Theories Integrated With Technology Acceptance Model (TAM) in Online Learning Acceptance and Continuance Intention: A Systematic Review

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***Abstract*—Since its inception, Technology Acceptance Model (TAM) has been a commonly adopted theory for understanding users' acceptance of various types of information systems (e.g., online learning systems). Over the years, different information systems theories have been integrated into TAM to further the understanding of users' intention to accept online learning. To examine the literature, four databases were utilized to discover research articles examining the online learning acceptance and continuance intention of users (e.g., students and teachers). The findings of the systematic review revealed that Task Technology Fit and Theory of Planned Behavior are the most integrated and educationally successful theories into TAM. Meanwhile, course information, satisfaction, perceived usefulness, attitude, system quality, perceived ease of use, and academic performance are the essential drivers for the acceptance or continuance usage of online learning systems. These findings serve as an evidence and reference for educational institutions in developing policies and strategies for the implementation of an online education.**

Keywords—Technology Acceptance Model, Online Learning, Systematic Review, Integrated Theories

I. INTRODUCTION

Recent innovations in the field of information technology have led to a widespread development and implementation of online learning platforms. Many educational institutions have already integrated online learning (subsequently referred to as e-learning) into their curricula and practice in order to expand the reach of knowledge acquisition beyond boundaries, space, and time. To guarantee the quality of online education, factors that affect users' (students and teachers) behavioral intention to adopt and use e-learning have been repeatedly investigated. Meanwhile, a systematic literature review from 2009 to 2018 about e-learning research shows that Technology Acceptance Model (TAM) is one of the most used theories by researchers [1]. TAM focuses on two specific variables, such as perceived usefulness and perceived ease of use, as fundamental elements of user acceptance of information technology [2]. Over the years, other information systems theories have been integrated into TAM to further the understanding of users' intention to accept online learning. For instance, more factors were added such as integrated multimedia instruction, perceived quality work of life, systems interactivity, social media influence, and internet connectivity experience [3]. To examine the literature, four databases were used to locate research articles examining the online learning acceptance and continuance intention of users (e.g., students and teachers). By synthesizing the present studies, educational institutions can develop informed policies and strategies for the implementation of an online education.

II. MATERIALS AND METHODS

A. Search Strategy

The search strategy followed the guidelines and protocol of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [4], mixed with an author-concept approach to categorize the literature according to relevance to the topics of the study. The process was carried out in five phases: (1) searching the literature in four databases (Google Scholar, IEEE Xplore, SCOPUS, and Web of Science) using relevant keywords, (2) screening the selected literature, (3) applying the inclusion/exclusion criteria, (4) categorizing and analyzing the literature, and (5) communicating the findings. The four databases were reviewed in July 2021 and the main keywords were the prefixes TITLE-ABS-KEY Technology Acceptance, TAM*, Comb*, Theory*, and Integr* to find any records that include these words in any form across title, abstract, or keywords. Of 2601 records obtained, we reviewed 120 possibly relevant research articles (103 with additional 17 records were retrieved from database search and through other sources, respectively). Then, we excluded 98 articles with a different focus and eight more for not being relevant to aims and objectives of the study. Finally, for this systematic review, we selected 14 publications from 2005 to 2021. It is important to note that some articles were eliminated because they were proposed studies with no empirical evidence, the methodology was not clearly defined, or the research articles were a pilot study. Figure 1 illustrates the procedure using PRISMA.

