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Review

A Systematic Review of the Technology Acceptance Model for the Sustainability of Higher Education during the COVID-19 Pandemic and Identified Research Gaps

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Abstract: Over the past three decades, the Technology Acceptance model (TAM) has garnered considerable attention in higher education. COVID-19 boosted the development of TAM as multiple studies were rapidly undertaken during the pandemic. This, however, created a gap in our current understanding of the directions and trends of TAM advancement. The purpose of this study is to obtain insight into the advancement of TAM throughout the pandemic. It would assist researchers in comprehending the advancement and direction of TAM studies in higher education, such as gaining an understanding of the prevalent external variables for TAM, the statistical analysis employed, research methodologies, the technologies studied, and the geographic location of the research conducted. Finally, research gaps and future directions for TAM studies are presented. A systematic review utilizing PRISMA was conducted on 104 sampled publications. It was found that self-efficacy, subjective norms, experience, and enjoyment were the external variables most frequently used in TAM, while internal motivation received minimal attention. The existing studies have focused mainly on student samples, so further investigation is needed into lecturers, higher education personnel, and mixed groups. Further study is also required on qualitative and mixed methods, with the partial least square structural equation model currently dominating statistical analysis. Future technologies such as 5G, AI, cloud computing, augmented reality, virtual reality, and BYOD represent new TAM-related research gaps. The majority of studies have been undertaken in Asian countries, such as China and those in southeast Asia. This new systematic literature review provides insight into the trend of TAM advancement in the sustainability of higher education during the pandemic, the identified research gaps, and recommendations for future research directions. These findings also serve as a reference for future research by enhancing the foundation established by previous reviews and research on TAM, thereby facilitating the model's ongoing expansion.

Keywords: technology acceptance model; self-efficacy; subjective norms; perceived enjoyment; higher education; research gap; COVID-19; systematic literature review; PRISMA

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1. Introduction

Understanding the acceptance and adoption of a technology is crucial in the era of information. The rapid development and deployment of cutting-edge technology have resulted in a more dynamic and organic technology dissemination process than in the past. Without sufficient data on the adoption or rejection of a technology, introducing an invention would be ineffective and a waste of resources. If acceptance factors are ignored during the invention process, it is questionable how a new technology could be improved, and the ways people cognitively process the innovation would be unknown.

In response to this, Davis [1] established the Technology Acceptance model (TAM) in 1989 to provide the industry with valid measures that would explain the acceptance of computer-related technologies, in this case, email. The initial TAM presentation included two determinants of acceptance, perceived usefulness (PU) and perceived ease of use (PEU). Later, an 'attitude toward using' element was introduced to the model as a function of the PU and PEU concepts [2]. Since then, TAM has been widely used to predict the acceptance of technology. In 1996, Davis and Venkatesh [3] argued that a more in-depth understanding of PEU was required to devise interventions that would increase user acceptance of technology. This initiative spearheaded the expansion of TAM using external variables.

TAM is now widely acknowledged as a well-recognized paradigm for technological acceptance on a worldwide scale. Around the globe, this model has assisted preparations for the unanticipated effects of the COVID-19 pandemic. The number of TAM-related studies has increased dramatically since the outbreak of the pandemic. In 2020, 945 papers were published in Scopus regarding TAM, more than the 885 articles published in 2019. One year after the COVID-19 outbreak, 1218 articles were published on many TAM-related themes and perspectives. Throughout the pandemic, 2764 articles on TAM were published in Scopus up to June 2022. The same database included 663 entries for education-related articles. The number of TAM-related studies conducted in previous years was significantly lower than during the pandemic. Given the aforementioned information, it is evident that the expansion of knowledge in TAM during the pandemic warrants investigation. The changes brought by the pandemic may have affected how humans perceived the acceptance of technology, and these enormous changes may not occur again in the next decades. Along with it could be a key piece of information regarding the expansion of knowledge about TAM. What is currently lacking, however, is an understanding of how TAM knowledge has been expanded, such as the types of samples and technologies studied, leveraging the TAM facet [4]. TAM is the foremost scientific framework for understanding the acceptance of technology in the educational field. It is applicable to the contexts of both secondary [5,6] and higher education [7]. TAM research in the latter context constitutes the majority of mobile learning research [8]. A similar emphasis on higher education is evident in the TAM research conducted during the COVID-19 period. Even though COVID-19 is anticipated to enter its endemic phase in the near future, its impact on education and the workplace has altered operations in these areas. The pandemic impacted students' career choices [9] and provided opportunities for digital and technological innovation in many industries [10]. Working from home, for instance, became a widely accepted workplace innovation and paved the way for working from multiple locations to become the norm [11]. Due to the pandemic, remote education now offers the flexibility, inclusiveness, and time efficiency that were previously lacking in education [12].

Now that all the effects of COVID-19 have occurred, it is timely to undertake a systematic examination of the changes in and directions of TAM research in higher education during the pandemic. If a holistic perspective of these research trends could be developed, this could influence the future of research and development not only within the education context but also in relation to workplace expansion and innovation as university students are the future workforce within the emerging digital economy. Several research paradigms must be constructed to accomplish this goal.

First, as TAM continues to evolve, researchers are perpetually faced with the conundrum of selecting which external components to incorporate into the model to build an expanded TAM with increased explanatory powers. The intensity of TAM research conducted during COVID-19 expedited the research and advancement in this field. Experimenting with diverse datasets and multiple external variables would generate voluminous and abundant data. If a systematic literature study could construct and illustrate the most popular external variables, as well as the current knowledge gaps, it would be possible to anticipate the future directions when these external variables are employed. This would have significant effects on TAM research advancements. For purposes other than academic, discovering the external variables would help higher education institutions to better comprehend their ecosystems and prepare for future improvement. This would open the door for significant workplace innovations that could create an efficient and cost-effective system. The samples employed in higher education-related TAM research must also be examined since this would reveal who is familiar with the innovation that has occurred during this evolution. Understanding the types of samples will help researchers and employers determine how prepared the future workforce is for digitally enhanced organizations.

To further stimulate research in a growing field such as TAM, academics must comprehend the progress and current status of the research undertaken in this area. Providing the scientific community with valuable information, such as the statistical analyses and particular research methods employed, would significantly benefit research endeavors.

Fourth, it is necessary to examine the nature of the studied technologies through which the future of higher education will be shaped. As open distance learning (ODL) has become mainstream, it is crucial to determine which educational tools are required to enable remote education. Employers also demand this information to determine which online collaboration tools and technologies are suited to the digital age workplace. This information would assist researchers and the scientific community in determining the current state of knowledge as well as the existing research gaps that could be the themes of future research initiatives.

Last but not least, the pandemic has been a global catastrophe and phenomenon. Consequently, it is essential that the global community comprehend the TAM research trends in terms of the geographical regions in which the research has been conducted. In an economic sense, this would inform investors as to which global regions are well-prepared for digital innovation and contain digitally ready citizens. Examining all the articles collected and analyzed was expected to enable the authors to formulate TAM research gaps and suggestions for future research into this topic.

To address the stated deficiency, the present new systematic review analyzes the research conducted during the pandemic, focusing on technology acceptance using TAM in higher education. In addition to closing the current research gap, this systematic review analyzes the sampled articles for trends in the use of external variables, the type of samples, statistical analysis, the research methodology, the technologies being studied, and the geographical distribution of the research conducted. Formulating and synthesizing these data using systematic analysis would assist TAM researchers in finding, incorporating, and subsequently developing theoretical and conceptual models that could serve as a foundational model for future research [13] in technology acceptance research in higher education, as Al-Nuaimi and Al-Emran [13] did for learning management systems and TAM. This new systematic review echoes the work of Granić and Marangunić [4], who provided researchers with an overview of TAM-related educational research conducted from 2003 to 2018. Thus, the following research questions are addressed:

1. What are the external variables used in the studies?
2. What are the types of samples included in the studies?
3. What were statistical analysis and research methods employed in the studies?
4. What are the technologies investigated in the studies?
5. Where were the studies conducted geographically?
6. What are the research gaps and directions for future research that can be identified through a systematic literature review?

