Review

Influencing Factors in MOOCs Adoption in Higher Education: A Meta-Analytic Path Analysis

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Abstract: (1) Background: Due to the rapid growth of Massive Online Open Courses (MOOCs), higher educational institutions across the world are investing heavily in MOOCs to support their traditional teaching, their students’ learning experience, and their performance. However, the success of MOOCs highly depends on several factors that influence their success in higher education. Prior studies have attempted to investigate and predict user acceptance of MOOCs in higher education by using a variety of theoretical viewpoints. Nonetheless, these studies have yielded conflicting findings and are inconclusive. (2) Purpose: This study aims to develop a model that integrates the Theory of Planned Behavior (TPB), the Unified Theory of Acceptance and Use of Technology (UTAUT), as well as the Task-Technology Fit (TTF) to explore the factors that influence the acceptance and use of MOOCs in higher education institutions, while synthesizing previous empirical findings in the field. (3) Methods: The model was tested using Meta-analytic Structural Equation Modelling (MASEM) based on the data gathered from 43 studies (k = 45 samples, n = 16,774). (4) Results: Effort expectance (EE), attitude (ATT), performance expectancy (PE), and TTF—determined by several task and technology characteristics—were identified as the direct predictors of behavioral intention (BI) to continue using MOOCs. (5) Conclusions: This model provides a cohesive view of MOOCs’ acceptance in higher educational institutions, and it helps to identify potential research opportunities in this area. (6) Implications: Results from MASEM offer managerial guidance for the effective implementation of MOOCs and provide directions for further research, to augment current knowledge of MOOCs’ adoption, by higher education institutions.

Keywords: higher education; MOOCs adoption; Task-Technology Fit; Theory of Planned Behavior; Unified Theory of Acceptance and Use of Technology

1. Introduction

For several years, higher education institutions (HEIs) have been under pressure to innovate due to two external forces: the need to reduce costs, while addressing the rising demand for higher education (HE); the need to demonstrate the relevance of their degree programs for employability in the ever-changing world [1]. Massive Online Open Courses (MOOCs) were introduced as the next big thing in HE and branded as the tool for ‘innovative disruption’ that will improve education [2]. This system—which alters remote education delivery and increases students’ and scholars’ access to open educational resources (OER)—has attracted over 800 colleges and universities that offer thousands of these courses to millions of registered individuals worldwide [3]. These numbers have positioned MOOCs as strong virtual platforms for education, and as a result, many HEIs are pioneering various initiatives to incorporate MOOCs into their teaching and learning...
activities. Despite the growing popularity of these courses in HE, understanding students’ and scholars’ acceptance of such courses is crucial to their success.

Existing studies have explained MOOCs’ user acceptance in the HE context using a multitude of human behavior theories, e.g., [4]. Among these, the Theory of Planned Behavior (TPB) [5], as well as the Unified Theory of Acceptance and Use of Technology (UTAUT), were some of the most frequently applied. TPB was developed to describe generic human behavior, whereas UTAUT was designed to explain specific MOOC user adoption. These theories describe several elements that impact a technology’s adoption, with behavioral intention (BI) (to intend to use the technology) and actual behavior (real usage of the technology) serving as indicators of acceptance. However, concentrating exclusively on users’ impressions of technology may be insufficient. According to the Task-Technology Fit (TTF) model, users will accept a technology if its qualities match the task requirements [6]. While users may acknowledge technological advancements, they may not utilize them if they believe such technologies are unsuitable for their activities or they do not increase users’ work efficiency [7]. Users are utilitarian individuals, whose usage of technology is based not only on perceptions and attitudes but also on a strong TTF.

Numerous scholars have conducted additional research on frameworks that incorporate at least one of these models, in the empirical literature, with regards to the persistence in using these courses in HE [8]. Several research works have compared TTF with the technology acceptance model (TAM) to predict learners’ desire to continue using these courses, while others merged TTF and UTAUT models to provide an enhanced MOOCs adoption model, e.g., [9]. Nonetheless, the majority of recent systematic reviews on the literature lack the rationale for selecting a model, or collection of models, for MOOCs adoption [10–12]. Additionally, the examination of the literature on MOOCs’ adoption revealed that none of the studies have examined the performance of the models and their underlying constructs. Not only would this analysis offer trends and evaluations of the models utilized but it would also present the cumulative performance of the constructs included in these models. None of the previous studies have incorporated these models within the context of MOOCs adoption. The novelty of conducting a quantitative review of the MOOCs’ usage, as well as the dearth of studies investigating relations among the constructs of these three models within a unified theoretical framework, forms the motivation for this study. It is also important to synthesize the existing findings on the acceptance of these courses in HE, as they provide additional insights into the possible mechanisms underlying these courses that are relevant to learning and teaching in HEIs.

Against this backdrop, the main objectives of this study are to: (1) develop a model that integrates the TPB, UTAUT, and TTF to explore the factors that influence MOOCs adoption in higher education while synthesizing previous empirical findings; (2) to compare the effect size in the causal relationships to provide evidence for the moderating role of sample size, gender, age, and culture. As such, this study attempts to integrate constructs from these three models into a comprehensive model of MOOCs’ adoption to explore the direct impact of attitude, technology characteristics, and acceptance on MOOCs adoption. The present findings show that our model surpasses any single theory—confirming the significance of all three of them as complementing viewpoints—while allowing us to gain a better understanding of what variables will influence MOOCs’ acceptability in HE and how much influence each element has. Given that the direct effects do not often convey the full picture, this study has been extended to determine the cumulative effect of variables affecting the acceptance of these courses in HEIs. In addition, the current moderator analysis clarifies uncertainties and examines the generalizability of the conflicting results, providing insights into how different factors influence MOOCs’ adoption in HE.

2. Theoretical Background

2.1. Massive Online Open Courses (MOOCs) Adoption

The factors that have an impact on educational innovations’ acceptance were always of interest to researchers and practitioners in HEIs. Numerous scholars have explored
Although UTAUT is not as widely used as TAM, it has garnered academic interest in recent years. Venkatesh [19] proposed that, when researchers are confronted with a significant number of identical constructs provided by many theories, they either “pick and choose” constructs from the models or choose a “preferred model”, whilst ignoring the others. For these reasons, UTAUT can contribute to the understanding of the elements that influence users’ adoption of MOOCs.

