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Examining Unified Theory of Acceptance and Use of Technology 2 through Meta-analytic Structural Equation Modelling

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Keywords

MASEM;
meta-analytic structural equation modelling;
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Abstract

Like its predecessor, the Unified Theory of Technology and Use of Technology (UTAUT), UTAUT2 has been adopted, adapted and used in extended forms due to its simplicity, parsimony and robustness. This study synthesised 39 empirical studies based on the UTAUT2 model in educational contexts, using the One-stage Meta-Analysis and Structural Equation Modelling (OSMASEM). Although the findings in this study aligned with the initial findings by Ventakesh et al. (2012), the model did not perform well compared to those in the initial UTAUT2 study in the explained variance in both behavioural intention and use behaviour. When new relationships were introduced into the UTAUT2 model in this study, constructs like performance expectancy, hedonic motivation, social influence, and price value were new predictors of use behaviour. The meta-analytic structural equation modelling approach used in this study, OSMASEM, allows researchers to use past empirical study data to examine the UTAUT2 framework without replicating similar studies. Using OSMASEM, researchers could easily add past empirical data to train the UTAUT2 model to study the trends in technology acceptance and use in educational contexts.

Introduction

Recent research has attempted to examine technology acceptance through meta-analytic approaches (Feng et al., 2021; Leong et al., 2022; Jeyaraj & Dwivedi, 2020; Mishra et al., 2023; Than et al., 2021; Zaremohzzabieh et al., 2022). Meta-analytic structural equation modelling (MASEM) is a powerful mechanism for synthesising prior research findings, reconciling inconsistent conclusions, and resolving variable relationships (Cheung, 2014; Jeyaraj & Dwivedi, 2020; Viswesvaran & One, 1995). The advantage of using the MASEM is that it can test models that involve variables not included in the primary studies (Bergh et al., 2016; Steinmetz & Block, 2022). This approach combines the strengths of meta-analysis, which quantitatively summarises the results of individual studies and structural equation modelling. MASEM is a widely used statistical technique in educational research for synthesising and integrating data from multiple studies because of its ability to synthesise data from multiple studies and estimate a weighted average effect size, which measures the strength of the relationship between two variables (Cheung, 2019; Furlow & Beretvas, 2010; Herhausen et al., 2021; Raeisi-Vanani et al., 2022). It allows researchers to overcome the limitations of individual studies and arrive at a more comprehensive and robust understanding of the relationship between educational variables and outcomes.

MASEM can be used in studies that examine the adoption and usage of technology in organisations, such as those based on popular models like the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Ventakesh et al., 2012). In UTAUT2 studies, MASEM can be used to synthesise data from multiple studies to understand the relationships between the factors proposed in the UTAUT2 model and the adoption and usage of technology. For example, MASEM can estimate each factor's weighted average effect size on the adoption and usage of technology, allowing researchers to determine which factors impact technology adoption and usage.

In recent years, structural equation modelling is gaining popularity as one of the meta-analyses methods (Jak & Cheung, 2020; Steel et al., 2021; Wilson et al., 2016). Tang and Cheung (2016) demonstrated that researchers could benefit from MASEM by introducing a two-stage meta-analytic structural equation modelling (TSSEM) using R packages such as metaSEM, while Jak et al. (2021) developed a one-stage MASEM (OSMASEM) for random-effects models. OSMASEM is a specific approach to MASEM where all of the data from multiple studies is combined in a single analysis rather than conducting separate meta-analyses for each moderator variable or each dependent variable, providing an advantage over traditional meta-analyses. While TSSEM (Tang & Cheung, 2016) and OSMASEM (Jak et al., 2021) gathered traction, such approaches were not commonly used in UTAUT2 studies. UTAUT2 studies could benefit significantly from the OSMASEM approach as it allows researchers to synthesise and cumulate research findings into a single effect size (Bergh et al., 2016). The effect size reflects the magnitude and directionality of the association between the two or more UTAUT2 variables. OSMASEM can also provide information on the degree of fit of the entire UTAUT model and can handle samples with missing correlations (Cheung & Cheung, 2016). As such, this study aims to utilise OSMASEM to synthesise past UTAUT2 research data and examine their findings from 2013 to 2022.

Literature review

UTAUT2

UTAUT2 was developed later to tailor to the consumer acceptance and use of technology. There were three critical features in UTAUT2: (1) the introduction of hedonic motivation (HM), price value (PV) and habit (H) as additional factors in consumer products and technology use; (2) some existing relationships were changed in the original UTAUT model; and (3) introduction of new relationships (Venkatesh et al., 2012) (Figure 1). According to Venkatesh et al. (2012), the effect of HM on BI is moderated by age, gender, and experience. The effect of PV on BI is moderated by age and gender. H has direct and mediated effects on UB, and individual differences moderate these effects.