2. Previous Reviews

TAM is the most popular of the models introduced by Fred Davis. There is widespread global recognition that the model can be used to comprehend the acceptance of technologies and beyond. For example, it can be used to predict the acceptance of new technologies [14] and identify the reasons why certain technologies are rejected by users [15]. The model has been used in numerous studies in diverse fields, including business [16], healthcare [17], engineering [18], and education [19].

In the context of education, TAM has been employed to conduct empirical studies at the secondary and post-secondary levels. Thus, after more than three decades of extensive research, the model has become the focus of studies within and outside the educational context. The model has been utilized not only in survey or correlational research designs but also by numerous researchers employing systematic review methods. Table 1 presents the previous review studies that have addressed the Technology Acceptance model, as identified in the current review.

Table 1. Previous review studies featuring TAM.

Article	Year	Focus	Coverage	Methodology	Studies Reviewed	Findings
[20]	2007	Healthcare	1996–2006	Systematic Review	18	The acceptance of technology by physicians can be predicted through system characteristics, practice, as well as personal and organizational factors.
[21]	2007	Cross-domain	1989–2004	Meta Analysis	145	From 1989 to 2004, seventy external variables were identified as extensions of TAM. The prevalent aspects were students as primary research subjects as well as subjective and objective measurement methods.
[22]	2007	Cross-domain	1989–2004	Meta Analysis	95	The attitude paradigm had been omitted from TAM, and it was unclear whether optimal emphasis had been placed on intention and self-reported use.
[23]	2010	Healthcare	1999–2008	Methodological Review	20	TAM is capable of predicting a substantial proportion of healthcare technology acceptance. Expansions of and alterations to the model were suggested.
[24]	2010	Cross-domain	1989–2007	Systematic Review	73	Behavioral Intention is a strong predictor of Actual Usage, according to TAM. Actual Usage is less likely to correspond to PU and PEU.
[25]	2011	Older adult	2005–2010	Systematic Review	19	TAM is the most widely used research model for investigating older adults. Prior researchers paid less attention to age-related factors. The majority of research techniques consist of questionnaires.
[26]	2011	E-learning	2002–2010	Systematic Review	42	TAM is the predominant model for e-learning comprehension. The magnitude of causal effects is affected by user type and e-learning variation.
[27]	2016	Smart devices	1995–2016	Meta Research	54	The acceptance of smart devices is influenced by design features. An extended version of TAM is useful for understanding the smart devices diffusion strategy.
[28]	2017	Healthcare	1999–2016	Meta Analysis	111	TAM is robust for e-health applications. The magnitude of the causal relationship's effect is affected by the type of user.
[29]	2017	Video game	2004–2016	Systematic Review	50	Behavioral Intention and attitude are predicted by Perceived Enjoyment, PU, and PEU.
[8]	2018	M–learning	2007–2018	Systematic Review	87	The focus of research has been on extending TAM with external factors and other theories/models. Across Asia, questionnaires are the primary instrument for research and study distribution.
[30]	2018	Social network sites	1989–2016	Systematic Review	26	Quantitative research on the acceptance of social network sites using the TAM paradigm is dominant. Knowledge gaps are related to the use of qualitative approaches such as semi-structured interviews and focus groups.
[31]	2018	Health informatics	1999–2017	Systematic Review	134	To meet the needs of the health service ecosystem, the Theory of Planned Behavior and the Unified Theory of Acceptance and Use of Technology have been incorporated into TAM. Popular external variables include subjective norms and self-efficacy.
[32]	2019	Education	2006–2017	Meta Analysis	45	TAM is highly effective for determining how teachers intend to utilize technology. Teachers' behavioral intentions were directly impacted by their perceptions of usefulness.
[4]	2019	Education	2003–2018	Systematic Review	71	Publications were produced at the highest frequency in 2014. Taiwan was the most common location for research. The most prevalent model was the original TAM, while the most common analysis was structural equation modeling.

Table 1. *Cont.*

Article	Year	Focus	Coverage	Methodology	Studies Reviewed	Findings
[33]	2020	E-learning	2001–2019	Systematic Mapping Study	41	Increasing interest was noted in applying TAM to Moodle. University students are the most-researched population. Asia and Europe dominate the geographical distribution of research publications.
[34]	2021	Healthcare	2010–2019	Systematic Review	142	TAM and the Unified Theory of Acceptance and Use of Technology are popular in healthcare. The United States and Taiwan have conducted extensive healthcare research from the perspective of technology acceptance.
[35]	2022	Healthcare	1999–2020	Systematic Review	37	The majority of studies were conducted in the United States and Spain. Most studies utilized TAM and its extended version. Popular predictors are subjective norms, facilitating conditions, and self-efficacy.

Previous literature reviews related to TAM were analyzed systematically. This enabled the researchers to probe the current situation of the topic through a systematic review [36]. In total, 1123 articles were reviewed by 17 research teams. The minimum number of articles included in a review was 18, while the maximum number of articles included was 145. On average, 66.06 articles were reviewed in each research study.

The first review was conducted in 2007 by Yarbrough and Smith [20], and the latest was undertaken in 2022 by Garavand et al. [35]. The reviews covered various topics, with the most frequently reviewed topic being healthcare. Meanwhile, education continued to be missing from the reviewed articles, as the most recent TAM review was written by Granić and Marangunić [4] in 2019, a year before COVID-19. E-learning was studied in 2020 by García-Murillo et al. [33]; however, the impact of COVID-19 was not included in this review as the studies covered were from 2001 to 2019. Five of the most recent reviews only covered studies conducted between 2001 and 2019, with only one review covering studies conducted in 2020. No review of TAM-related papers published during the pandemic has been conducted, demonstrating a knowledge gap.

Despite the extensive and multidimensional synthesis offered by previous reviews, whether in an educational or non-educational context, there is a glaring research gap that has persisted as these reviews were conducted prior to the pandemic. As COVID-19 has revolutionized the landscape of human existence, including education, the significant research undertaken between 2020 and 2022 will be extremely beneficial to the advancement of TAM and human life. It is noticeable that no review related to TAM in education has been published after the pandemic; in contrast, healthcare has received greater attention, with two review articles. This shows a knowledge gap concerning how the educational sector, especially higher education, was able to sustain the impact of COVID-19 from the TAM perspective. Therefore, a new systematic review to bridge this gap is needed.

3. Methodology

This study represents a systematic literature review of the research published during the COVID-19 pandemic on TAM in higher education. The study was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement and guidelines. The PRISMA statement was created to assist researchers in conducting a systematic review that would allow for a systematic and coherent reporting of the review's purpose, what the authors did, and what they discovered [37,38]. It is a widely accepted set of guidelines for systematic reviews, and it fits the purpose of this new systematic review on TAM perfectly.

3.1. Inclusion and Exclusion Criteria

Based on a set of inclusion and exclusion criteria, articles were chosen for inclusion or exclusion from this collection. The established criteria were among the initial criteria used to choose articles for additional analysis. The inclusion and exclusion criteria employed in this study are detailed in Table 2.