2. Theoretical Background

2.1. Massive Online Open Courses (MOOCs) Adoption

MOOCs have gained considerable interest in recent years, particularly due to their wide availability and the variety of academic subjects they cover [14]. Prior studies have examined the potential applications of these courses in a variety of academic subjects [14]. Scholars have also focused their attention on learning theories and pedagogical approaches for MOOCs [16]. In the contemporary information systems (ISs) literature, user acceptance of these courses is frequently portrayed among the most mature fields of study [17]. Numerous theoretical models have been developed in this field to account for individuals’ intentions to enroll in these courses. In this study, the TPB, UTAUT, and TTF serve as bases for an integrated framework to determine MOOCs adoption in HEIs.

2.2. Theory of Planned Behavior (TPB)

The TPB [18], derived from social psychology, is a forerunner to other models, and it is frequently used as an explanation of behavior and for understanding technology usage and its adoption [19]. As illustrated in Figure 1, the TPB states that user behavior is dictated by their perception of control, while their intention is affected by their attitude on behavior (ATT), subjective norms (SN), and perceptions of behavioral control (PBC) [5]. Additionally, some scholars have provided empirical support for TPB in their research on MOOCs [20].

![Figure 1. Theory of Planned Behavior.](image)

2.3. The Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT [19] is based on eight theories and models: namely, the technology acceptance model (TAM), the theory of reasoned action (TRA), the motivational model (MM), the TPB, the combined TAM TPB model (C-TAM-TPB), the model of PC utilization (MPCU), the innovation diffusion theory (IDT), and the social cognitive theory (SCT). Although UTAUT is not as widely used as TAM, it has garnered academic interest in recent years for its ability to explain user acceptance of MOOCs [21], as demonstrated in Figure 2. According to Venkatesh [19], the eight models explain between 17% and 53% of the variance in users’ intentions to use information systems (ISs)/information technology (IT). UTAUT, on the other hand, outperformed all eight models tested on the same data, accounting for more than 70% of the variance in BI and 50% in technology use [19,22]. Venkatesh [19] proposed that, when researchers are confronted with a significant number of identical constructs provided by many theories, they either “pick and choose” constructs from the models or choose a “preferred model”, whilst ignoring the others. For these reasons, UTAUT can contribute to the understanding of the elements that influence users’ adoption of MOOCs.
According to Wu and Chen [25], TTF is a widely used model for assessing how IT affects user performance. Both these factors have an impact on TTF, which, in turn, defines user performance. Figure 3 considers technology as a beneficial instrument for enhancing individual performance and can be used if its capabilities fit the tasks that users must perform [24]. According to Wu and Chen [25], TTF is a widely used model for assessing how IT affects user performance by correlating task characteristics (TAC) and technology characteristics (TEC). Both these factors have an impact on TTF, which, in turn, defines user performance. The TTF model is the primary subject of interest of this research. According to the TTF model, a user accepts an IT system only if it is a good fit for the activities at hand and increases efficiency [6]. TTF has been broadly used and integrated with related models, such as UTAUT, to investigate the adoption of IT systems since their debut, e.g., [26].

![UTAUT Model](image)

**Figure 2.** UTAUT Model.

2.4. **Task-Technology Fit (TTF)**

The TTF model is currently being explored and used with a range of ISs [23]. It (Figure 3) considers technology as a beneficial instrument for enhancing individual performance and can be used if its capabilities fit the tasks that users must perform [24]. According to Wu and Chen [25], TTF is a widely used model for assessing how IT affects user performance by correlating task characteristics (TAC) and technology characteristics (TEC). Both these factors have an impact on TTF, which, in turn, defines user performance.

![Task-Technology Fit Model](image)

**Figure 3.** The Task-Technology Fit Model.

2.5. **Research Model and Hypotheses**

The TPB, UTAUT, and TTF are three prominent models in the ISs sector that focus on the distinct component of IT adoption. Academics, on the other hand, rarely incorporate the TTF, TPB, and UTAUT into a single model. This paper argues that TTF and user’s perception of technology, when paired with ATT, affect the user’s decision to accept MOOCs. On this basis, TTF has been incorporated into the suggested model. On top of that, numerous surveys have suggested that UTAUT might be used with other models, such as TTF, to account for MOOC user acceptance [27]. The authors discovered that, when TTF and UTAUT are combined, the resulting model reveals a more in-depth explanation of adoption intention compared to the separate utilization of UTAUT. Users will not adopt a technology if the TTF is not satisfied [6,28]. Similarly, if MOOCs are unable to match the objectives of
the tasks, users are more likely to avoid them. Thus, the TTF model provides a theoretical foundation for evaluating TEC and TAC in these courses.

On the other hand, TAM is excluded from this model because it does not give enough insight into users’ perceptions of new technologies, overlooks the link between user attitude and intention, and, instead, directly examines the external factors of perceived ease of use and perceived usefulness [29,30]. More specifically, two of its constructs are similar to UTAUT constructs. Perceived ease of use, for example, can be mapped to effort expectancy (EE), whereas perceived usefulness can be mapped to performance expectancy (PE) [19,31]. Although more research was called for in view of the importance of subjective norm, e.g., [32], the original TAM omitted this aspect. Acknowledging the aim of the study and the related literature, this study used TPB, UTAUT, and TTF, consisting of ten variables: ATT, PE, EE, social influence (SI), facilitating condition (FC), TAC, TEC, TTF, BI, and actual use (AU) of MOOCs. The study also includes gender and age as moderating variables (see Figure 4).

Figure 4. Proposed Theoretical Model.

2.5.1. Behavioral Intention and Actual Use of MOOCs

According to Ajzen [33] and Venkatesh [34], BI is defined as a person’s intention to follow and utilize a certain tool in the near future. As stated by Alalwan [35], most technology adoption studies employed BI to forecast IT adoption. According to Ajzen [33], BI is also perceived as having a direct influence on adoption. In the MOOCs adoption literature, studies have shown that the BI to use these courses has a strong effect on the actual use of these courses [21,36]. Thus, this study proposes the following hypothesis:

Hypothesis 1 (H1). Behavioral intention (BI) to continue use MOOCs positively impacts the actual use of MOOCs.