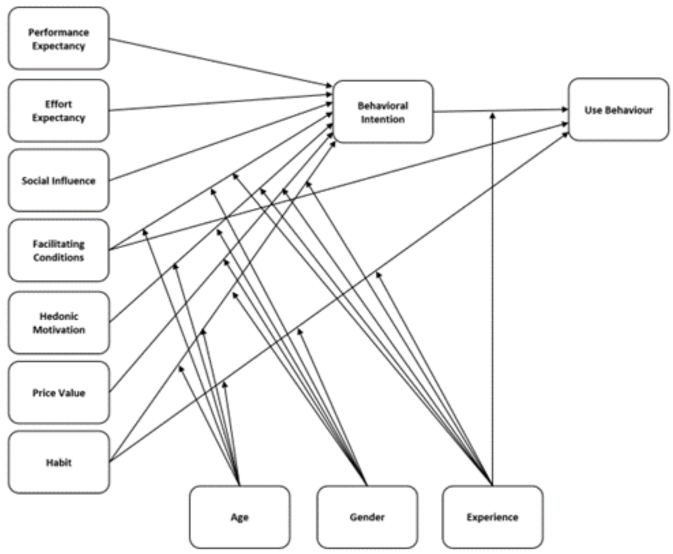

Figure 1: UTAUT2. Note: Adapted from Venkatesh et al. (2012).

UTAUT2 is considered the most comprehensive model in information system and technology adoption research (Tamilmani et al., 2017; Tamilmani et al., 2021). The model has been used in many past studies to examine factors influencing technology acceptance. For instance, Goto and Munyai (2022) utilised UTAUT2 to examine factors affecting law students' acceptance and use of online learning, while Avci and Avci (2022) examined the factors affecting teachers' use of digital learning resources.

As in UTAUT, Venkatesh et al. (2012) posited that PE was a predictor of BI, and the proposition remains constant in later empirical studies utilising UTAUT2. For instance, Hu et al. (2020), in their UTAUT2 study with 638 academic staff that explored factors affecting the adoption of emerging mobile technologies, revealed that PE remained a predictor of BI. Similarly, Jung & Lee (2020) found that PE was a predictor of BI in their cross-cultural study examining the adoption of open educational resources with 152 Korean and Japanese educators.

Similar to the UTAUT findings, the empirical results from UTAUT2 studies with EE as a predictor of BI have been inconsistent. Some studies showed that EE did not significantly affect BI. For instance, in the study with 206 undergraduates on the acceptance of Google Classroom, Kumar and Bervell (2019) found that EE was not a predictor of BI. In a similar research on the acceptance of Google Classroom with 163 students, Bervell et al. (2021) found that EE had a significant effect on SI instead of BI. De Moraes and Cabello (2017), in their study on the use of educational applications by 133 Brazilian students, revealed that EE has no significant effect on BI.

Based on the literature, SI was posited to be a predictor of BI. In many later UTAUT2 studies, it was found that SI continued to have a significant effect on BI (Ashraf et al., 2023; Aziz et al., 2020; Fathima Sanjeetha & Sabraz Nawaz, 2020; Goto & Munyai, 2022; Moorthy et al., 2019a; Raman & Don, 2013; Raman & Thabbimalai, 2021; Tseng et al., 2019).