Table 2. Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
Published during the COVID-19 pandemic (2020–2022)	Studies published before the COVID-19 pandemic
Research on TAM, as developed by Davis [1]	Studies on technology acceptance using models other than the model developed by Davis (TAM) [1]
Includes PU, PEU, Behavioral Intention (BI), OR two of the TAM variables	Studies on TAM but with insufficient variables included in the model
Involves samples from higher education	Studies not using samples from higher education
Empirical research	Studies that were not empirical, such as reviews
Written in English	Studies not written in English

3.2. Data Sources and Search Strategies

The literature search was conducted between the end of May 2022 and the beginning of June 2022. The search was limited to articles published between January 2020 and two different end periods: 31 May 2022 for the Scopus database and 6 June 2022 for the Web of Science database. The 2020 to 2022 range was selected because the global outbreak of COVID-19 began in 2020; it remains a pandemic at the time of writing. As stated, Scopus and Web of Science were searched as part of this systematic literature review because these two databases cover a wide variety of publishers and are widely recognized globally as reputable indexing bodies.

The search was conducted using specific keywords and search terms based on the logic of Boolean operators. The keywords used for Scopus were Technology Acceptance Model AND Education AND COVID. This resulted in the following search information: (TITLE-ABS-KEY (technology AND acceptance AND model) AND TITLE-ABS-KEY (education) AND TITLE-ABS-KEY (COVID)). The same search terms were used to search the Web of Science database. The search process produced 227 documents from Scopus and 294 documents from Web of Science based on the keywords used. This brought the total number of documents to 521.

The article information from Scopus and Web of Science was then downloaded for additional analysis and comparison to ensure that there was no duplication between the two databases. From the initial 521 documents, 157 were identified as duplicates, reducing the total number of documents to 364.

Then, the documents were further analyzed in detail, based on the stated inclusion and exclusion criteria. Based on these criteria, another 243 documents were excluded. Finally, 104 documents underwent all the identification, screening, and eligibility filtration and were selected for the review analysis. The research flow diagram based on PRISMA guidelines is shown in Figure 1.

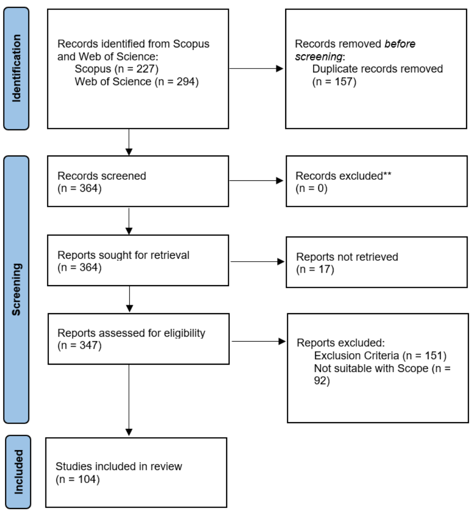

Figure 1. The PRISMA flow diagram.

4. Results

The 104 documents were analyzed analytically to answer the formulated research questions in this systematic literature review. The list of articles analyzed in this review is in Appendix A.

4.1. External Variables of TAM

The majority of the reviewed articles constituted an expansion of the original TAM. Only 26 studies implemented TAM in its original form, without modification or the incorporation of external variables. To increase the explanatory power of TAM, the remaining reviewed articles incorporated between one and four external variables. The integration of external variables is derived from the criticism that the model would be overly simple if no external variables were included [39,40]. Figure 2 depicts fourteen of the most popular external factors.

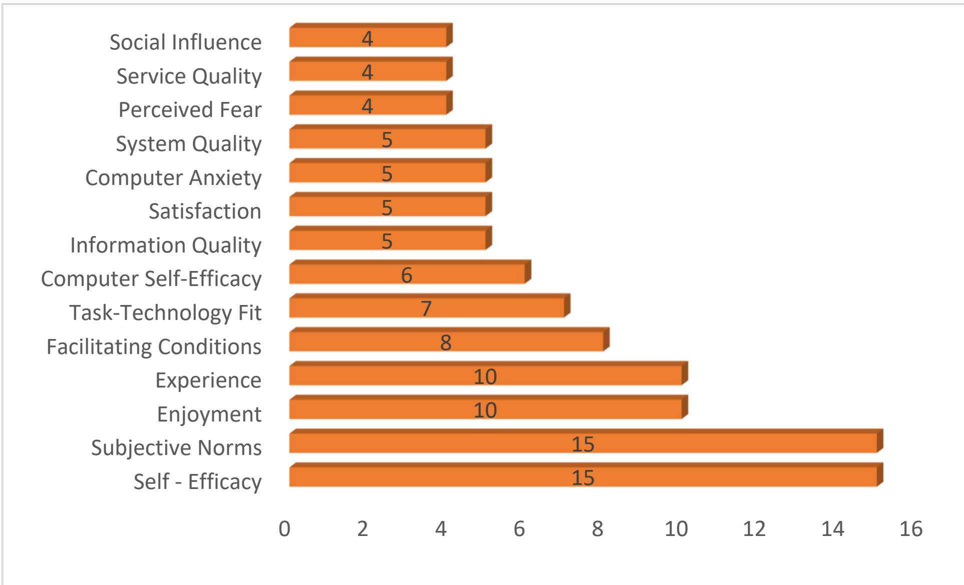

Figure 2. The popular external variables of the TAM.

Self-efficacy and subjective norms were the external variables included most often in the TAM versions identified in this systematic review, followed by enjoyment, experience, and facilitating conditions. The subjective norms variable originated from the Theory of Reasoned Action, developed by Fishbein and Ajzen [41]. Task–Technology Fit and Information System Success (information quality, system quality, and service quality) models were the external models that were integrated most frequently into TAM. Other external factors such as computer anxiety, satisfaction, perceived fear, and social influence also comprised the external variables used to extend TAM. Innovativeness, insecurity, job relevance, optimism, output quality, perceived convenience, perceived playfulness, perceived pleasure, perceived risk, and perceived satisfaction were additional variables that received less attention yet merit mentioning.

4.2. Research Samples

Research samples are a crucial component of empirical research, particularly when examining technology acceptance. Previous studies have always incorporated human subjects as research samples [41,42]. Through the current analysis, it was discovered that the studies related to TAM in higher education during the pandemic exhibited several noteworthy patterns, such as the use of various sample types, as shown in Figure 3. The same phenomenon was observed by Granić and Marangunić [4].

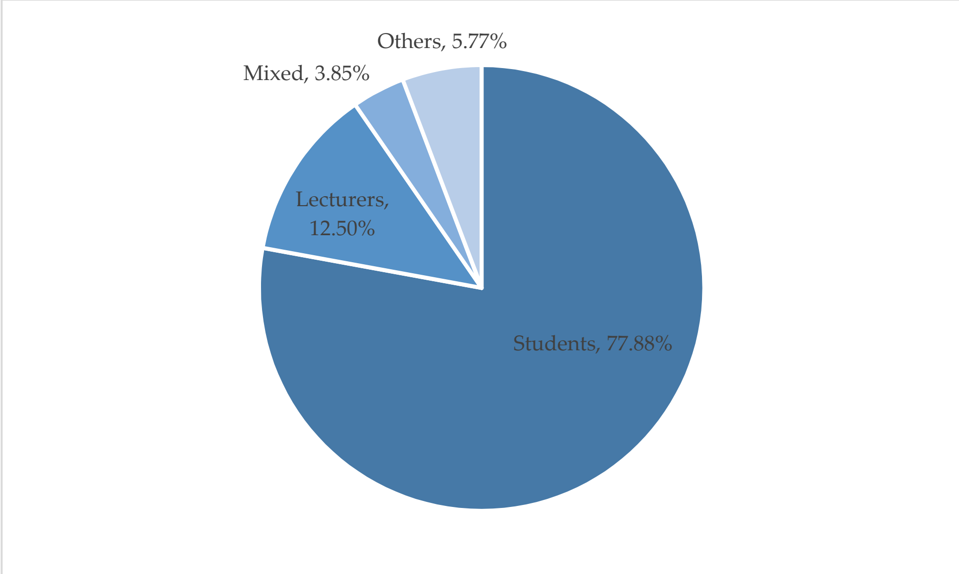

Figure 3. Sample types.