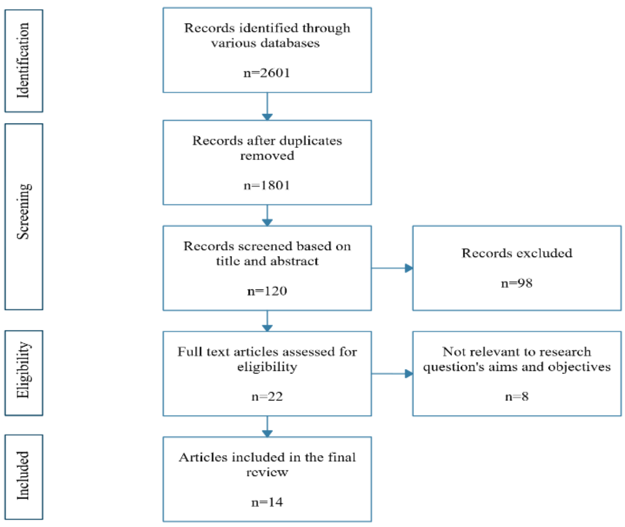

Fig 1. PRISMA Flow Diagram

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B. Research Questions

We established the research questions in accordance with the significant purpose of this systematic literature review, which is to synthesize and gain insight into the research area of online learning with a specific emphasis on the integration of other theories with TAM. Moreover, the study emphasizes existing evidence, gaps, and the field's future direction. The formulated study questions are listed in Table I.

TABLE I. RESEARCH QUESTIONS AND ITS MOTIVATIONS

ID	Research Question	Motivation
RQ1	Which theories were combined with TAM?	To identify the theories integrated with TAM.
RQ2	What variables had the most impact?	To identify the most significant variables in the integrated theories.
RQ3	What was the outcome of the integrated theories?	To identify the outcomes of the integrated theories.
RQ4	What were the limitations of the integrated theories?	To identify the limitations of each integrated theory.

C. Inclusion and Exclusion Criteria

The study applied several inclusion and exclusion criteria to filter research articles. The inclusion criteria are as follows: (1) the study must have included at least one theory integrated with TAM to investigate intention to use online learning, (2) peer-reviewed full-papers from journals and conferences, (3) empirical research (both qualitative and quantitative), and (4) well-defined research methods. On the other hand, the review excludes papers (1) not targeting online learning adoption, (2) extended abstracts, (3) 'work-in-progress' research articles, (4) research methods not adequately explained.

III. RESULTS AND DISCUSSION

Majority of the studies were published in journals (n=12, 85.8%), with two papers in conference proceedings (14.2%). The most common research design was cross-sectional (n=13, 92.9%), with one study employed an experimental design. In terms of external validity, all research adequately defined the setting or location. Moreover, the reviewed studies achieved a satisfactory Cronbach alpha (α > 0.07). Meanwhile, majority of the studies in this review targeted university students (n=9), while the remaining included instructors/teachers (n=3) and secondary school students (n=1). Students were normally the respondents because they are the primary e-learning users.

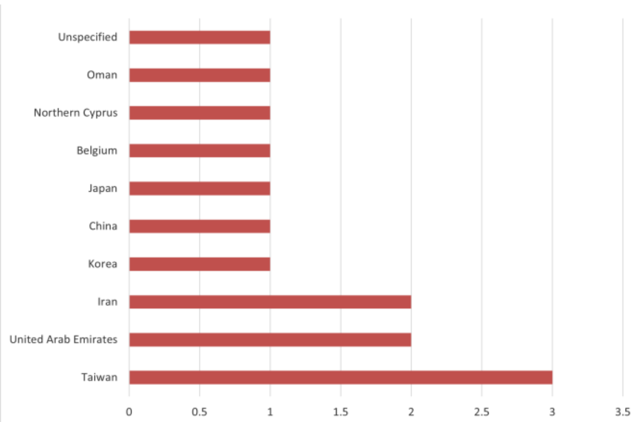

Fig 2. Number of Research Studies per Country

Additionally, three studies were performed in Taiwan, two in the United Arab Emirates, and two in Iran. Other research articles were conducted in Belgium, China, North Cyprus, Oman, South Korea, and Taiwan. The location of studies is illustrated in "Fig 3". Only one study did not report a specific country but identified the study location as Europe. Samples were composed of individuals aged between 16 and 60 years. The sample size varied greatly, with the least being 102 [5] and the highest 864 [6]. The average response rate in studies that reported a response rate (n=5) was 87.7 %. Seven studies evaluated behavioral intention (BI) to use the e-learning system, four examined continuation intention (CI), and two looked at actual usage (AU). The objective was measured using self-reported instruments based on the 7-point (n=9, 69%) or 5-point (n=4, 31%) Likert scales. In one study, however, the measurement scale was not reported [7]. Annual research publications are illustrated in Figure 3.

