. Procedia Computer Science 176 (2020) 2812–2821

Sabah, N.M. (2016). Exploring students‟ awareness and perceptions: Influencing factors and individual differences driving m-learning adoption. Computers in Human Behavior,

65(2016), 522-533. Retrieved from http://dx.doi.org.10.1016/j.chb.2016.09.009

Spector, J. M. (2016). Smart Learning Environments: Concepts and Issues. SITE 2016Savannah, GA, United States, March 21–26. https:// www. learn techl ib. org/ prima ry/p/ 172078/. Accessed 9 Feb 2022

Thong, J.Y.L., Hong, W., & Tam, K.Y. (2002). Understanding user acceptance of digital libraries: what are the roles of interface characteristics, organizational context, and individual differences? Int. J. Human-Computer Studies, 57(2002), 215–242.

Vankatesh, V., & Davis, F.D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies, Management Science, 46(2), 186-204.

Venkatesh, V., Thong, J., and Xu, X., (2012). Consumer Acceptance and Use of Information Technology Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, 36(1), 157-178.

Uyouko, A., & Wong, S. (2015). Teachers' Cultural Perceptions of ICT in Nigerian Schools. International Journal of Education and Training (InjET), 1(1), 12-18.

Yot-Dominguez, G., & Marcelo, C. (2019). University Students' Self-Regulated learning using Digital technologies. International Journal of Educational Technology in Higher Education, 14, 8. https://doi. org/ 10. 1186/ s41239- 017- 0076-8

Yin, R. (2003). Case Study Research: Design and Methods (3rd ed.). Thousand Oaks, CA: Sage Publications

Yusof, M., Kuljis, J., Papzafeiropoulou, A., and Stergioulas, L. (2006). Towards a Framework for Health Information Systems Evaluation. Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS'06).

Zhu, Z., & He, B. B. (2012). Smart education: A new frontier of educational informatization. EEducation Research, 12, 1–13.

Zogheib, Bashar, Ahmad Rabaa'i, Salah Zogheib, and Ali Elsaheli. "University student perceptions of technology use in mathematics learning." Journal of Information Technology Education 14 (2015).

Zhu, Z., Yu, M., & Riezebos, P. (2016). A research framework of smart education. Smart Learning Environments, 3(1), 1–17. https:// doi. org/ 10. 1186/ s40561- 016- 0026-2