Of all the research samples, 77.88% (81 studies) involved students from universities or colleges in the ecosystem of higher education. Researchers may have wished to assist students in coping with COVID-19-induced stress, leading to a high rate of student participation. Understanding students' perspectives is also essential for universities [43]. Students constitute the largest portion of the higher education community, which explains this result. Students would have borne the brunt of the effects of COVID-19 on higher education, as they would have been confined to their homes, had limited access to campus, and potentially encountered hardware and technical difficulties.

Only 13 research studies involved lecturers as samples; 6 studies involved samples other than students or lecturers. Another four studies combined samples of students and lecturers to better understand technology acceptance by obtaining two different view paradigms. This finding demonstrates that much remains unexplored in relation to lecturers' technology acceptance during COVID-19 based on the TAM theme.

In terms of quantitative research, the largest sample size employed in the reviewed articles was the 1880 university students engaged by Akour et al. [44], followed by Navarro et al. [45], who included 1011 engineering university students; in comparison, 974 samples were used by Sukendro et al. [46]. These studies were conducted in the Asian countries of the United Arab Emirates, the Philippines, and Indonesia. The smallest sample sizes identified from the selected articles were the 20 university students included in the study by Motamedi [47], the 27 university students in the work by Quadir and Zhou [48], and the 50 university students included by Marpaung et al. [49]. This information could serve as a benchmark for future research on TAM sample size requirements for specific studies.

4.3. Analysis Technique and Research Approaches

TAM is a widely used framework for analyzing the acceptance of new and existing technologies. In its initial appearance, TAM was synonymous with quantitative approaches. Davis [1] implemented multitrait–multimethod analyses in producing the instrument for the model. Almost a decade later, quantitative approaches continued to be implemented, with the aim of strengthening the model [50]. As the popularity of the structural equation model grew over time, TAM began to be studied with the same analytic method [51,52]. In 2010, mixed-methods research was also employed to better comprehend the model [53]. A year later, Lindsay, Jackson, and Cooke [54] applied qualitative approaches using ethnographic design to TAM. However, after the pandemic affected higher education, the pattern of analysis techniques and research methods may have changed.

Based on the sampled articles, the systematic analysis utilizing PRISMA identified quantitative approaches as the most common type of research method employed in TAM studies, as illustrated in Figure 4. Of the sampled articles, 93 (89.42%) utilized quantitative methods. Only two articles were qualitative, while nine utilized the mixed-methods paradigm.

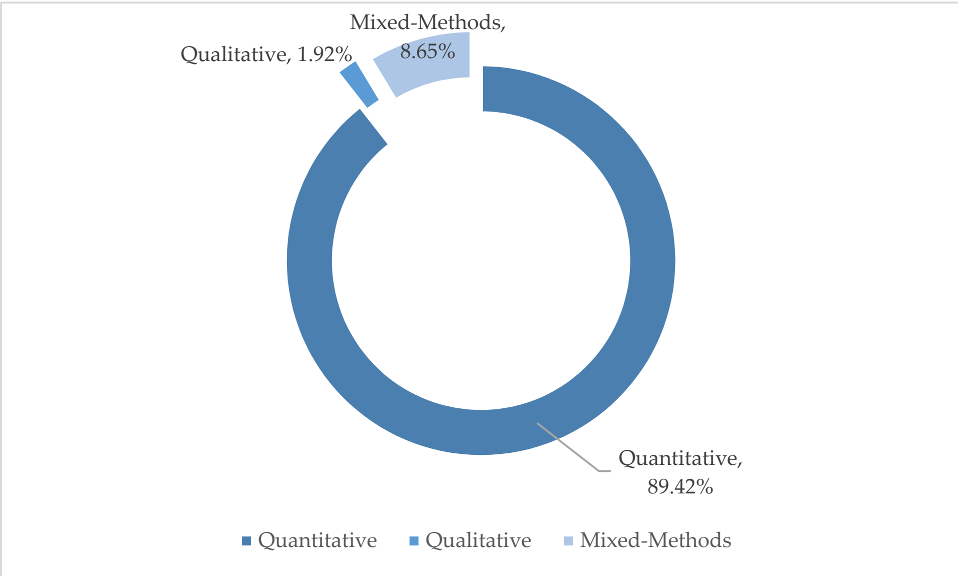

Figure 4. Distribution of research approaches.

The most prevalent quantitative method was analyses based on the structural equation model. Within this model, the covariance-based structural equation model (CB-SEM) was the most frequently used paradigm, as shown in Figure 5. However, the CB-SEM poses far more demanding requirements than the partial least squares structural equation model (PLS-SEM) [55]. This may explain why 53 of the sampled articles utilized PLS-SEM instead of CB-SEM, which was employed in only 22 studies.

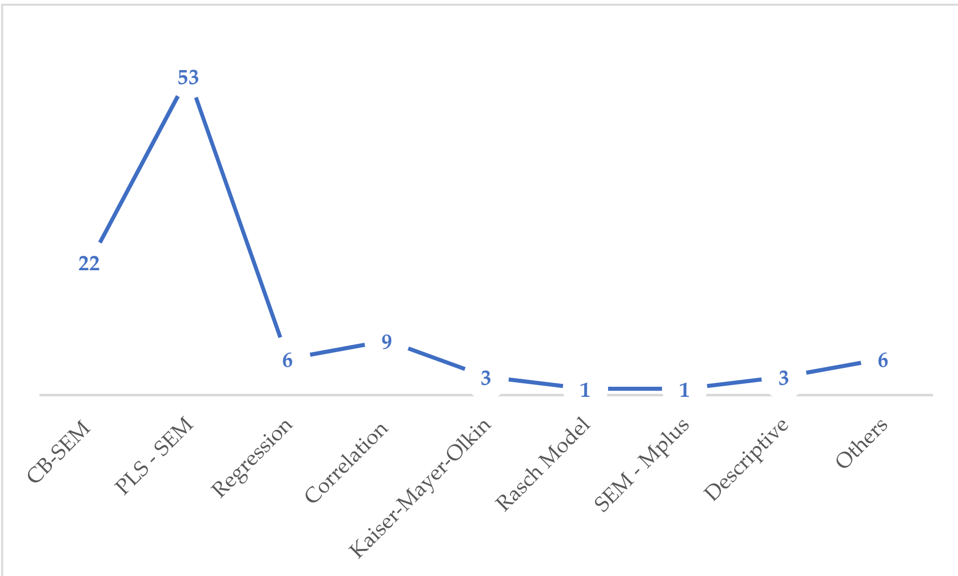

Figure 5. Prevalent quantitative approaches.

4.4. The Technologies Studied

Of the 104 documents included in this review, which covered numerous types of technologies, 34 of them concerned learning management systems or e-learning. This covered 32.69% of all the articles published on TAM in the higher education context during the COVID-19 pandemic. Other technologies that attracted research attention were mobile learning, with eight studies that comprised 7.69% of the total. Technologies related to online teaching and learning activities also gained significant attention. It was discovered that 7.69% of the studies covered online learning (n = 8), 4.81% referred to online teaching (n = 5), and 5.77% examined remote teaching (n = 6). The distribution of the technologies studied is depicted in Figure 6.