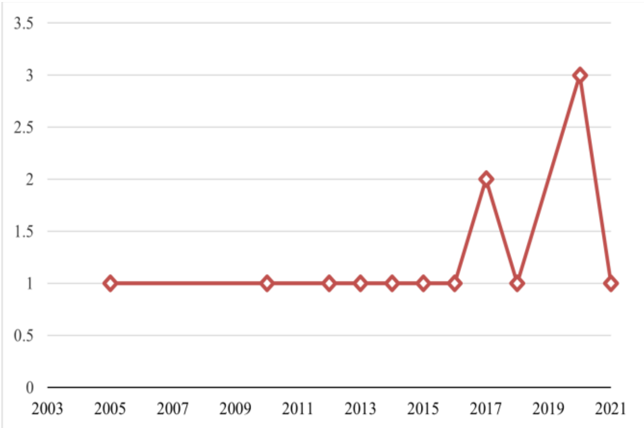

Fig 3. Number of Research Studies per Year

Over half of the research articles (n=8, 57%) investigated the integrated structural model to measure how it represented the data. In the retained studies, the authors analyzed the goodness-of-fit index (GFI) or comparative fit index (CFI) indices. The indices ranged between 0.85 and 1.0. As a result, the goodness-of-fit indices in these investigations met the acceptable standards, indicating that the integrated research models produced a satisfactory fit for the data. However, the remaining studies (n=6) did not report goodness-of-fit indices; thus, the findings may be inconclusive. Table III presents the studies that reported the goodness-of-fit indices.

TABLE II. GOODNESS-OF-FIT INDECES

Goodness-of-fit Indices	Value	References
GFI CFI	0.99 1	Motaghian et al., 2013 [8]
GFI	0.867	Vanduhe et al., 2020 [9]
CFI	0.985	Fathali, & Okada, 2018 [10]
GFI CFI	0.91 0.95	Lee, 2010 [11]
GFI CFI	0.98 0.90	Mohammadi, 2015 [12]
CFI	0.987	Joo et al., 2016 [13]
GFI CFI	0.991 0.987	Alshurideh et al., 2020 [7]
GFI CFI	0.864 0.948	Lin & Chen, 2012 [14]
GFI CFI	0.924 0.901	Wu & Chen, 2017 [15]

A. Which theories were combined with TAM?

We identified seven different theories that were combined with TAM, which include Expectation Confirmation Model (ECM), Information System Success Model (ISSM), Social Motivation (SM), Self-determination Theory (SDT), Theory of Planned Behavior (TPB), Task Technology Fit (TTF), and Flow Theory. Remarkably, ECM (*n*=4) and TBP (*n*=3) were the most prevalent theories among integrated models. ECM was applied to determine continuance intention, and TPB to determine behavioral intention and continuance intention. Of note, the four studies that integrated ECM reported favorable outcomes, with most of the hypotheses supported (86.8%). In the case of TPB, studies also reported positive effects, with 93% of hypotheses being supported. These findings provide an additional support for ECM's and TPB's suitability for integration with TAM in the context of behavioral intention or actual usage of an online learning system.

TABLE III. IDENTIFIED THEORIES INTEGRATED WITH TAM

Integrated Theories	References
TAM+ECM	[7, 13, 16]
TAM+ISSM	[8, 12]
TAM+SDT	[10, 17]
TAM+TPB	[6, 18]
TAM+TTF	[9, 15]
TAM+ECM+TPB	[11]
TAM+Flow Theory	[5]

Additionally, among the thirteen selected studies, there were seven distinct integrated models with TAM+ECM (*n*=3) and TAM+ISSM (*n*=3) as the most dominant, followed by TAM+SDT (*n*=2) and TAM+TPB (*n*=2). Notably, the two most prevalent theories, ECM and TPB, were combined with TPB in one study (TAM+ECM+TPB) [11] to investigate 363 students' continuance intention to use a web-based learning system. Other integrated theories are illustrated in Table 3.