2.5.2. The Effects of UTAUT Constructs on Behavioral Intention

The UTAUT model consists of four original core constructs: PE, EE, SI, and FC. PE is described as an individual’s belief that using MOOCs will help him or her achieve performance improvements. EE is defined as the degree of ease associated with the use of MOOCs. Both PE and EE are regarded as crucial determinants of use intention in the UTAUT model, especially in the early stages, while processing a new behavior [37]. PE has been found to influence MOOC usage intention in several studies [13]. An empirical study conducted by Karels [38] also shows that EE is a factor that promoted MOOCs adoption. Ease of access/download, flexibility of the software, and 24-h online presence are important
factors that influence MOOC usage intention [39]. Based on the above-mentioned literature, the following hypotheses are developed:

**Hypothesis 2 (H2).** Performance expectancy (PE) positively impacts user’s intention to continue using MOOCs.

**Hypothesis 3 (H3).** Effort expectancy (EE) positively impacts user’s intention to continue using MOOCs.

The degree to which a person perceives that other people believe that he or she should use MOOCs is described as SI. Subjective norms represent the part of TPB that reflects SI [40]. Several studies have suggested that SI has an influence on MOOC usage intention [41,42]. Finally, FC is one’s belief that there is enough technical and non-technical support from an institution to enable system use [19]. FC is similar to the PBC construct of TPB since it reflects the impact of a user’s knowledge, competence, and resources [19]. FC was employed as a proxy variable for PBC in this case, which may have introduced undesirable variance into the outcome, resulting in insignificant correlations between FC and BI to utilize MOOCs [43]. As a result, FC takes the place of PBC in the model. Furthermore, studies conducted by Amid and Din [44], as well as Mulik [41], show that the FC variable influences MOOC usage intention. The current study, therefore, proposes the following hypotheses:

**Hypothesis 4 (H4).** Social influence (SI) positively impacts user’s intention to continue using MOOCs.

**Hypothesis 5 (H5).** Facilitating condition (FC) positively impacts user’s intention to continue using MOOCs.

### 2.5.3. Attitude towards MOOCs and Behavioral Intention

In the TPB, ATT has a relevant effect on BI [5,32]. ATT, in the context of technology, is defined as one’s favorable or negative assessment of the entrance of new types of technology into any setting [45]. According to Ab Jalil’s [46], there is a substantial positive association between university students’ ATT regarding MOOCs and their BI to design MOOCs. Most respondents had a positive ATT about using MOOC platforms, according to Al-rahmi [47], showing that MOOCs are thought to be effective in improving conceptual understanding during the teaching and learning process. Thus, in the current study, the following hypothesis is proposed:

**Hypothesis 6 (H6).** User’s attitude (ATT) towards MOOCs positively influences user’s intention to continue using MOOCs.

### 2.5.4. The Effects of TTF Constructs on Behavioral Intention

Task-Technology Fit indicates how technological capabilities meet the tasks that individuals execute, highlighting task and technology characteristics as two basic components for determining Task-Technology Fit. Tasks are defined as the actions taken to convert some inputs into useful outputs to meet human requirements, while technology is defined as the mix of user support and information technology, such as software, equipment, and data [48]. The Task-Technology Fit—which impacts user usage and performance—is influenced by both types of characteristics: namely, task and technology [49]. The TTF model has been frequently employed in the MOOCs environment since its introduction [50]. Based on these arguments, we hypothesized that:

**Hypothesis 7 (H7).** Technology characteristics (TEC) of MOOCs positively impact Task-Technology Fit (TTF).
Hypothesis 8 (H8). Task characteristics (TAC) positively impact the Task-Technology Fit (TTF).

According to TTF, people will not accept a technology if the Task-Technology Fit is not met. Similarly, users are less inclined to use MOOCs if they fail to satisfy the needs of their tasks. Previous research has found a link between TTF and the behavioral intention to use these courses [50]. Following these findings, we hypothesized that:

Hypothesis 9 (H9). Task-Technology Fit (TTF) positively impacts a user’s intention to continue using MOOCs.

2.6. Potential Moderators

This study looks at the impact of four categorical moderators (age, gender, sample size, and culture) on each of the nine causal links in the suggested research model. Uncovering the moderating roles of gender, age, sample size, and culture in empirical research on MOOCs adoption is critical, as it reveals whether these moderators’ influence variations in a certain model effects sizes. Within the MOOCs literature, some researchers, e.g., [38], used small samples (e.g., \( n = 141 \)), while others [51] relied on big samples (e.g., \( n = 854 \)). Several studies [52] were set in Asian cultures, while others [38] examined MOOCs’ adoption in non-Asian cultures (e.g., The Netherlands).

In addition, several studies have already recognized the value and importance of examining age and gender disparities in MOOCs’ acceptance [53]. There is extensive evidence that suggests that gender identity (related gender roles) and age categories [54] can contribute to significant disparities in e-learning between males and females, as well as between young and old users [55]. According to Van Dijk [56], disparity is the outcome of categorical inequalities in society, which leads to unequal access to digital technologies. Furthermore, gender disparity is common in these courses, according to Ho [57]. Although females are usually underrepresented in MOOCs participation, it is unclear if this varies by country and, if so, how. MOOCs participants are a very diverse mix of people of various ages. Morris [58], on the other hand, discovered that students who use MOOCs are more likely to be adults. Based on the above survey of the literature, it’s crucial to figure out whether disparities in direction and intensity among effect sizes are caused by sample size, culture, age, or gender.

3. Materials and Methods

3.1. Study Selection

Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA) criteria were used to present the current study findings [59].

3.2. Eligible Studies for Inclusion

The selected publications were screened based on the following criteria: (1) studies were considered if they assessed academics/university students’ willingness to adopt/accept MOOCs; (2) quantitative studies were included if they applied the TPB, UTAUT, and TTF constructs; (3) studies were included if the results were presented in English; (4) studies were only included if they were published in peer-reviewed journals, book chapters, conference papers, theses (Ph.D. and Master), and working papers; (5) correlation coefficients of the variables of interest, or any data that may be transformed into a correlation coefficient, such as \( t \)-values, \( p \)-values, or Fisher’s \( Z \), are reported in research; (6) the study was conducted in a higher education setting. Nonetheless, to ensure that all relevant publications were examined, the authors did not limit the scope of this evaluation by any fixed criteria.