One of the critical features of UTAUT2 is the change of some existing relationships in the original UTAUT model (Venkatesh et al., 2012). In the original UTAUT model, FC is posited to be a predictor of UB (Venkatesh et al., 2003). However, in the UTAUT2 model, FC is posited to predict both BI and UB (Venkatesh et al., 2012). FC remained a predictor of BI in many later UTAUT2 studies (Arain et al., 2018; Azizi et al., 2020; Bhimasta & Suprapto, 2016; El-Masri & Tarhini, 2017; Faqih & Jaradat, 2021; Farooq et al., 2017; Fathima Sanjeetha & Sabraz Nawaz, 2020; Gengfu & Chotiyaputta, 2019; Gunawan et al., 2019; Hu et al., 2020; Kalinkara & Talan, 2022; Meet et al., 2022; Mishra et al., 2022; Raman & Don, 2013; Rudhumbu, 2022; Tseng et al., 2019; Widjaja et al., 2020; Zacharis & Nikolopoulou, 2022). The discussion on FC as a predictor of UB is sometimes not straightforward as in many studies. UB was often omitted in many UTAUT2 empirical studies (Abdul Rabu et al., 2019; Al-Azawei & Alowayr, 2020; Almahri et al., 2020; Arain et al., 2018; Arain et al., 2019; Bhimasta & Suprapto; 2016; de Moraes & Cabello, 2017; El-Masri & Tarhini, 2017; Faqih & Jaradat, 2021; Gengfu & Chotiyaputta, 2019; Gunawan et al., 2019; Jung & Lee; 2020; Kaur et al., 2021; Le et al., 2022; Meet et al., 2022; Mehta et al., 2019; Moorthy et al., 2019a; Moorthy et al., 2019b; Rudhumbu, 2022; Sharif et al., 2019; Xu et al., 2022). For studies that included UB as a construct, in most cases, findings revealed that FC was a predictor of UB (Ain et al., 2016; Ashraf et al., 2023; Cao & Nguyen, 2022; Goto & Munyai, 2022; Hu et al., 2020; Kalinkara & Talan, 2022; Musa et al., 2022; Nikolopoulou et al., 2020; Raman & Don, 2013; Tseng et al., 2019; b et al., 2020; Zhou et al., 2020; Zawain, 2019; Zawin & Haboobi, 2019).

HM is the fun or pleasure of using a system or technology (Brown & Venkatesh, 2005). HM has been included as a critical predictor in past consumer behaviour research and prior information system research in the consumer technology use context (Brown & Venkatesh, 2005; Holbrook & Hirschman, 1982). In information system research, HM has been found to influence technology acceptance and use (Childers et al., 2001; Thong et al., 2006; Van der Heijden, 2004). From the literature, HM is generally a predictor of BI, a finding that is aligned with what was proposed by Venkatesh et al. (2012) (Ashraf et al., 2023; Avci & Acvi, 2022, Azizi et al., 2020; Bervell et al., 2021; de Moraes & Cabello, 2017; Fathima Sanjeetha & Sabraz Nawaz, 2020; Hu et al., 2020, Kalinkara & Talan, 2022; Kumar & Bervell, 2019; Moorthy et al., 2019b; Nikolopoulou et al., 2020; Raman & Don, 2013; Zhou et al., 2022). However, when Tamilmani et al. (2019) conducted a meta-analysis of 79 UTAUT2 studies, the researchers found that only 46 (58%) of the studies utilised HM as a construct, while 33 studies (42%) omitted the construct.

Venkatesh et al. (2012) extended the original UTAUT to examine the use of information technology in consumer contexts. Hence, in UTAUT2, PV is crucial as consumers have to bear the costs associated with purchasing devices and services. Consumer behaviour research has included cost-related constructs to explain consumers' actions (Dodds et al., 1991). In marketing research, PV is conceptualised with the quality of products and services to determine their perceived value (Zeithaml, 1988).

While adding PV as a construct may set UTAUT2 apart from the original UTAUT2, many later studies did not include it as part of the latter model. Tamilmani et al. (2018a) conducted a meta-analysis on 79 UTAUT2 empirical studies and found that only 32 studies (41%) utilised PV, while 47 studies (59%) omitted the construct from their research models. The main argument for excluding PV as a construct in their UTAUT2 models was that the technology involved in the studies was free of cost, like mobile applications and social networking sites. Among the 47 studies examined, only 4 were in the educational contexts examining LMS, informal learning and podcasting (Lai et al., 2016; Lin et al., 2013; Raman & Don, 2013). The researchers recommended that PV be a key predictor of individual technology adoption with UTAUT2. In other words, for utilising the UTAUT2 model for studies, PV should be one of the essential constructs in future research. Or (2023a) argued that since past studies had shown that PV had no significant effect on BI when examining technologies that were free of charge, it was recommended that the original UTAUT model be adopted or extended with added constructs instead of citing it as UTAUT2 research. For studies that included PV as a construct, it has been found that PV was a predictor of BI (Azizi et al., 2020; Farooq et al., 2017; Gengfu & Chotiyaputta, 2019; Meet et al., 2022; Mehta et al., 2019; Moorthy et al., 2019b; Tseng et al., 2019; Xu et al., 2022).