B. What variables had the most effect?

We have observed the effect of independent variables on the dependent variables and extracted variables with the most significance. The average number of variables adopted in the twelve studies is eight. Among these articles, one study had the highest with twelve variables [17], while the least number of variables used was six [5, 13, 18]. It can also be noted that constructs including Perceived Usefulness, Perceived Ease of Use, Attitude, Satisfaction, Course Information, Academic Performance, System Quality represent the drivers impacting online learning usage intention. Literature [19-21] shows the importance and effect of TAM variables (Perceived Ease of Use and Perceived Usefulness) on both Behavioral Intention or Continuance Intention. Similarly, our findings align with previous studies that identified System Quality, Satisfaction, Attitude, and Academic Performance as all significant. More interestingly, these new variables arise from several models that have been combined with TAM. Thus, these variables should be explored further in a single model in future studies. It is worthy to note that the variables of TTF and TPB had the most substantial impact when combined with TAM to assess behavioral intention or continuance usage of online learning.

TABLE IV. PREDICTOR AND INDEPENDENT VARIABLES

Predictor Variable	Dependent Variables	References
Perceived Usefulness	Behavioral Intention, Continuance Intention	[5-10, 13, 15, 17]
Perceved Ease of Use	Behavioral Intention	[6, 8, 10, 15, 17, 18]
Attitude	Behavioral Intention, Continuance Intention	[6, 9, 11, 18]
Satisfaction	Behavioral Intention, Continuance Intention	[7, 12, 14, 16]
System Quality	Behavioral Intention	[8, 12, 14]
Course Information	Behavioral Intention	[14]
Academic Performance	Continuance Intention	[16]

C. What were the outcomes of the integrated models?

TAM+TTF had the most significant effect in our analysis, with 60% of its variables predicting Continuance Intention. Additionally, this integrated model explains 95.6% variance in intention to adopt MOOCs. Further, the model reported a model of indices of *GFI*=0.924 and *CFI*=0.901, which shows a suitable model fit (>0.9). However, another study that used TAM+TTF to predict the Continuance Intention exhibited a variance of 54.7% [9]. Similarly, 60% of the variables used in the study had a significant effect on Continuance Intention to use online learning. Moreover, the study had a *GFI*=0.867, also representing an acceptable fit. On the other hand, the integrated model of TAM+TPB applied a Machine Learning algorithm to predict behavioral intention using six variables, with a predictive model accuracy of 89.26%. Meanwhile, another study using TAM+TPB had a variance between 13% and 16% [6]. Therefore, this shows that while TAM+TPB can have positive effects when predicting behavioral intention, future studies should still validate this integrated model.