3.3. Search Strategy

Two authors independently searched ERIC, ACM Library, IEEE Xplore, Google Scholar, DOJA, ProQuest, PsycInfo, ScienceDirect, and Scopus from the inception of the study to
16 April 2021. The following keywords were used: “TPB” OR “UTAUT” OR “TTF” OR “performance expectancy” OR “effort expectancy” OR “social influence” OR “facilitating conditions” OR “attitude” OR “Task-Technology Fit” OR “task characteristics” OR “technology characteristics” were used for “academics” OR “students” OR “higher education/university/college”. The terms were searched (individually, systematically, and concurrently) using search functions specific to each database (e.g., asterisk, quotation mark) in conjunction with the Boolean “AND” operator with “MOOCs adoption” OR “MOOCs acceptance”. A manual search was also conducted on the reference lists from all of the papers chosen. On top of that, full-text reviews and pertinent reviews were also carried out.

3.4. Study Selection and Data Collection Process

The same authors evaluated the filtered studies, starting with their titles and abstracts. The full texts of possibly qualified studies were then obtained. Only the research with greater sample sizes were included when duplication occurred [60]. Two authors (1st and 3rd authors) conducted data extraction independently. In addition to the correlation of the constructs, these authors classified each study by author name, year and publication type, country, mean and standard deviation of measurements, age, gender, and sample characteristics.

4. Data Analysis

This study follows Borenstein’s [61] guidelines for conducting and publishing meta-analyses to minimize typical pitfalls. To compute pooled effect sizes, the third version of Comprehensive Meta-Analysis software (CMA-3) was employed, and a random-effects model was applied to ensure data generalizability to comparable studies [61]. Mukaka [62] proposed the following cutoff points: $0.00 < r < 0.30$ indicates negligible correlation, $0.30 < r < 0.50$ indicates low correlation, $0.50 < r < 0.70$ indicates moderate correlation, $0.70 < r < 0.90$ indicates high correlation, and $0.90 < r < 1.00$ indicates very high correlation. The relationships found were interpreted using these cutoffs.

Furthermore, the study analyzed zero-order correlations, corrected for sampling error ($r+$), using a random-effects meta-analysis model since all included studies were regarded as samples from a diverse population. Furthermore, all included studies were subjected to heterogeneity testing (Q and $I^2$ statistics). Besides that, the I-squared ($I^2$) and significant Q-values revealed a diverse distribution, indicating the necessity for moderator analysis. To estimate the effect of age, gender, sample size, and culture as potential moderators for each of the causal paths in the model, a subgroup analysis was conducted.

MASEM was utilized to analyze the model after obtaining meta-analytic correlation matrices. This was carried out using the AMOS 26.0 software (Armonk, NY, USA). The critical ratios (CRs) were used to determine the relevance of model paths [63], and the modification indices (MIs) were used to determine the presence of unexpected paths [64]. When CRs were less than the required limit of greater than 1.96, the non-significant routes were removed from the model [63].

5. Results

5.1. Selection and Inclusion of Studies

As a PRISMA chart, Figure 5 demonstrates the selection and inclusion of research. Following the removal of duplicated research, two authors reviewed the titles and abstracts of 2239 papers for a primary assessment. This preliminary screening yielded 63 publications, which were further screened based on inclusion and exclusion criteria, such as study results, accessibility, sample composition (academics and university students), usage of the TPB, UTAUT, and TTF constructs, reporting $p$-values, correlation coefficients, T-statistics, and sample size. At this stage, 43 studies ($k = 45$) were included in the analysis.
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Figure 5. The Flow Diagram of the Study Adapted from [59].

5.2. Publication Bias Assessment

Publication bias—also referred to as the ‘file drawer problem’—relates to the possibility of unpublished studies that were not retrievable and excluded in the meta-analysis [65]. Hence, the Egger test and fail-safe N were used to alleviate this problem. The results obtained demonstrated that the fail-safe N was substantial for each effect size, indicating that there was no evidence of publication bias, according to the ad hoc rule (fail-safe N should be over 5k + 10). For instance, in this meta-analysis of the relationship between EE and BI in utilizing MOOCs, the fail-safe N value was 4694, meaning that the current meta-findings analysis might be invalidated if 4694 studies were found to be non-significant.
Additionally, Egger’s test was applied to examine potential publication bias. The p-values were all over 0.05, indicating that there was no proof of any publication bias.

5.3. Study Characteristics
The 43 included studies (45 samples, \( n = 16774 \)) were published between 2016 and 2022. The study included three theses, one conference proceedings paper, and 37 journal publications that met the study’s requirements. In terms of study origin, they comprise studies from 16 nations, with the majority of them conducted in China (\( k = 11 \)). The sample sizes ranged between 111 and 1148 respondents (Table 1).

5.4. Weight Analysis
Univariate and multivariate weightings were used in synthesizing matrices. With univariate weighting, each association is treated independently, and each factor is pooled separately across studies. As univariate weighting techniques, univariate-r and univariate-z were utilized (Table 2). Since the CI did not include zero, the findings suggested that all the average weighted correlations were very different from the zero values. BI, to utilize MOOCs, showed a low correlation with PE (0.454), SI (\( r^+ = 0.391 \)), EE (\( r^+ = 0.381 \)), FC (\( r^+ = 0.343 \)), and ATT (\( r^+ = 0.452 \)), according to several research works. TTF was substantially linked to both the TAC and TEC of MOOCs (\( r^+ = 0.492 \) and 0.493, respectively). Additionally, the correlation between BI to participate in these courses and the actual participation in these courses was significant and moderate (\( r^+ = 0.645 \)). The results show that the actual MOOCs usage and its antecedents have low and moderate levels of correlation.