H is critical in predicting technology use (Kim & Malhotra, 2005; Kim et al., 2005; Limayem et al., 2007). It is defined as the degree to which individuals tend to perform behaviours automatically because of learning (Limayem et al., 2007), while Kim et al. (2005) equate H with automaticity. In other words, H is viewed as prior behaviour measured as the extent to which an individual believes the behaviour to be automatic (Kim & Malhotra 2005; Limayem et al. 2007). Tamilmani et al. (2018b) discovered in their systematic review that out of 66 empirical studies that utilised UTAUt2, only 23 (35%) included H as a construct in the studies. They recommended that researchers studying the initial stages of technology adoption in mandatory user settings should refrain from using H as a construct. On the other hand, using H as a construct is encouraged in research to examine established technologies driven by intrinsic consumer motivation. From the literature, H was generally found to have a significant effect on BI (Almahri et al., 2020; Ashraf et al., 2023; Avci & Avci, 2022; Azizi et al., 2020; de Moraes et al., 2017; Fathima Senjeetha & Sabraz Nawaz, 2020; Hu et al., 2020; Jung & Lee, 2020; Malešević et al., 2021; Mishra et al., 2021; Moorthy et al., 2019; Nikolopoulou et al., 2020; Raman & Thannimalai, 2021, Zhou et al., 2022) and UB (Avci & Avci; 2022; Azizi et al., 2020, Hu et al., 2020; Malešević et al., 2021; Nikolopoulou et al., 2020).

The current UTAUT2 study using OSMASEM

The current study synthesised 39 empirical research on UTAUT2 in educational contexts and capitalised on the advantage of synthesising correlation matrices through correlation-based OSMASEM (Jak et al., 2021). The current UTAUT2 study addresses these research questions:

1. To what degree do pooled correlation matrix relationships among the constructs show significant variations in UTAUT2 empirical studies from 2013 to 2022 using the OSMASEM approach?
2. To what degree does the UTAUT2 model fit the data from a pooled correlation matrix using the OSMASEM?
3. Are there new direct relationships among the UTAUT2 constructs found using the OSMASEM?

Method

Literature search and screening procedures

The Google Scholar database was searched to identify the relevant literature to the current UTAUT2 study. The following search terms and Boolean operators were used, "UTAUT2" AND "education". The other advanced search settings were included "anywhere in the articles" and "return articles dated between 2013 and 2023." After the search, an initial screening of the identified 10,900 studies was performed based on the following criteria: (1) the studies must address school or university's technology acceptance; (2) the studies must describe the relationships between the UTAUT2 constructs; and (3) the studies must analyse, report and discuss the findings in English. The initial screening resulted in 1,130 eligible empirical studies. Some studies were then excluded by applying the following criteria: (1) the studies did not target teachers, lecturers, educators or students in K-12, college or university education; (2) the studies were not based on the UTAUT2 model, but the UTAUT model. Past research using the OSMASEM approach had been conducted previously (Or, 2023a); (3) the studies had insufficient statistical reporting of the correlations between UTAUT2 constructs; (4) correlations between variables were negative where R package, metaSEM, is unable to compute; and (5) UTAUT2 was examined outside of educational contexts. Figure 2 summarises the results of the literature search and screening procedures. Table 1 lists the various research from which the data is used in this OSMASEM study.

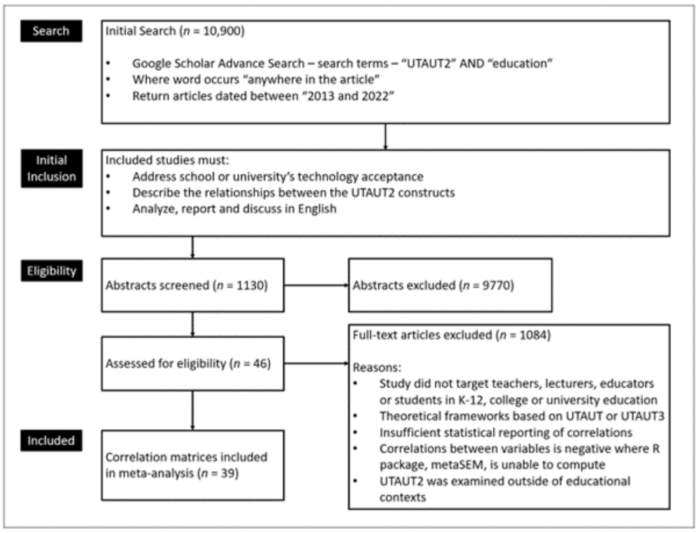

Figure 2. Diagram describing the literature search and the selection of eligible studies for meta-analysis.

Table 1. UTAUT2 studies from which data are used.