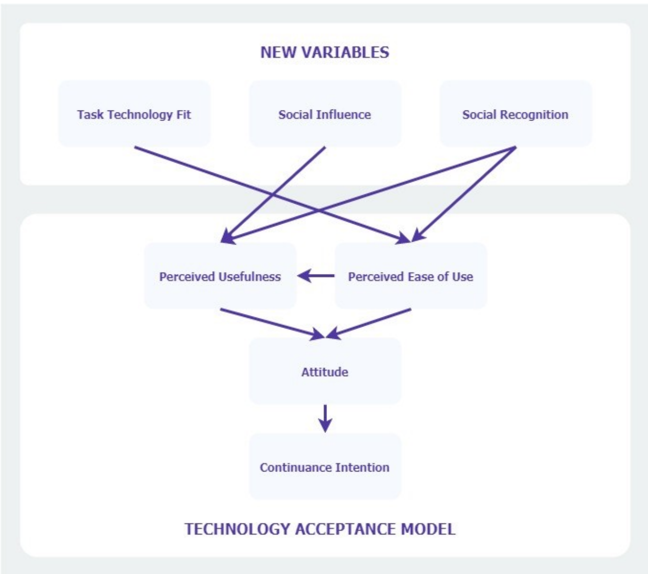

Fig 4. Technology Acceptance Model + Task Technology Fit

TABLE V. STUDY OUTCOMES

Study	N	Theory	Outcome Measures and Result
[6]	864	TAM+ TPB	Perceived Usefulness is the strongest predictor of attitude (p<0.001) and BI (p<0.001). Variance explained in Actual Usage is low (13% and 16%)
[8]	115	TAM+ ISSM	Perceived Usefulness, Perceived Ease of Use, and System Quality positively affect Behavioral Intention. Perceived Usefulness had most significant effect.
[9]	375	TAM+ TTF	Perceived Usefulness, Perceived Ease of Use, Social Recognition, Social Influence, and Attitude significantly affected Continuance Intention. (Model has 54.7% variance)
[10]	162	TAM+ SDT	Perceived Usefulness, Perceived Ease of Use significantly predicted Intention. Perceived Competence influences Perceived Usefulness. (p<0.01) and Perceived Ease of Use (p<0.001) Model explains 58% variance in user intention.
[17]	140	TAM+ SDT	Perceived Ease of Use and Perceived Usefulness significantly affected Behavioral Intention. Model explains 50% variance in Behavioral Intention.
[16]	295	TAM+ ECM	Significant correlation between Academic Performance and Continuance Intention (p<0.021).
[11]	363	TAM+ TAM+ TPB	Attitude predicted by Perceived Ease of Use (p<0.001) and Perceived Usefulness (p<0.01). Model explains 80% variance of user intention.
[18]	489	TAM+ TPB	Attitude (p<0.05), Subjective Norm (p<0.05) and Perceived Behavioral Control (p<0.05), predicted Behavioral Intention. Attitude predicted with 88.11% accuracy and Intention with 89.26% accuracy.
[12]	390	TAM+ ISSM	Intention significantly and positively predicted by Tech System Quality and Service quality (p<0.01). Satisfaction predicted Actual Usage (p>0.001).
[13]	222	TAM +ECM	Continuance Intention predicted Actual Usage (p<0.05). Meanwhile, Perceived Usefulness (p<0.05) and Satisfaction (p<0.05) predicted Continuance Intention.
[7]	448	TAM+ ECM	Perceived Usefulness, Perceived Ease of Use, and Satisfaction influence Continuance Intention. Meanwhile, Continuance Intention predicted Actual Usage Model explains 33% variance in Actual Usage.
[5]	102	TAM+ Flow Theory	Perceived Usefulness and Concentration predict user intention.
[14]	412	TAM+ ISSM	System Quality, Platform Info and Course Info significantly related to Satisfaction and Behavioral Intention.
[15]	252	TAM+ TTF	Perceived Usefulness, Perceived Ease of Use, Reputation, Social Influence, and Social Recognition significant in predicting Continuance Intention.

D. What were the limitations of the integrated theories?

We extracted limitations observed in the selected studies. Table 6 provides an overview of eight limitations identified in the analysis. According to the findings of this study, it was identified that it might be difficult to generalize the results of the selected study as they were restricted to a specific group or locality. Nevertheless, there is a need for the studies to be generalized for external validity, and as such, future studies should consider the cross-cultural perspective. Notably, most studies were cross-sectional for a short period, with only one study conducted over a more extended period. Given this, the user behavior is deemed dynamic, and longitudinal research may provide more vital insight into the development of user behavior. Furthermore, the focus should be on these variables when designing an online learning system. New constructs should ideally solidify and support prediction. Hence, future research should investigate the impact of constructs in other integrated theories that have not been applied nor identified in this review. In addition, the majority of the retained studies were quantitative with different sampling approaches. This, in return, can affect the study outcome and make it difficult to make conclusions. Hence the need to apply a qualitative or mixed-method approach to validate the findings and arrived at a better understanding. Another factor not considered in most studies is the impact of user experience and years of experience. Literature [21-23] shows that user experience is critical to user adoption. It follows that a positive or negative user experience with an online learning system can promote or discourage behavioral intention or continuous usage. Prior computer experience significantly influences their Perceived Ease of Use and attitude towards online learning technologies [24, 25]. On the other hand, TAM does not consider prior computer experience and other factors that may influence the users' intention to use technology like e-learning systems. It necessitates the introduction of new variables to address this.