The variance–covariance matrices were then used to weight correlations in the synthesis of correlation matrices across studies for multivariate weighting \[94\]. In the correlation matrix, a minimum of two associations for each cell of the matrix were used, as was common in the MASEM analysis \[95\]. The results of the meta-analysis were incorporated into a correlation matrix based on the average weighted sample size, which served as the foundation for the path analyses (Table 3).
Table 1. An overview of the studies used in the meta-analysis processes.

| No. | Author(s)         | Year | Type | Country        | Sample Size | Variable(s)             | Mean Age | Gender (Male %) | No. | Author(s)         | Year | Type | Country        | Sample Size | Variable(s)             | Mean Age | Gender (Male %) |
|-----|-------------------|------|------|----------------|-------------|--------------------------|----------|-----------------|-----|-------------------|------|------|-----------------|-------------|--------------------------|----------|-----------------|
| 1   | Mulik [41]        | 2018 | J    | India          | 310         | PE, EE, SI, FC, BI       | 35.72±   | 72.90           | 24  | Haron [66]       | 2020 | J    | Malaysia        | 350         | EE, PE, SI, FC, BI     | –        | –               |
| 2   | Khan [67]         | 2016 | T    | Germany        | 491         | PE, EE, SI               | 44.5±    | 49              | 25  | Mohan [68]       | 2020 | J    | India           | 412         | EE, PE, SI, FC, BI     | –        | 23.5±            |
| 3   | Zhou [69]         | 2016 | J    | China          | 475         | ATT, BI                  | 21.40±   | 50.5            | 26  | Azami & Ibrahim [52] Tamjidiyamcholo [71] | 2020 | J    | Malaysia        | 111         | ATT, SI, BI             | –        | 72.1             |
| 4   | Lim [70]          | 2017 | C    | Malaysia       | 780         | PE, EE, SI, FC, BI, AU   | –        | –               | 27  | Virani [73]      | 2020 | J    | India           | 286         | SI, ATT, BI, PE, EE, SI, FC, TAC, TFF, BI | –        | 68               |
| 5   | Othman [72]       | 2017 | C    | Malaysia       | 513         | ATT-BI                   | 23.03±   | 43.9            | 28  | Ouyang [74]      | 2017 | J    | China           | 464         | ATT, EE, FC             | 36.4±    | 36.4             |
| 6   | Wu & Chen [25]    | 2017 | J    | China          | 252         | ATT, TI, TAC, TFF, SI    | 35.7±    | 59.1            | 30  | Altalhi [76]     | 2021 | J    | Saudi Arabia    | 169         | ATT, EE, FC, SI, PE    | 21.36±   | 82               |
| 7   | Yang & Su [77]    | 2017 | J    | Taiwan         | 272         | AU, BI, ATT              | 23.71±   | 30.2            | 31  | Alyoussef [9]    | 2021 | J    | Saudi Arabia    | 277         | ATT, TFF                | 23.23±   | 60.6             |
| 8   | Zhou [78]         | 2017 | J    | China          | 435         | SI, BI                   | 24.5±    | 56.6            | 33  | Zahrani [79]     | 2017 | J    | Saudi Arabia    | 235         | ATT, AU, PE, EE, SI, FC, BI, UB | –        | –               |
| 9   | Abu-Shanab & Musleh [80] | 2018 | J    | Jordan         | 184         | SI, BI                   | 20±      | 25              | 33  | Amid & Din [44]  | 2017 | J    | Malaysia        | 218         | SI, FC, BI              | 22.21±   | 24.3             |
| 10  | Karels [38]       | 2018 | T    | The Netherlands | 141         | PE, EE, SI, FC, BI, PE, BI | –        | 58.9            | 34  | Navarro [81]     | 2021 | J    | Philippines     | 1011        | BI, TFF, TEC, TAC, EE, SI, PE, BI | 21.01±   | 76.06            |
| 11  | Chen [31]         | 2018 | J    | Taiwan         | 854         | PE, BI                   | –        | 65              | 35  | Chen [82]        | 2021 | J    | China           | 337         | EE, PE, SI, FC, BI     | –        | 25.8             |
| 12  | Jo [83]           | 2018 | J    | South Korea    | 237         | TFF, BI                  | 28.05±   | 51.9            | 36  | Chu & Dai [36]  | 2021 | J    | China           | 771         | TFF, TEC, TAC, SI, BI  | –        | 45.8             |
| 13  | Khan [30]         | 2018 | J    | Pakistan       | 414         | TEC, TAC, TTE, SI, BI, AU | –        | 56              | 37  | Haron [21]      | 2021 | C    | Malaysia        | 400         | EE, PE, SI, FC, BI, AU  | –        | –               |
| 14  | Morales Chan [54] | 2018 | J    | Guatemala      | 131         | BI, ATT, FC              | –        | 83.33           | 38  | Kim & Song [85] | 2021 | J    | South Korea     | 252         | TFF, BI                 | –        | 45.2             |
| 15  | Ab Jalil [46]     | 2019 | J    | Malaysia       | 238         | ATT-BI                   | –        | –               | 39  | Li & Zhao [8]   | 2021 | J    | China           | 312         | PE, EE, SI, FC, BI     | 23.11±   | 44.90            |
| 16  | Al-Rahmi [47]     | 2021 | J    | Malaysia       | 1148        | ATT-BI                   | 21.9±    | 46.3            | 40  | Singh & Sharma [86] | 2021 | J    | India           | 326         | SI, FC                  | –        | –               |
| 17  | Kamp [87]         | 2019 | T    | The Netherlands | 305         | ATT, BI, PE, EE, SI, FC  | 21.75±   | 24.3            | 41  | Wang [88]       | 2021 | J    | China           | 298         | FC, SI, EE, PE, BI     | 26.92±   | 77.7             |
| 18  | Lung-Guang [89]   | 2019 | J    | Taiwan         | 222         | ATT, BI                  | 33.7     | 51.4            | 42  | Chaveesuk [90]  | 2022 | J    | Poland          | 455         | PE, EE, SI, FC, BI     | –        | 71.5             |
| 19  | Teo & Dai [91]    | 2019 | J    | China          | 209         | ATT, BI                  | –        | 32.54           | 43  | Chaveesuk [90]  | 2022 | J    | Thailand        | 490         | PE, EE, SI, FC, BI     | –        | 41               |
| 20  |                  |      |      |                |             |                          |          |                 |     |                  |      |      |                 |             |                          |          |                 |
Table 1. Cont.