S/N	Technology / System	Sample Size	UTAUT2 Constructs	Study
1	AR	281	PE; EE; SI; FC; HM; PV; BI	Faqih & Jaradat (2021).
2	Blended Learning	203	PE; SI; HM; BI	Kaur et al. (2021).
3	Blended Learning	432	PE; EE; SI; FC; HM; PV; H; BI	Rudhumbu. (2022).
4	Chatbots	431	PE; EE; SI; FC; HM; H; BI	Almahri et al. (2020, March).
5	Digital Learning Resources	355	PE; EE; SI; FC; HM; PV; H; BI; UB	Avci & Avci. (2022).
6	Digital Library	483	PE; EE; SI; FC; HM; H; BI	Moorthy et al. (2019).
7	Distance Learning System	208	PE; EE; SI; FC; HM; H; BI; UB	Kalinkara & Talan. (2022).
8	e-Books	326	PE; EE; SI; FC; HM; PV; H; BI	Bhimasta & Suprapto. (2016, November).
9	e-Books	257	PE; EE; SI; FC; HM; PV; H; BI	Gengfa & Chotiyaputta. (2019).
10	e-Learning	418 (American) 389 (Qatari)	PE; EE; SI; FC; HM; PV; H; BI	El-Masri & Tarhini. (2017).
11	e-Learning	197	PE; EE; SI; FC; HM; PV; H; BI; UB	Goto, J & Munyai. (2022).
12	e-Learning	160	PE; EE; SI; HM; PV; H; BI	Mehta et al. (2019).
13	e-Learning	1024	PE; EE; FC; PV; H; BI; UB	Osei et al. (2022).
14	e-Learning	159	PE; EE; SI; FC; HM; PV; H; BI	Raman & Thannimalai. (2021).
15	e-Learning	314	PE; EE; SI; FC; HM; H; BI; UB	Zacharis & Nikolopoulou. (2022).
16	e-Services	173	PE; EE; SI; FC; H; BI; UB	Malešević et al. (2021).
17	Google Classroom	163	PE; EE; SI; FC; HM; PV; H; BI; UB	Bervell et al. (2022).
18	Google Classroom	163	PE; EE; SI; FC; HM; PV; H; BI; UB	Kumar & Bervell. (2019).
19	Interactive Whiteboards	171	PE; EE; SI; FC; HM; H; BI; UB	Zhou et al. (2022).
20	Learning Management System	320	PE; EE; SI; FC; HM; H; BI; UB	Raman & Don. (2013).

S/N	Technology / System	Sample Size	UTAUT2 Constructs	Study
21	Learning Management System	178	PE; EE; SI; FC; HM; PV; H; BI	Sharif et al. (2019).
22	Learning Management System	228	PE; EE; SI; FC; HM; H; BI; UB	Zwain. (2019).
23	Learning Management System	113	PE; EE; SI; FC; HM; H; BI; UB	Zwain & Haboobi. (2019).
24	Lecture Capture System	481	PE; EE; SI; FC; HM; PV; H; BI; UB	Farooq et al. (2017).
25	Micro-lectures	161	PE; EE; SI; FC; HM; PV; BI; UB	Tseng et al. (2022).
26	Mobile Internet	262	PE; EE; SI; FC; HM; PV; H; BI; UB	Nikolopoulou et al. (2021).
27	Mobile Learning	469	PE; EE; SI; HM; PV; BI	Al-Azawei & Alowayr. (2020).
28	Mobile Learning	730	PE; EE; SI; FC; HM; H; BI	Arain et al. (2019).
29	Mobile Learning	730	PE; EE; SI; FC; HM; H; BI	Arain et al. (2018).
30	Mobile Technologies	152	PE; EE; SI; FC; HM; PV; H; BI	Jung & Lee. (2020).
31	MOOCs	321	PE; EE; SI; FC; HM; PV; BI	Wijaya & Weinhandl. (2022).
32	Online Learning	376	PE; EE; SI; FC; HM; H; BI; UB	Musa et al. (2022).
33	Online Learning	566	PE; EE; SI; FC; HM; H; BI	Xu et al. (2022).
34	QR Code	200	SI; FC; HM; BI	Abdul Rabu et al. (2019).
35	Smartphone	831	PE; EE; SI; FC; HM; H; BI; UB	Cao & Nguyen. (2022).
36	Smartphone	540	PE; EE; SI; FC; HM; PV; H; BI: UB	Nikolopoulou et al. (2020).
37	Social Media	291	PE; EE; SI; FC; HM; H; BI; UB	Fathima Sanjeetha & Sabraz Nawaz. (2020).
38	Social Media	315	PE; EE; SI; FC; HM; H; BI; UB	Mishra et al. (2022).