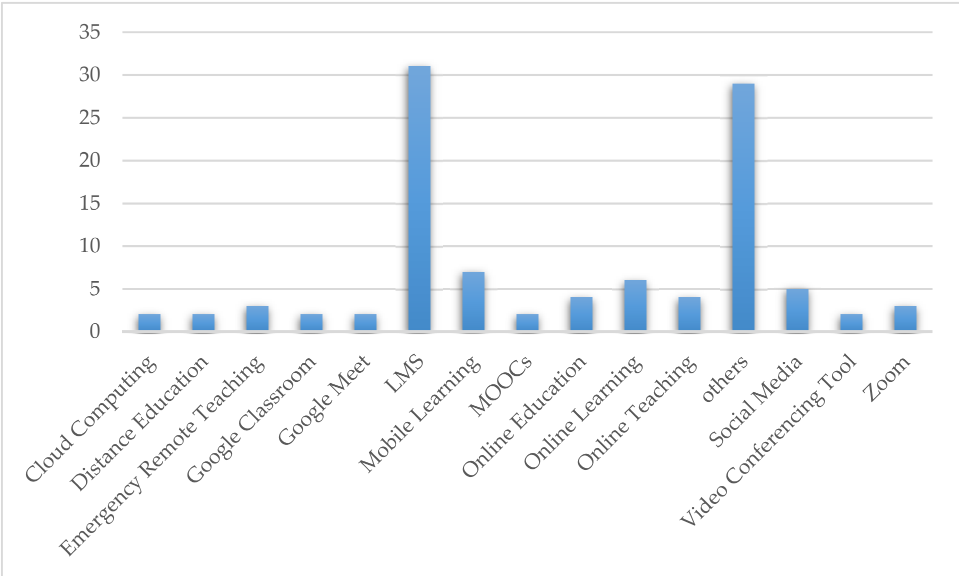

Figure 6. Distribution of technologies studied.

Artificial intelligence, 5G technology, augmented reality, virtual reality, and robotics received less attention. However, these technologies are required to accommodate the effects of Industrial Revolution 4.0, which may present a research opportunity for future scholars.

4.5. Geographical Distribution

The majority of the studies examining the acceptance of technologies in higher education based implicitly on TAM were conducted in Asia, with China leading the region with 11 studies. Ten studies were conducted in Indonesia, six in Malaysia and Vietnam, three in Thailand, and two in the Philippines, all within the southeast Asia region, where researchers placed significant emphasis on educational sustainability during the pandemic. In the Middle East, Saudi Arabia (n = 9), the United Arab Emirates (n = 6), Jordan (n = 5), and Iraq (n = 2) dominated the research in this region. The same pattern of research, focused on the Asian context, was observed in south Asia, where six of the sampled articles were from India and three from Pakistan.

5. Discussion

TAM has been a highly popular model for explaining technology acceptance among users. However, a gap remains in our current knowledge in relation to how the trends and development of the model can ensure the sustainability of higher education during the pandemic. Thus, this systematic literature review aimed to understand how the model had evolved and developed to support the sustainability of higher education. Moreover, this review would enable researchers to understand the current TAM knowledge gap through the trends and patterns emerging from this study.

5.1. Prevalent External Variables

The articles studied revealed several intriguing discoveries. Self-efficacy, subjective norms, experience, and enjoyment were among the external factors most often included when researchers applied the expanded TAM. Introduced by Albert Bandura, self-efficacy has had a long history of integration with TAM. Among the first to integrate self-efficacy into TAM were Igbaria and Iivari [56]; this is still practiced today. A significant variable, it has remained relevant over time despite being measured using several sample types. Granić and Marangunić [4] comprehensively evaluated the literature before the pandemic, and their findings are consistent with those of our review. Interestingly, the current findings actually resemble those from the 2015 review conducted by the same researchers [57]. It is anticipated that self-efficacy will continue to be applicable to future TAM research for at least another decade, based on the findings of this study and the patterns derived from previous research [4,57]. Self-efficacy is also essential in the workforce of the present day [58]. Researchers are recommended to include self-efficacy in future studies, either in the original model suggested by Bandura [59] or its modified version [39].

The subjective norms variable is the second most commonly used external variable, which agrees with the findings of previous research [57]. This conclusion can be supported because this factor derives from the Theory of Reasoned Action. As TAM is an extension of the Theory of Reasoned Action, this theory undeniably influences the behavioral intentions of users. The theory was also utilized in the unification and expansion of TAM when there was an attempt to create a new model of the Unified Theory of Acceptance and Use of Technology (UTAUT) [60]. Other domains, such as transportation [61], retail [62], and tourism [63], also exhibit the roles played by subjective norms. These findings enable the suggestion that incorporating additional subjective norms into TAM might be fruitful. According to reports during the pandemic, subjective norms have a major predictive influence on the uptake of technology [35,64,65]. Consequently, this factor may be a significant indicator of the current, endemic, and post-pandemic circumstances. As it did for TAM2, TAM3, UTAUT, and UTAUT2, it may have a similar effect on the future evolution of TAM.

Based on the data, experience is also a popular external variable for TAM. It may initially appear that experience was never a significant factor in TAM. However, these findings are not novel because they have been previously reported, albeit with some exclusions [32]. Scherer and Teo [32] determined that prior studies had covered the experience component generically rather than focusing on technology, making it impossible to comprehend the implications. In contrast, the integration of experience into TAM was reported in the literature [57]. Despite this, the absence of a theoretical basis for experience, in contrast to self-efficacy and subjective norms, may hinder the expansion of this variable. Simultaneously, user experience with technology can be connected with the pandemic's impact since activities such as online learning and working from home are improving daily. These activities enhance consumers' knowledge of different forms of technology. Experience may not be the most important factor in future studies, at least for the time being. When analyzing the development of TAM3 in situations unrelated to pandemics, it is possible that experience would become the most important factor [66].

Enjoyment has been added to TAM to supplement the lack of intrinsic drive in the original form, which led to criticism [67]. The current factor of perceived usefulness is overly extrinsic and perhaps ignores the intrinsic drive of consumers. This is an opportunity for a greater examination of TAM by incorporating several perspectives, such as the full spectrum of the Self-Determination Theory [39]. Although not supported by previous studies [26,32], enjoyment is an important aspect of the larger hedonic motivation to accept future technologies [68]. Including hedonic motivation in an acceptance theory such as UTAUT would enhance usefulness, the most accurate predictor of acceptance [69]. Thus, researchers are recommended to investigate enjoyment, either directly or indirectly, through the use of perceived enjoyment perspectives since this could potentially enhance the explanatory power of TAM.

During the pandemic, the Task–Technology Fit and Information System Success models were used to supplement TAM. A common practice among researchers is to utilize model components or the entire model to develop an extended TAM [70–73]. This methodology was not evident in previous reviews in non-educational contexts [35], but the trend has become more common in educational reviews [13]. Combining TAM with another information technology model, such as Task–Technology Fit, significantly increases the usage variation and enables it to be applied in more context-related circumstances [74]. As Al-Nuaimi and Al-Emran [13] suggested, attention should be paid to the post-adoption stage because one gap in the existing literature concerns how this could drive the integration of the Information System Success model, which centers on the continuous use of technology rather than solely on the usage intention based on the TAM paradigm.

5.2. Types of Samples

Research using students as samples is compatible with the existing body of knowledge [4,26]. Compared to the previous reviews, examinations of academics' adoption of technology have gained momentum. Nevertheless, this represents a knowledge vacuum and a significant opportunity for investigation. In addition to the lack of research employing lecturers as samples, an extremely interesting pattern was seen to have emerged through the use of samples comprising both students and lecturers [75–78]. It would be exciting to pursue this innovation in future research. The second gap that researchers could address is the inclusion of non-academic personnel who belong to the higher education ecosystem as study samples, in addition to students and faculty members. As few scientists have explored this topic, the knowledge of samples other than students and instructors remains limited [79–81].