| No. | Author(s) | Year | Type | Country | Sample Size | Variable(s) | Mean Age | Gender (Male %) | No. | Author(s) | Year | Type | Country | Sample Size | Variable(s) | Mean Age | Gender (Male %) |
|-----|-----------|------|------|---------|-------------|-------------|----------|-----------------|-----|-----------|------|------|---------|-------------|-------------|----------|----------------|
| 21  | Tseng [42] | 2019 | J    | Taiwan  | 161         | EE, PE, SL, FC, BI, AU | 46.95 a | 63.5            | 44  | Chaveesuk [90] (study c) | 2022 | J    | Pakistan | 513         | PE, EE, SI, FC, BI | –        | 28.5         |
| 22  | Dai [92]  | 2020 | J    | China   | 160         | ATT-BI      | 30.62    | 19.07          | 45  | Meet [93] | 2022 | J    | India   | 483         | PE, SI, EE, FC, BI | 22.03 a  | 49.7         |
| 23  | Fianu [13]| 2018 | J    | Ghana   | 204         | EE, PE, SI, FC, BI, AU | –       | –              | –   | –         | –    | –    | –       | –           | –          | –        | –              |

Note: Journal article = J; Conference paper = C; Thesis = T; a Based on the information provided in the included studies, the mean age was calculated indirectly.
Table 2. Random effects of average correlation and heterogeneity statistics.

| Paths     | K   | N    | $r+$  | $r^2$  | CI 95%  | LI    | Q-Test | $\chi^2$ | Fail Safe N | Egger’s Test |
|-----------|-----|------|-------|--------|---------|-------|--------|----------|-------------|--------------|
| BI-AU     | 9   | 3794 | 0.516 | 0.570  | 0.266-0.701 | 658.820 *** | 98.786 | 3188     | 0.346       |
| FC-BI     | 18  | 5762 | 0.343 | 0.358  | 0.221-0.455 | 438.045 *** | 96.119 | 3181     | 0.622       |
| PE-BI     | 21  | 8456 | 0.454 | 0.489  | 0.338-0.556 | 1604.944 *** | 98.754 | 7319     | 0.005       |
| EE-BI     | 18  | 6962 | 0.381 | 0.402  | 0.244-0.503 | 697.219 *** | 97.551 | 4694     | 0.482       |
| SI-BI     | 25  | 8870 | 0.391 | 0.413  | 0.280-0.491 | 841.468 *** | 97.148 | 8762     | 0.649       |
| ATT-BI    | 13  | 3343 | 0.452 | 0.487  | 0.318-0.568 | 249.157 *** | 95.184 | 2185     | 0.079       |
| TTF-BI    | 8   | 4009 | 0.427 | 0.457  | 0.246-0.580 | 283.021 *** | 95.527 | 1225     | 0.108       |
| TAC-TTF   | 4   | 2141 | 0.492 | 0.539  | 0.216-0.696 | 152.983 *** | 98.039 | 7319     | 0.005       |
| TEC-TTF   | 3   | 1889 | 0.493 | 0.540  | 0.331-0.627 | 34.079 ***  | 94.131 | 211      | 0.377       |

Note. N = sample size; *** $p$ value < 0.001.

Table 3. Meta-analysis correlation matrix among the constructs (N = 16774).

| Construct | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1. PE     |     | 1   |     |     |     |     |     |     |     |
| 2. EE     | 0.572 |     | 1   |     |     |     |     |     |     |
| 3. SI     | 0.545 | 0.479 |     | 1   |     |     |     |     |     |
| 4. FC     | 0.575 | 0.562 | 0.496 |     | 1   |     |     |     |     |
| 5. ATT    | 0.770 | 0.443 | 0.542 | 0.304 |     | 1   |     |     |     |
| 6. TTF    | 0.546 | 0.506 | 0.502 | 0.546 | 0.105 |     | 1   |     |     |
| 7. TAC    | 0.659 | 0.485 | 0.309 | 0.467 | 0.438 | 0.492 |     | 1   |     |
| 8. TEC    | 0.529 | 0.317 | 0.193 | 0.297 | 0.246 | 0.444 | 0.590 |     | 1   |
| 9. BI     | 0.454 | 0.381 | 0.391 | 0.343 | 0.343 | 0.427 | 0.493 | 0.493 |     |
| 10. AU    | 0.473 | 0.443 | 0.457 | 0.414 | 0.477 | 0.620 | –   | –   | 0.516 |

Note. All correlation values are significant ($p < 0.001$). A dash (–) shows that no studies reflected in the meta-analysis had evaluated the association between the corresponding variables.

5.5. Moderator Analysis

The Q-test for heterogeneity shows that all Q-values are statistically significant, at $p < 0.001$, for each of the nine causal paths under investigation (Table 2). Furthermore, the findings demonstrate that genuine heterogeneity accounts for more than 75% of the overall diversity across beta-based impact estimates ($I^2 > 75\%$). Thus, we find support for a substantial level of variability among MOOCs studies using these two assessments, indicating the presence of possible moderating factors [96]. In the absence of a sufficient number of studies to do the moderator analysis ($k = 10$), this analysis was omitted [97] between TAC-TTF, TEC-TTF, TTF-BI, and BI-AU.

Only three significant moderating effects were found in the subgroup analysis, as shown in Tables 4–7. Table 4 revealed that the moderating effect of sample size on the association between FC and BI had a significant Q value ($Q = 22.114; p < 0.001$). This data implies that the FC–BI relationship is moderated by sample size. This association was particularly significant in studies with high sample sizes ($\beta_{\text{Large}} = 0.464; p < 0.001$) compared to studies with small sample sizes ($\beta_{\text{Small}} = 0.336; p < 0.01$). Table 7 showed that culture did not significantly moderate the causal relationships. However, researchers discovered that in some associations—such as FC-BI, EE-BI, and ATT-BI—the Asian subgroup’s mean path coefficient was higher than the non-Asian’s.

Table 4. The sample size moderating effect.

| Subgroups | FC → BI | PE → BI | EE → BI | SI → BI | ATT → BI |
|-----------|---------|---------|---------|---------|---------|
| Large sample size |         |         |         |         |         |
| Meta $\beta$ | 0.288   | 0.620   | 0.266   | 0.464   | 0.312   |
| $p$-value ($\beta$) | 0.000   | 0.000   | 0.000   | 0.000   | 0.000   |
| Z-value       | 16.77   | 496.82  | 16.86   | 32.484  | 10.123  |
Table 4. Cont.

| Subgroups | FC → BI | PE → BI | EE → BI | SI → BI | ATT → BI |
|-----------|---------|---------|---------|---------|---------|
| Small sample size | | | | | |
| Meta $\beta$ | 0.389 | 0.557 | 0.971 | 0.336 | 0.435 |
| $p$-value ($\beta$) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Z-value | 20.53 | 33.98 | 28.302 | 21.238 | 22.453 |
| Heterogeneity | | | | | |
| Q-statistic | 0.322 | 3.062 | 1.364 | 22.114 | 0.793 |
| $p$ (heterogeneity) | 0.571 | 0.080 | 0.243 | 0.000 | 0.373 |