Internal structure

R Studio (version 2022.12.0, Build 353) and its metaSEM package (version 1.3.0) were used to examine the fit of Model 1. The analysis examined whether the actual factor structure and loadings aligned with the theorised structure. It is done by statistically testing the fit between the proposed measurement model and the observed correlations (Albright & Park, 2009; Bollen, 1989; Hair et al., 2006; Kline, 2005). The following indices were used to assess the fit of Model 1 to the data: (a) $\chi 2$/ Degree of Freedom $\chi 2/df$), (b) Root Mean Square Error of Approximation (RMSEA) (Steiger, 1990), (c) Standardised Root Mean Square Residual (SRMR), (d) Comparative Fit Index (CFI) (Bentler, 1990) and (e) Tucker-Lewis fit index (TLI; Bentler & Bonett, 1980) (Table 2). The values for the UTAUT2 model were within the recommended thresholds for acceptable model fit based on all five indices ($\chi 2/df$ = 2.062; RMSEA = .008; SRMR = .026; CFI = 1.000, TLI = .984) (Table 2). The data reliability was analysed using IBM SPSS (version 28.0.1.1) and was highly reliable (N = 39; α = .993).

Table 2. Goodness-of-fit indices of Model 1.

Measure	Threshold	Value
χ^2	--	10.886
Df	--	5.000
χ^2/df	< 3.000	2.172
p-value	> .050	.053
RMSEA	< .050	.009
SRMR	<.080	.002
CFI	> .950	.997
TLI	> .950	.981

The correlation matrices obtained from the 39 UTAUT2 studies were analysed with the R package, metaSEM (version 1.3.0). With the R software, the metaSEM package derived originally from the openMX package provides analysis for the OSMASEM method using the SEM approach. The OSMASEM approach, most suitable for processing longitudinal relationships between variables at continuous time points (Cheung, 2014), was a good fit for this study that extracted empirical studies from the last decade, 2013 to 2022. Furthermore, the metaSEM package increased the sensitivity of significance tests by utilising the maximum likelihood estimation for analyses and used the sum rather than the average of sample sizes to compute the standard errors for the path coefficients.

Model 1 in this current meta-analysis underperformed as compared to the original model by Venkatesh et al. (2012). The original UTAUT2 model performed at an adjusted R2 of 74% for BI. The UTAUT2 model in this study only attained an R2 of 53.6%. For the explained variance of UB, Model 1 also underperformed compared to the original UTUAT2 model at R2 of 48.4% (Table 3). The original UTAUT model attained an explained variance at 52% for UB.

Table 3. Comparison of variances explained.

	Variance Explained (R^2)	
	Original Model	Model 1
BI	.740	.536
UB	.520	.484

Like the original UTAUT2 model proposed by Ventakesh et al. (2012), H remained the best predictor of BI (β= .250; p<.001) compared to PE, EE, SI, FC, HM and PV in the current model: (1) PE had a significant effect on BI (β= .173; p< .001); (2) EE had a significant positive effect on BI (β= .068; p< .001); (3) SI had a significant positive effect on BI (β= .204; p<.001); (4) FC had a significant positive effect on BI (β= .070; p<.001); (5) HM had a significant positive effect on BI (β= .172; p<.001); and (6) PV had a significant positive effect on BI (β= .094; p<.001). Similar to the original UTAUT2 findings by Ventakesh et al. (2012), BI had a significant positive effect on UB (β= .525; p< .001); FC had a significant effect on UB (β= .193; p< .001), and H had a significant effect on UB (β= .264; p< .001). In Model 1, BI continued to be the best predictor of UB, consistent with Ventakesh et al.'s findings (2012). The results for the variables are summarised in Figure 3 and Table 2.

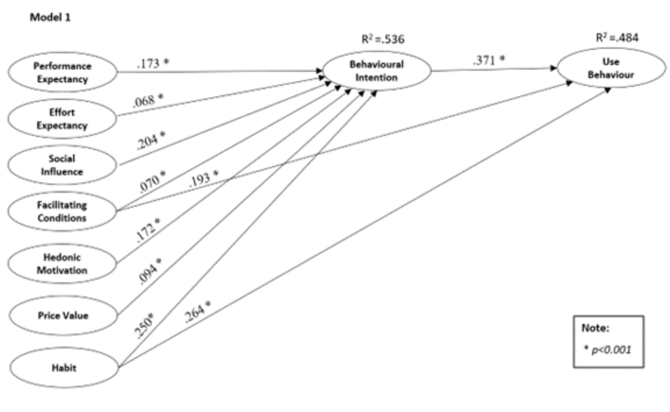

Figure 3. Path Diagram of UTAUT2 Model 1.