5.3. The Prominent Statistical Method and Research Approach

The use of PLS-SEM, the most prominent form of statistical analysis, contrasts with the approaches used in previous reviews [4]. During the pandemic, the deployment of CB-SEM was replaced by that of PLS-SEM, from which it might be deduced that CB-SEM requires more stringent requirements and assumptions than PLS-SEM. During the global COVID-19 outbreak, social distancing was practiced. As a result, researchers had less access to samples. CB-SEM necessitates larger sample sizes than PLS-SEM [55], explaining why researchers preferred PLS-SEM. Second, CB-SEM requires multivariate normal and normally distributed data. PLS-SEM, on the other hand, offers substantial benefits by being less perturbed by non-normal data [82]. Because of the restrictions imposed during the COVID-19 pandemic, researchers had fewer options when selecting samples, and acquiring normally distributed data might have been more difficult. This is supported by the evidence that some reviewed articles also utilized non-parametric statistical analysis [78].

PLS-SEM, CB-SEM, correlation, and regression analyses dominated the statistical analyses conducted, causing other approaches, such as the implementation of the Rasch model [83] and autoethnography [84], to be less clarified. Consequently, it is unclear what contributions these analyses could make to the development of TAM. Therefore, it was theorized that the future application of quantitative analyses other than structural equation models represents a noteworthy research gap and a potential future direction of TAM.

The majority of the quantitatively oriented publications could be explained by the intrinsic character of TAM. It was conceived as a questionnaire-based study with closed-ended questions, which is synonymous with quantitative research methods [1,50]. As TAM is basically a self-reported measure, qualitative techniques received less consideration. In future directions involving TAM, qualitative paradigms, such as the use of interviews, observations, and data analytics, are proposed. Scherer and Teo [85] made the same proposal of switching to non-self-reporting techniques, an existing research gap in TAM. Thus, qualitative and mixed methods are suggested for future research.

5.4. The Technologies Studied

During the COVID-19 pandemic, the explored technologies were crucial to the sustainability of higher education. Evaluating the examined technologies would enable future researchers to comprehend the technologies that were widely used and accepted throughout the pandemic period. As COVID-19 has altered the environments of higher education and the job market, as well as provided more opportunities for online engagement and collaboration, this knowledge would be useful when formulating new industry strategies.

In higher education, learning management systems (LMSs) are the most-researched technologies. Due to the rapid transition from traditional classrooms to online environments, higher education had little time to select an alternative learning platform to the current LMS. The application of LMS has long been practiced, even before the pandemic [86]. Thus, it is one of the most effective and productive options available to universities and colleges. The findings support the previous literature from before and up to the COVID-19 era [4].

Less popular than LMS, pedagogically focused technologies such as online learning [87–91], mobile learning [15,44,73,92–95], online education [81,84,96], online teaching [97–100], and emergency remote teaching [78,101,102] were investigated to a substantial degree. This illustrates an emerging trend to understand the acceptance of tools (such as LMS) rather than approaches. This appears to reflect that TAM, as a technology or tool, should be perceived as useful before being employed by users. The existing research also conceived of tools such as electric vehicles [103] and cloud computing [104]. Likewise, the study of instructional approaches is less common than the study of technologies. This causes a diminished awareness of the scientific community's endorsement of instructional practices. Future studies should address this constraint.

New cutting-edge technologies such as 5G technology [105], artificial intelligence [106], cloud computing [107], augmented reality [108], and virtual reality [108] have also been under-researched. Policies pertaining to ICT integration, such as bring-your-own-device (BYOD) [109] and virtual tours [79], have received little consideration. These technologies are essential for the workplaces of the future [110,111]. As they remain under-researched, future research on these technologies will have a significant impact.

5.5. Research Locations

The majority of the chosen papers were from Asia. China may have taken the lead in the research due to its proactive measures and vigorous response to prevent the spread of the virus via its "zero-COVID" policy. Lockdowns in China's metropolitan areas, such as Shanghai, may explain the strong demand for COVID-19-compatible education mechanisms. China's strong economic and financial capacities to allocate research funding to its local university scholars may be a contributory element to this spike. Meanwhile, China has been garnering global interest in the realm of research as China-related research is frequently published. It is expected that research into TAM in China will become more popular. Southeast Asia is home to a number of emerging economies, including Malaysia, Vietnam, Thailand, Indonesia, and the Philippines, which may account for the high number of studies undertaken in that region.

6. Identified Research Gaps

This systematic review centered on six review perspectives concerning TAM: external variables, sample types, statistical analysis, research approaches, researched technologies, and research locations. Based on a comprehensive analysis of 104 articles, the author posits that several research gaps should be addressed in future studies. The gaps are presented in Table 3.

Table 3. Identified research gaps.

Perspective	Identified Gaps	Suggestions for Future Research
External variables used with TAM	Lack of research on the intrinsic motivation of samples. Perceived usefulness is extrinsic in nature; hence, a need was identified for research that considers the intrinsic perspectives of users.	Future studies should include self-efficacy, subjective norms, and experience as these elements have major theoretical roots in TAM and have been included in its enhanced and expanded forms.
Sample types	Regarding academic studies and understanding (among lecturers and college teachers), little is known about the adoption of technologies. Also under-researched is the non-academic workforce in higher education. There is a lack of mixed-sample research that includes, for instance, both students and faculty members as samples.	More studies using educators and lecturers as samples. TAM should refocus its efforts on sample mixtures.
Statistical analysis and research approaches	Little focus has been placed on implementing qualitative and mixed methods in research involving TAM.	CB-SEM may continue to be applicable in the future, given the growing recognition of the importance of PLS-SEM. The Rasch model should be investigated in the future.
Researched technologies	Compared to technology tools, there is a dearth of research that employs a pedagogical approach.	It is recommended that researchers study future workplace technologies, such as 5G, AI, cloud computing, virtual tours, AR, and VR. Industry-relevant policies, such as bring-your-own-device (BYOD), also require attention.
Research locations	Insufficient research from the African, American, and European continents.	It was suggested that research be conducted in the context of China and emerging economies.

7. Limitations

The database search was conducted towards the end of May and the beginning of June in 2022. Therefore, articles that were indexed after this date may not be included in our review. As the scope of this review is limited to Scopus and Web of Science, which index publications of sufficient quality, this review was unable to include articles not indexed by these databases. Some articles may have been accidentally omitted due to human error; however, we are sure that the vast majority of relevant articles have been covered.

8. Conclusions

The Technology Acceptance model has attracted substantial attention from researchers worldwide. The unanticipated outbreak of COVID-19 has further accelerated the growth of TAM in other academic domains, especially higher education. Even though several systematic reviews on TAM have been published, the vast majority were written before the crisis. Consequently, there was a deficiency in knowledge regarding the research trends and directions of TAM during the pandemic. As COVID-19 has altered the way the world functions, such information is crucial for global future development.

This new systematic review examined the literature from six research viewpoints, namely, external variables, sample types, statistical analysis, methodological approaches, researched technologies, and research locations. It is determined that TAM will remain relevant to technology acceptance research for an extended period. Self-efficacy, subjective norms, and experience may also remain significant external variables of TAM. The continued integration of models such as Task–Technology Fit and Information System Success models is expected. Future researchers also need to focus on intrinsic motivation.