Table 5. The gender moderating effect.

| Subgroups | FC → BI | PE → BI | EE → BI | SI → BI | ATT → BI |
|-----------|---------|---------|---------|---------|---------|
| Female | | | | | |
| Meta $\beta$ | 0.428 | 0.622 | 0.337 | 0.299 | 0.387 |
| $p$-value ($\beta$) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Z-value | 18.88 | 497.69 | 21.564 | 18.927 | 16.363 |
| Male | | | | | |
| Meta $\beta$ | 0.310 | 0.395 | 0.440 | 0.445 | 0.353 |
| $p$-value ($\beta$) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Z-value | 9.972 | 22.023 | 17.524 | 27.570 | 14.070 |
| Heterogeneity | | | | | |
| Q-statistic | 1.457 | 0.105 | 0.542 | 0.646 | 24.907 |
| $p$ (heterogeneity) | 0.483 | 0.949 | 0.762 | 0.724 | 0.000 |

Table 6. The age moderating effect.

| Subgroups | FC → BI | PE → BI | EE → BI | SI → BI | ATT → BI |
|-----------|---------|---------|---------|---------|---------|
| Age > 24 years | | | | | |
| Meta $\beta$ | 0.403 | 0.965 | 0.240 | 0.153 | 0.308 |
| $p$-value ($\beta$) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Z-value | 13.223 | 5.05 | 9.518 | 6.088 | 12.132 |
| Age < 24 years | | | | | |
| Meta $\beta$ | 0.302 | 0.543 | 0.647 | 0.413 | 0.372 |
| $p$-value ($\beta$) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Z-value | 15.73 | 20.258 | 21.208 | 17.884 | 9.759 |
| Heterogeneity | | | | | |
| Q-statistic | 1.109 | 0.938 | 5.098 | 19.847 | 10.756 |
| $p$ (heterogeneity) | 0.557 | 0.626 | 0.078 | 0.000 | 0.013 |

Table 7. The culture moderating effect.

| Subgroups | FC → BI | PE → BI | EE → BI | SI → BI | ATT → BI |
|-----------|---------|---------|---------|---------|---------|
| Asian | | | | | |
| Meta $\beta$ | 0.336 | 0.382 | 0.372 | 0.386 | 0.405 |
| $p$-value ($\beta$) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Z-value | 22.357 | 33.241 | 30.067 | 5.66 | 23.013 |
| Non-Asian | | | | | |
| Meta $\beta$ | 0.327 | 0.623 | 0.298 | 0.322 | 0.367 |
| $p$-value ($\beta$) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Z-value | 13.598 | 497.518 | 9.504 | 3.610 | 7.979 |
| Heterogeneity | | | | | |
| Q-statistic | 0.358 | 1.545 | 0.018 | 0.186 | 0.253 |
| $p$ (heterogeneity) | 0.55 | 0.214 | 0.893 | 0.66 | 0.615 |

The Q statistic indicating the moderating influence of gender on the connection between ATT and BI is statistically significant, according to Table 5 (Q = 24.907; $p < 0.001$).
These findings support the idea that gender has a moderating effect on the ATT–BI relationship. Precisely, this association is stronger for female ($\beta_{\text{female}} = 0.387; p < 0.001$) vis-à-vis male ($\beta_{\text{male}} = 0.353; p < 0.001$). Finally, the findings revealed a significant Q statistic for age’s moderating influence on the link between SI and BI ($Q = 19.847; p < 0.001$). This finding implies that the SI-BI relationship is moderated by age. Precisely, this association is stronger for MOOCs users with an age below 24 years old ($\beta_{\text{age} < 24 \text{ years}} = 0.413; p < 0.001$) when compared with MOOCs users with an age above 24 years old ($\beta_{\text{age} > 24 \text{ years}} = 0.153; p < 0.001$).

5.6. Meta-Analytic Findings

The present study performed MASEM to assess hypotheses 1 to 9. This research began with a completely unconstrained model that included all possible direct associations. Apart from that, the study incorporates a proposed covariance between the error terms for TTF, BI, and AU, based on an analysis of the fit indices. The model fit was also examined using the Chi-square ($\chi^2$) goodness of fit, the root mean square error of approximation (RMSEA), the normed fit index (NFI), as well as the comparative fit index (CFI). When the CFI and NFI are greater than 0.90, the model is considered to be a good fit [98]. A lower RMSEA indicates a better fit, with scores less than 0.05 indicating a greater fit and scores between 0.05 and 0.08 indicating a reasonable fit [99]. However, the resulting path model fit the data poorly in this study: $\chi^2 (11) = 2244.857, p = 0.001$, CFI = 0.864, GFI = 0.835, RMSEA = 0.366, and NFI = 0.864. All direct relationships involving TTF and AU were positive and statistically significant in the model. FC and SI were not significant predictors of BI. EE, PE, and ATT were significant positive predictors of BI. Combined, the predictors accounted for 49%, 82%, and 67.1% of the variance in TTF, BI, and AU, respectively.

The new model was constructed using the findings from the previous proposed model and the MIs. Based on the results of the first model, we trimmed the two negative relationships—SI on BI and FC on BI—since they did not support Hypotheses 4 and 5 and assessed the fit of this new model. However, the MIs revealed two surprising paths. Using the proposed model as a starting point, the paths provided by MIs were included where applicable. Firstly, the TAC-BI path was analyzed as containing the highest MIs (581.164) and was incorporated into the model. Secondly, the unexpected TEC-BI path was discovered as containing the second highest MIs (503.630) and was subsequently incorporated into the model. Although this relationship was not expected at the outset, it can be explained using earlier studies in diverse contexts. The inclusion of every unexpected path led to an incremental improvement in fit statistics: $\chi^2 (7) = 1181.163, p = 0.001$, SRMR = 0.066, CFI = 0.90, GFI = 0.907, RMSEA = 0.265, and IFI = 0.90. In the final model, all paths were statistically significant, with the predictors accounting for 49%, 24%, and 44% of the variance in TTF, AU, and BI, respectively (Figure 6).