One additional model (Model 2) tested in this MASEM study was to include all possible exogenous variables and stimulate the various possible direct relationships between them (Figure 4). It was observed that when a direct relationship between EE and UB was added, the model fit indices fell below the desired thresholds. However, without a direct relationship between EE and UB, it was found in Model 2 that PE, EE, SI, FC, PV, HM and H were all predictors of BI and PE, SI, FC, HM, PV and PV and H were also predictors of UB. The goodness-of-fit indices for Model 2 fell within the recommended thresholds for acceptable model fit (*χ2/df* = 2.226; RMSEA = .010; SRMR = .008; CFI = .999, TLI = .980) (Table 3).

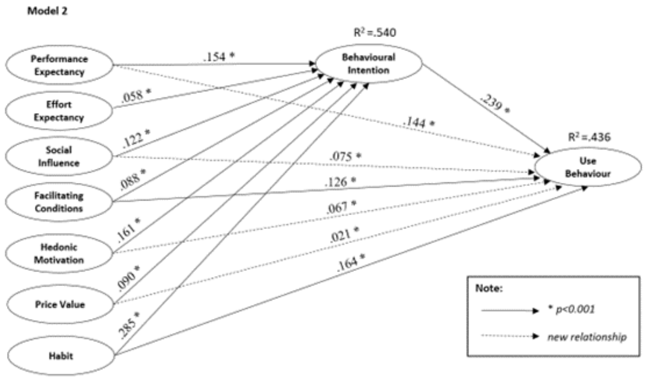

Figure 4. Path Diagram of UTAUT2 Model 2.

Table 4. Alternative UTAUT2 Model Goodness-of-fit Indices

Measure	Threshold	Value
		Model 2
χ^2	--	2.226
Df	--	1.000
χ^2/df	< 3.000	2.226
p-value	> .050	.136
RMSEA	< .050	.010
SRMR	<.080	.008
CFI	> .950	.999
TLI	> .950	.980

While there was an excellent internal data structure in Model 2, the explained variance for BI (54%) and UB (43.6%) underperformed as compared to the initial UTAUT2 model introduced by Venkatesh et al. (2012) (BI, 74%; UB, 52%) (Table 4). In Model 2, H remained the strongest predictor of BI (β= .285; *p*<.001), as compared to PE, EE, SI, FC, HM and PV: (1) PE had a significant effect on BI (β= .154; *p*<.001); (2) EE had a significant effect on BI (β= .058; *p*<.001); (3) SI had a significant effect on BI (β= .122; *p*<.001); (4) FC had a significant effect on BI (β= .088; *p*<.001); (5) HM had a significant effect on BI (β= .161; *p*<.001); and (6) PV had a significant effect on BI (β= .090; *p*<.001). Although BI remained to be the strongest predictor of UB (β= .239; *p*<.001), four other direct relationships between PE, SI, HM and PV were observed: (1) PE had a significant effect on UB (β= .144; *p*<.001); (2) SI had a significant effect on UB (β= .075; *p*<.001); HM had a significant effect on UB (β= .067; *p*<.001); and PV had a significant effect on UB (β= .021; *p*<.001). Like the initial UTAUT2 model introduced by Ventakesh et al. (2012), FC had a significant effect on UB (β= .126; *p*<.001), and H had a significant effect on UB (β= .164; *p*<.001). Compared to Model 1(53.6%), Model 2 performed slightly better, with a BI variance of 54%. However, in terms of variance explained for UB, Model 2 underperformed (43.6%) as compared to Model 1 (48.4%) (Table 5).

Table 5. Comparison of model variances explained.

	Variance Explained		
	Original Model	Model 1	Model 2
BI	.740	.536	.540
UB	.520	.484	.436

Discussion

The MASEM approach was employed to revisit the UTAUT2 model first introduced by Ventakesh et al. (2012). In Model 1, the results showed that H remained the strongest predictor of BI, with PE, EE, SI, FC, HM and PV having a significant positive effect on BI. FC, H and BI served as predictors of UB, and BI as a mediator. These results are all in line with the findings from the original UTAUT2 model. In Model 2, after adding new direct relationships into the alternative model, the findings showed that while PE, SI, FC, HM, PV and H each had a significant effect on UB, EE did not. Recent UTAUT2 studies have reported other direct relationships similar to those simulated in Model 2. For instance, Goto and Munyai (2022) reported that PV had a significant effect on UB in their study on the acceptance and use of online learning with 197 South African law students. Hu et al. (2020) found that PE and HM had a significant effect on UB when the researchers explored the factors affecting the adoption of mobile technologies with 638 Chinese academics. However, the direct relationship between SI and UB was not reported thus far in the educational context. Among the 39 studies included in this MASEM research, it was observed that two variables were commonly omitted from the UTAUT2 model: PV and UB. Of the 39 studies, 17 (43.59%) omitted PV, and 19 (48.72%) did not examine UB as an exogenous variable in the theoretical models.