Future studies must focus on samples other than students, and the use of mixed samples is highly encouraged. Qualitative research would enable a deeper understanding of TAM from users' perspectives, whereas PLS-SEM is anticipated to be the primary quantitative analysis technique. Additional studies on 5G, AI, VR, and BYOD, as well as in locations outside Asia, would contribute to the existing body of knowledge.

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Appendix A

Table A1. List of the sampled articles.

Label	Article	External Variables	Sample Types	Statistical Analysis	Research Approaches	Researched Technologies	Research Location
A1	[75]	Self-Efficacy, Subjective Norms, Enjoyment, Computer Anxiety	Mixed (Students and lecturers)	SEM (PLS)	Quantitative	LMS	Korea
A2	[112]	Satisfaction	Students	SEM (CB)	Quantitative	Online Class	Korea
A3	[113]	None	Students	Descriptive	Quantitative	LMS	Bangladesh
A4	[114]	Perceived Fear, Enjoyment, Perceived Technicality	Students	SEM (PLS)	Quantitative	Google Meet	Arab Region
A5	[115]	Social Influence	Students	SEM (PLS)	Quantitative	YouTube	Malaysia
A6	[116]	Cost Effectiveness, Interactivity, Learners Characteristics	Students	SEM (CB)	Quantitative	Digital Collaboration Platform	India
A7	[117]	Information System Success Model, Computer Self-Efficacy, Quality of Education, Information Quality	Students	Correlation, Regression	Quantitative	Distance Education	Turkey
A8	[15]	Perceived Convenience, Self-Efficacy, Perceived Compatibility, Perceived Enjoyment	Students	SEM (CB)	Quantitative	Mobile Learning	Jordan
A9	[105]	Meaning Access, Competence Access, Material Access	Students	SEM (PLS)	Quantitative	5G	China
A10	[118]	None	Students	Kaiser–Mayer–Olkin	Quantitative	ICT	India
A11	[97]	Subjective Norms, Voluntariness, Experience, Image, Job Relevance, Output Quality	Lecturers	Correlation	Quantitative	Online Teaching	USA
A12	[119]	None	Students	SEM (PLS)	Quantitative	Zoom	Indonesia
A13	[120]	Facilitating Conditions	Lecturers	SEM (CB)	Quantitative	Social Media	Indonesia
A14	[121]	Perceived Critical Mass, Collaborative Capability, Information and Resource sharing capability, Perceived Enjoyment	Students	SEM (PLS)	Quantitative	Social Media	Thailand
A15	[122]	Perceived Closeness, Peer Referents, Subjective Well Being	Students	SEM (PLS)	Quantitative	LMS	Saudi Arabia
A16	[106]	Subjective Norms, Trust	None	N/A	Quantitative	AI	N/A
A17	[123]	None	Students	SEM (PLS)	Quantitative	LMS	Malaysia
A18	[124]	Perceived Advantages, Perceived Satisfaction	Students	SEM (PLS)	Quantitative	LMS	Spain

Table A1. *Cont.*

Label	Article	External Variables	Sample Types	Statistical Analysis	Research Approaches	Researched Technologies	Research Location
A19	[125]	None	Students	Chi-Square	Mixed-Methods	Web 3.0	Unknown
A20	[65]	Experience, Subjective Norms, Enjoyment, Computer Anxiety, Self-Efficacy	Students	SEM (PLS)	Quantitative	LMS	Poland
A21	[126]	Self-Efficacy, COVID-19 fear	Students	SEM (PLS)	Quantitative	LMS	Jordan
A22	[127]	Computer Self-Efficacy, Facilitating Conditions	Students	SEM (PLS)	Quantitative	Cloud Classroom	Thailand
A23	[128]	Output Quality, Computer Playfulness, Subjective Norm	Students	SEM (CB)	Quantitative	Video Conferencing Tool	Vietnam
A24	[70]	Support Service Quality, Technical System Quality, Self-Regulated Learning	Students	SEM (PLS)	Quantitative	LMS	Jordan
A25	[92]	Perceived Fear, Expectation Confirmation, Satisfaction	Students	SEM (PLS)	Quantitative	Mobile Learning	UAE
A26	[129]	None	Students	Correlation	Quantitative	Digital Tool	Malaysia
A27	[96]	Perceived Playfulness, University Support	Students	SEM (PLS)	Quantitative	Online Education	China
A28	[101]	Student Enjoyment, Computer Self-Efficacy, Experience	Students	Descriptive, Qualitative	Mixed-Methods	Emergency Remote Teaching	Indonesia
A29	[107]	Competitive Advantage, Technology Compatibility, Complexity of Technology, Technology Readiness, Senior Leadership Support, Security Concern, Cost Advantage, Recognized Usefulness, Recognized Usability, Government Support, Vendor Support	Universities	SEM (CB)	Quantitative	Cloud Computing	India
A30	[130]	None	Students	SEM (CB)	Quantitative	LMS	China
A31	[131]	Facilitating Conditions, Perceived Control, Self-Efficacy	Students	SEM (PLS)	Quantitative	LMS	Saudi Arabia
A32	[76]	New Technology Anxiety	Mixed (Students and lecturers)	SEM (PLS)	Quantitative	MS Teams	Cross nations
A33	[132]	Anxiety, Environment Concern	Lecturers	SEM (PLS)	Quantitative	Zoom	India
A34	[90]	Facilitating Conditions, Self-Efficacy, Technological Compatibility, Security, Reliability, Portability	Students	Correlation	Quantitative	Philippines	Online Learning
A35	[49]	None	Students	SEM (PLS)	Quantitative	Indonesia	MOOCs
A36	[104]	Optimism, Innovativeness, Discomfort, Insecurity	HEI Individuals	SEM (PLS)	Quantitative	Malaysia	Cloud Computing
A37	[71]	Task–Technology Fit, Instructor Attitude, Family Support	Students	SEM (PLS)	Quantitative	China	LMS
A38	[108]	Hedonic Motivation, Perceived Price Value	Students	SEM (PLS)	Quantitative	China	AR, VR
A39	[133]	Flexibility, Care Competence	Students	Correlation, Regression	Quantitative	Taiwan	Virtual Learning
A40	[134]	Subjective Norms, Social Trust	Students	SEM (PLS)	Quantitative	Jordan	Online Learning System
A41	[91]	Perceived Enjoyment	Students	SEM (PLS)	Quantitative	Indonesia	Online Learning
A42	[135]	Perceived Convenience, User Training	Students	SEM (PLS)	Quantitative	China, Philippines	LMS
A43	[77]	Job relevance, Perceived Resource, Subjective Norms, Voluntariness	Mixed (Students and lecturers)	SEM (PLS)	Quantitative	Thailand	LMS
A44	[72]	System Quality, Information Quality, Content Quality, Service Quality	Students	SEM (PLS)	Quantitative	Mobile Exam Platform	UAE