TABLE VI. STUDY LIMITATIONS AND RECOMMENDATIONS

Description of Limitations	Recommendation
Not Generalisable – most studies were limited to only one country (external validity)	Future studies should be carried out at different universities using diverse study populations to improve the generalizability of the results.
All studies were performed over a short period.	Need for Longitudinal Studies
Gender bias – the majority of the participants were female	Need for more balanced gender to avoid gender bias
Did not measure Actual Usage – the focus was mainly on behavioural intention	Investigate factors related to the actual usage of online learning.
Different sampling approaches used in the studies	More studies using a specific sampling approaching to determine its appropriateness
Personal characteristics of samples were not considered	Personal characteristics of subjects can affect the study outcome
Did not consider the experience level of users and their years of experience	Future studies should account for level of experience and years of user experience
All studies were quantitative or experimental	Qualitative or mixed-mode studies should be considered

IV. CONCLUSION

This study explored the theories combined with TAM to predict user acceptance and sustained use of online learning. In addition, significant variables predicting user acceptance and continued usage of online learning were investigated. In this context, our research demonstrates the relevance of the TAM+TTF and TAM+TPB models for investigating online learning continuance intention. TAM+TTF is also a common model combination in other pedagogical applications within e-learning implementation like gamification [26]. Moreover, the result of this systematic review demonstrates that Course Information, Perceived Usefulness, Attitude, System Quality, User Satisfaction, Perceived Ease of Use, and the Academic Performance are the essential drivers for acceptance and/or continuance usage of online learning systems.

Consequently, online learning technology services should be designed in accordance with users' acceptance level of technology and intention to continue using it. Future studies should also explore the possibility of using other models or combining more than two models and theories. Similarly, the present findings underscore the need for systems developers to establish a solid understanding of the factors impacting the user acceptance of an online learning. Because of this insight, they can develop online learning systems that are in line with the needs of their target learners. Future research is needed to substantiate our findings and make them more extensively relevant to validate the models identified in this analysis. The findings, nevertheless, are an essential contribution to current models of technology acceptance process utilized in online learning literature. Most studies have been conducted using only one model, primarily focusing on e-learning. It not only adds to the current literature in various ways but also assists scholars and practitioners in gaining a better knowledge of user behaviors in the online learning context.

REFERENCES

[1] J. Valverde-Berrocoso, M. d. C. Garrido-Arroyo, C. Burgos-Videla, and M. B. Morales-Cevallos, "Trends in Educational Research about e-Learning: A Systematic Literature Review (2009–2018)", 2020.

[2] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, 1989.

[3] M. B. Garcia, "E-Learning Technology Adoption in the Philippines: An Investigation of Factors Affecting Filipino College Students' Acceptance of Learning Management Systems," *International Journal of E-Learning and Educational Technologies in the Digital Media*, vol. 3, no. 3, pp. 118-130, 2017.

[4] D. Moher, A. Liberati, J. Tetzlaff, and D. G. Altman, "Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement," vol. 339, p. b2535, 2009.

[5] S. H. Liu, H. L. Liao, and C. J. Peng, "Applying the technology acceptance model and flow theory to online e-learning users' acceptance behavior," *E-learning*, 2005.

[6] B. Pynoo and J. van Braak, "Predicting teachers' generative and receptive use of an educational portal by intention, attitude and self-reported use," *Computers in Human Behavior*, vol. 34, 2014.

[7] M. Alshurideh, B. Al Kurdi, S. A. Salloum, I. Arpaci, and M. Al-Emran, "Predicting the actual use of m-learning systems: a comparative approach using PLS-SEM and machine learning algorithms," *Interactive Learning Environments*, pp. 1-15, 2020.

[8] H. Motaghian, A. Hassanzadeh, and D. K. Moghadam, "Factors affecting university instructors' adoption of web-based learning systems: Case study of Iran," *Computers & Education*, 2013.