Figure 6. The revised model and the standardized path coefficients. All paths are significant ($p < 0.001$).
6. Discussion and Implications

The MASEM approach is a method for analyzing quantitative data. It was used to incorporate the UTAUT, TTF, and TPB, in terms of their abilities, to investigate MOOCs’ adoption in HE. Although the results of previous studies recommended several determinants of learner engagement in MOOCs platforms, the meta-analytic results made several implications to the extant literature. First, the research findings established the model’s applicability and validity, in the context of MOOCs, by providing cumulative insights from earlier empirical research. Secondly, this study has proven that the combined model proposed—consisting of TPB, UTAUT, and TTF—is capable of explaining MOOCs’ adoption, in the context of HE, using BI. The model’s application provides a well-developed theoretical foundation, as well as robust, testable predictions applicable for multiple fields. Thirdly, this model directs future research aimed at further developing theoretical explanations. It also suggests that future research should focus on this integrated model to reduce the number of alternative intention models. Fourthly, our study has revealed certain associations not identified in the original UTAUT, TTF, and TPB models, and it has provided new insights into the intentions and behaviors of learners and educators regarding the decision to use MOOCs in higher education. Practically, the results of this study can also help in the development of best practices to assist lecturers in teaching and implementing innovative approaches that promote these courses to improve teaching and learning outcomes, as well as to serve as a guide for developing methodologies to adopt MOOCs in higher education.

The results of this study further reveal that seven out of nine hypotheses were significantly supported. It was discovered that PE and EE have substantial effects on BI, which is consistent with earlier UTAUT bodies of research [90,100]. However, this is inconsistent with an earlier report, which indicates that PE and EE have a non-significant effect on BI [101]. More precisely, this study established that PE is involved in the formation of BI (H1). This means that users will be more receptive to MOOCs if they believe that technology could enhance teaching and learning. It was also discovered that EE has a role in explaining BI in the context of MOOCs (H2). This implies that the easier it is for a MOOC service to learn and perform MOOCs-related tasks, the greater the proclivity to engage in the technology. In a similar way, this MASEM analysis has established that ATT is a critical variable for BI reinforcement (H6). This concurs with a previous study on university students’ intentions towards the usage of a cloud computing classroom, e.g., [100]. As a result, if an individual had a positive ATT about using MOOCs platforms, a high degree of adoption intention is formed. These MASEM findings demonstrate that, while analyzing the factors affecting MOOC users’ uptake, the UTAUT-based technology perceptions must not be considered in isolation but, rather, have to also take into account the impact of the TTF. Additionally, the findings indicated that TAC and TEC were both significant predictors of TTF, with technology attributes having a greater effect [102,103].

Two hypotheses, 4 and 5, were rejected, as SI and FC had no effect on the user’s intention to utilize MOOCs. Based on the results of the first model, the authors trimmed the two relationships: SI on BI and FC on BI. This finding contradicts several related studies reporting SN and FC as predictors of MOOCs adoption [8,75]. It is possible that the effect of SN, within a given culture, differs from country to country, rendering the effect of SN on intention to use MOOCs contextually different. The finding might also reflect learners’ and educators’ uncertainty regarding the availability of various software or hardware conditions that enable them to use MOOCs. Furthermore, two new pathways emerged from the analysis: namely, the TAC and TEC. These two had direct effects on the BI to continue to use MOOCs. It is proposed that the nature of the tasks performed by the users will dictate whether MOOCs are beneficial. D’Ambra [104], Dishaw and Strong [26], as well as Koo [105] discovered strong associations between TAC and technology use. The variable TAC was chosen as a factor that would potentially influence consumers’ utilization of MOOCs, based on the results of the MASEM analysis. Additionally, this study has established a positive relationship between TEC and user’s utilization of MOOCs. TEC reflects the characteristics of MOOCs that are relevant for task comple-
tion. TEC has been shown to influence a system’s usefulness, ease of learning, accuracy, adaptability, and dependability [106]. Integrating TEC with task characteristics can aid in determining the technology’s best fit for the activity. D’Ambra [104], Hollingsworth [107], as well as Koo [105] have discovered that substantial correlations exist between TEC and technology adoption.

Finally, the meta-analysis concluded that the moderator analysis supported the variance effects of the integrated framework’s constructs on the actual MOOCs usage. The analysis of the type of sample size—acting as a moderator—offers insight into the effect sizes and resultant findings. Age was identified as a significant moderating role in a user’s decision to use ICT [19,22]. Despite being the primary predictor across all age brackets, the SI and ATT appeared to have greater effects on youths than on adults. The other predictors exhibited an opposite pattern. Gender has been extensively researched as a key demographic factor influencing ICT adoption [19,22]. Additionally, the findings revealed that ATT is more predictive of females than of males. Our findings corroborate prior research on the impact of age and gender on technology acceptance [108,109].

7. Conclusions and Directions for Future Studies

In conclusion, TPB, UTAUT, and TTF, were integrated into the revised model for determining MOOCs acceptance and usage in HE. The revised model explained 42% of variance in actual MOOC usage, 52.6% of variance in BI to use MOOCs, and 33% of variance in TTF. According to the MASEM analysis, user’s perception (PE, EE, ATT, TAC, and TEC) can positively influence BI’s willingness to use MOOCs. Additionally, TAC and TEC were strong predictors of TTF. The findings indicated that the model recommended in this study can be applied effectively to comprehend the effects of BI and a user’s behavior in the MOOC context. The fact that the model is applicable for both academics and students suggests its generalizability across these sub-samples and, therefore, points to its relevance for both student education and academic professional development.

Additionally, this research contains four limitations that should be considered in future studies. Firstly, the meta-analysis is limited to empirical studies on MOOCs. As such, it may be beneficial to investigate the distinctions between various types of e-learning platforms. Secondly, future studies might assess other models’ abilities to explain the acceptance of MOOCs in HE. Thirdly, this study has omitted the two moderators observed in the original UTAUT model (experience and voluntariness) [19]. This is mainly because previous studies did not analyze or report on those factors. The current study was limited to examining only those relations and moderators (age and gender) that were previously researched. Hence, future studies should focus on specific moderators. Finally, the integrated model provided additional empirical support for the inclusion of the UTAUT, TTF, and TPB components. Another important area for future MASEM studies is to evaluate the three models’ strengths in the context of HE.

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