While there was an attempt to examine other direct relationships between the variables in Model 2, the explained variance of both BI and UB did not perform better than the original UTAUT2 model proposed by Venkatesh et al. (2012). The possible reason would be that behavioural intentions had shifted as educational technologies changed between the period 2012 to 2023. The various technologies examined among the 39 studies covered mainly e-learning, learning management system and mobile learning. Take mobile learning, for example; in the surveys conducted by Educause Review in 2016 and 2018, students were asked to identify reasons why they did not want their teachers to use mobile apps and devices for coursework (Chen et al., 2023). For 2016 and 2018, limited internet connectivity and limited funds were among the cited reasons. In 2021, while the lack of mobile device access, limited technical support and funds were not problems for students in the 2021 survey, lack of interest was the reason. 53% of the students in the 2021 survey indicated that they would not want to use mobile apps or devices in their studies because they were not interested in mobile learning.

Conclusions

While UTAUT2 was developed for the consumer context, the findings from this MASEM study supported the model's applicability in the educational context. In Model 2, some new relationships of variables were discovered, including the direct effects of PE, SI, HM and PV on UB, which is a departure from the original findings by Ventakesh et al. (2012). Recalling that the UTAUT2 was developed for the consumer context, in the case of HM being a predictor of both BI and UB, the acceptance and use of educational technologies are driven through the extrinsic motivation of teachers and students to improve the performance of their intended tasks (Tamilmani et al., 2019). It is an important reminder to policymakers and higher education executives that extrinsic motivation plays a vital role in the successful implementation of education technologies.

PV was discovered as a predictor of both BI and UB in this study. However, only 22 of the 39 studies (56.41%) included PV as a construct in the research model. Researchers had chosen not to include PV because the users of the intended educational technologies did not need to incur any monetary cost. In contrast, some did not explain why PV was omitted in their research. Both Tamilmani et al. (2018a) and Or (2023b) suggested that PV is not an appropriate construct to be included in research models examining the adoption and use of technology made available freely to students and faculty members in higher education.

The current study synthesised empirical data from UTAUT2 studies from 2013 to 2022 in the educational context using the OSMASEM approach (Jak et al., 2021). OSMASEM synthesises correlation matrices rather than single correlations, demonstrating how the approach can be applied to examine theory-driven models. Tamilmani et al. (2019) suggested that researchers use correlation-based analysis to calculate explained variances, which this study managed to do. Many diverse findings have been discovered from past UTAUT2 studies since its inception in 2012. OSMASEM, the method introduced in this study, offers an alternative approach for researchers to use past empirical data to examine the UTAUT2 model without replicating similar studies. As more empirical data in the near future are added to train the UTAUT2 data model, researchers utilising methods like the OSMASEM can study how educational technology trends change over time, an observation established by Mishra et al. (2023) in their MASEM study on TAM research. As such, the OSMASEM approach allows researchers to focus on the critical relationships within the UTAUT2 model and advise their colleagues and executives accordingly who are implementing technologies in higher educational institutions. At the time of this writing, OSMASEM has never been utilised in the meta-analysing of the UTAUT2 model in educational contexts.

The popularity of OSMASEM in educational research is not well-established at the time of this writing, as its use is relatively recent compared to other methods in the field. One limitation of the metaSEM package used in the R software is that it cannot compute negative correlations. Future research will benefit as the software package develops in the next few years to enable it to do so. Nevertheless, OSMASEM is gaining popularity as a valuable tool for synthesising and analysing data from multiple studies, particularly in education and psychology. Its popularity may increase as researchers become more aware of its potential benefits over traditional meta-analytic methods and the availability of software packages such as metaSEM that supports the implementation of OSMASEM increases. In conclusion, OSMASEM is a recent yet valuable tool for technology acceptance studies like the UTAUT2 model. It allows researchers to synthesise data from multiple studies and evaluate measurement invariance, leading to a more comprehensive and robust understanding of the relationships between the factors proposed in the UTAUT2 model and the adoption and usage of technology in higher education.

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