Table A1. *Cont.*

Label	Article	External Variables	Sample Types	Statistical Analysis	Research Approaches	Researched Technologies	Research Location
A45	[136]	System Quality, Information Quality, Service Quality, Interaction	Students	SEM (PLS)	Quantitative	LMS	Indonesia
A46	[137]	Subjective Norms	Students	SEM (PLS)	Quantitative	Google Meet	UAE
A47	[84]	Support, Equipment	Lecturers	Autoethnography	Qualitative	Online Education Technology	USA
A48	[79]	Perceived Utility, Situated Learning, Immersion, Social Presence	Users	SEM, Qualitative	Mixed-Methods	Virtual Tour	Australia, China
A49	[64]	Subjective Norms, Experience, Enjoyment, Computer Anxiety, Self-Efficacy	Students	SEM (CB)	Quantitative	LMS	India
A50	[138]	None	Students	SEM–Mplus	Quantitative	FACS	China
A51	[139]	Computer Self-Efficacy, Computer Playfulness, Context	Students	Descriptive	Quantitative	Video Conferencing Tool	Vietnam
A52	[140]	Satisfaction, Confirmation	Students	SEM (PLS)	Quantitative	LMS	Indonesia
A53	[93]	Expectation Confirmation, Perceived Fear, Satisfaction	Students	SEM (PLS)	Quantitative	Mobile Learning	UAE
A54	[141]	Observability, Complexity, Trialability	Students	SEM (PLS)	Quantitative	MOOCs	Saudi Arabia
A55	[142]	Subjective Norms, Facilitating Conditions	Lecturers	SEM (CB)	Quantitative	LMS	South Africa
A56	[143]	Information Quality, System Quality, User Satisfaction	Students	Correlation	Quantitative	Blended Learning	Cyprus
A57	[144]	Experience, Anxiety, Enjoyment, Self-Efficacy, Interest, Social Influence, Trialability, Compatibility, Technology Infrastructure Quality	Lecturers	Convergence Validity	Quantitative	Learning Technologies	UAE
A58	[78]	None	Mixed (Students and lecturers)	Correlation, ANOVA	Quantitative	Emergency Remote Teaching	Chile
A59	[145]	System Quality, Service Quality, Information Quality, Satisfaction	Lecturer	SEM (CB), Qualitative	Mixed-Methods	Google Classroom	Iraq
A60	[146]	Subjective Norm, Computer Playfulness, Self-Efficacy, Accessibility, Task Technology Fit, System Quality	Students	SEM (PLS)	Quantitative	LMS	Iraq
A61	[147]	Self-Efficacy, experience	Students	Correlation	Quantitative	Zoom	Saudi Arabia
A62	[102]	None	Lecturers	Correlation, Thematic	Mixed-Methods	Emergency Remote Teaching	China, Australia
A63	[94]	None	Students	SEM (PLS)	Quantitative	Mobile Learning	Sri Lanka
A64	[148]	None	Students	SEM (PLS)	Quantitative	LMS	Hungary
A65	[149]	None	Students	SEM (PLS)	Quantitative	LMS	South Korea
A66	[89]	Social Influence, Service Quality, Learning Assistance	Students	SEM (CB)	Quantitative	Online Learning	Jordan
A67	[150]	None	Students	Correlation	Quantitative	Low-Cost Remote Laboratory	None
A68	[151]	Self-Study Ability	Students	SEM (CB)	Quantitative	Digital Transformation	Vietnam
A69	[152]	None	Students	SEM (PLS)	Quantitative	Social Media	Pakistan
A70	[153]	Using social media for Collaborative Learning, Using social media for Engagement	Students	SEM (CB)	Quantitative	Social Media	Saudi Arabia
A71	[154]	Subjective Norms, Political Influence	Students	SEM (PLS)	Quantitative	Intelligence Tutoring System	China
A72	[155]	System Interactivity, Internal Influence, External Influence, Computer Self-Efficacy	Students	SEM (CB)	Quantitative	LMS	Vietnam

Table A1. *Cont.*

Label	Article	External Variables	Sample Types	Statistical Analysis	Research Approaches	Researched Technologies	Research Location
A73	[48]	System Features, Learning Performance	Students	Regression	Quantitative	Tencent Meeting	China
A74	[156]	Experience, Enjoyment, Computer Anxiety, Self-Efficacy	Students	SEM (PLS)	Quantitative	Distance Education	Poland
A75	[157]	None	Students	SEM (PLS)	Quantitative	LMS	Saudi Arabia
A76	[109]	None	Students	Kaiser–Mayer–Olkin (KMO), Qualitative	Mixed-Methods	BYOD	South Africa
A77	[73]	Task–Technology Fit, Students' Satisfaction, Personal Innovativeness	Students	SEM (PLS)	Quantitative	Mobile Learning	Saudi Arabia
A78	[158]	Experience	Lecturers	Regression	Quantitative	Online Education Platform	China
A79	[98]	None	Lecturers	SEM (PLS), Qualitative	Mixed-Methods	Online Teaching	India
A80	[159]	Playfulness	Students	SEM (PLS)	Quantitative	Google Drive	Spain
A81	[160]	None	Students	SEM (CB)	Quantitative	LMS	Colombia
A82	[39]	Motivation, Amotivation, Intrinsic Motivation, Self-Efficacy	Students	SEM (CB)	Quantitative	Technology Enhanced Learning	Malaysia
A83	[161]	Optimism, Innovativeness, Discomfort, Insecurity	Students	SEM (CB)	Quantitative	LMS	Indonesia
A84	[80]	Subjective Norms, Perceived Risk	Operator	SEM (CB)	Quantitative	Telepresence Robot	USA
A85	[83]	Subjective Norms, Perceived Playfulness, Connectedness to learning	Students	Rasch Model	Quantitative	WhatsApp	Indonesia
A86	[99]	None	Lecturers	Correlation	Quantitative	Online Teaching	Pakistan
A87	[162]	Task–Technology Fit	Students	SEM (PLS), Qualitative	Mixed-Methods	LMS	Vietnam
A88	[163]	Subjective Norms, Relevance, Self-Efficacy, Computer Anxiety, Experience	Students	SEM (PLS)	Quantitative	LMS	Sri Lanka
A89	[88]	Self-Efficacy, Perceived Risk	Students	SEM (PLS)	Quantitative	Online Learning	Vietnam
A90	[81]	None	Medical Staff	Regression	Quantitative	LMS	Egypt
A91	[164]	Perceived Pleasure, Self-Usefulness	Students	SEM (PLS)	Quantitative	Social Networks	Iran
A92	[165]	None	Students	SEM (PLS)	Quantitative	LMS	Malaysia
A93	[45]	Task–Technology Fit, Perceived Satisfaction	Students	SEM (CB)	Quantitative	LMS	Philippines
A94	[166]	Perceived Pleasure, Self-Efficacy, Learnability, Knowledge Sharing, Knowledge Application	Students	SEM (CB)	Quantitative	Business Simulation Games	Pakistan
A95	[47]	None	Students	FGD	Qualitative	LMS	USA
A96	[95]	None	Students	Kaiser–Mayer–Olkin (KMO)	Quantitative	Mobile Learning	Indonesia
A97	[167]	Task–Technology Fit, Technology Characteristics	Students	SEM (PLS)	Quantitative	Video Based Learning	India
A98	[168]	Game-Based Learning Theory, Expectancy Value Theory	Students	ANOVA, MANOVA	Mixed-Methods	Digital Games	USA
A99	[169]	None	Students	Regression	Quantitative	Google Classroom	Indonesia
A100	[46]	Facilitating Conditions	Students	SEM (PLS)	Quantitative	LMS	Indonesia
A101	[100]	Self-Efficacy, Perceived Enjoyment, Online Teaching Skills, Digital Tool Access	Lecturers	SEM (CB)	Quantitative	Online Teaching Skills	Saudi Arabia

Table A1. *Cont.*

Label	Article	External Variables	Sample Types	Statistical Analysis	Research Approaches	Researched Technologies	Research Location
A102	[44]	Perceived Fear	Students	SEM (PLS)	Quantitative	Mobile Learning	UAE
A103	[87]	Experience, Technology Anxiety, Facilitating Conditions, Students' Engagement, Task–Technology Fit	Students	SEM (PLS)	Quantitative	Online Learning System	Saudi Arabia
A104	[170]	Facilitating Conditions, Social Influence	Lecturers	SEM (PLS)	Quantitative	Web-based Video Conferencing	UK

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