[9] V. Z. Vanduhe, M. Nat, and H. F. Hasan, "Continuance intentions to use gamification for training in higher education: Integrating the technology acceptance model (TAM), Social motivation, and task technology fit (TTF)," *IEEE Access*, vol. 8, pp. 21473-21484, 2020.

[10] F. Somayeh and O. Takeshi, "Technology acceptance model in technology-enhanced OCLL contexts: A self-determination theory approach," *Australasian Journal of Educational Technology*, 2018.

[11] M.-C. Lee, "Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation–confirmation model," *Computers & Education*, vol. 54, no. 2, 2010.

[12] H. Mohammadi, "Investigating users' perspectives on e-learning: An integration of TAM and IS success model," *Computers in Human Behavior*, vol. 45, pp. 359-374, 2015/04/01/ 2015.

[13] Y. J. Joo, N. Kim, and N. H. Kim, "Factors predicting online university students' use of a mobile learning management system (m-LMS)," *Educational Technology Research and Development*, vol. 64, no. 4, pp. 611-630, 2016/08/01 2016.

[14] L. Tung-Cheng and C. Ching-Jen, "Validating the Satisfaction and Continuance Intention of E-learning Systems: Combining TAM and IS Success Models," *International Journal of Distance Education Technologies (IJDET)*, vol. 10, no. 1, pp. 44-54, 2012.

[15] B. Wu and X. Chen, "Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model," *Computers in Human Behavior*, 2017.

[16] R. M. Tawafak et al., "A Combined Model for Continuous Intention to Use E-Learning System," *International Journal of Interactive Mobile Technologies*, vol. 15, no. 3, 2021.

[17] S. A. Nikou and A. A. Economides, "Mobile-based assessment: Investigating the factors that influence behavioral intention to use," *Computers & Education*, vol. 109, pp. 56-73, 2017/06/01/ 2017.

[18] A. Q. M. Alhamad, "Predicting the Intention to use Mobile Learning: A Hybrid SEM- Machine Learning Approach," *International Journal of Engineering Research & Technology*, vol. 9, no. 3, 2020.

[19] S. A. Kamal, M. Shafiq, and P. Kakria, "Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM)," *Technology in Society*, 2020.

[20] C. S. L. M. Lazim, N. D. B. Ismail, and M. D. A. K. Tazilah, "Application of technology acceptance model (TAM) towards online learning during covid-19 pandemic: Accounting students perspective," *International Journal of Business, Economics and Law*, vol. 24, no. 1, 2021.

[21] Y. Wang, "Humor and camera view on mobile short-form video apps influence user experience and technology-adoption intent, an example of TikTok (DouYin)," *Computers in Human Behavior*, vol. 110, p. 106373, 2020/09/01/ 2020.

[22] J. C.-L. Goh and F. Karimi, "Towards the Development of a 'User-Experience' Technology Adoption Model for the Interactive Mobile Technology," in *HCI in Business*, Cham, 2014, pp. 620-630: Springer International Publishing.

[23] K. Hornbæk and M. Hertzum, "Technology Acceptance and User Experience: A Review of the Experiential Component in HCI," vol. 24, no. 5, *ACM Trans. Comput.-Hum. Interact.*, 2017.

[24] A. Qashou, "Influencing factors in M-learning adoption in higher education," *Education and Information Technologies*, 2021.

[25] S. P. John, "The integration of information technology in higher education: A study of faculty's attitude towards IT adoption in the teaching process," *Contaduría y Administración*, vol. 60, 2015.

[26] A. S. Mustafa, G. A. Alkawsi, K. Ofosu-Ampong, V. Z. Vanduhe, M. B. Garcia, and Y. Baashar, "Gamification of E-Learning in African Universities: Identifying Adoption Factors Through Task-Technology Fit and Technology Acceptance Model," in *Next-Generation Applications and Implementations of Gamification Systems*, P. Filipe and Q. Ricardo Eds. Hershey, PA, USA: IGI Global, 2022, pp. 73-96.