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Factors influencing behavioral intention to use e-learning in higher education during the COVID-19 pandemic: A meta-analytic review based on the UTAUT2 model

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Abstract

Amidst the COVID-19 pandemic, the e-learning demand among in tertiary education sector has surged, which has produced prolific research on factors influencing students' and faculties e-learning adoption. Anchored in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework, this study employed a meta-analytic approach to investigate the effects of seven key antecedents (i.e., Performance Expectation, Effort Expectation, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit) and possible moderators on Behavioral Intention (BI) towards using e-learning. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines, the study identified 91 empirical studies involving 37,910 participants including both university faculties and students. The results show that Habit was the most influential antecedent on BI. Apart from Habit, Hedonic Motivation, Price Value, Performance Expectation, and Facilitating Conditions were strongly correlated with BI towards using e-learning, whereas Effort Expectation, Social Influence, and BI had moderate relations with BI. The moderation analyses demonstrate that the variables of gender, user type, region, cultural orientation, and income level all significantly moderated the relations between various antecedents and BI. The study results provide some practical implications on how e-learning providers or institutions may more effectively improve e-learning adoption among faculties and students. Possible strategies may include designing strategies to enhance habit formation of users, leveraging hedonic motivation by incorporating interactive and engaging contents, and offering technical support and cost-effective e-learning platforms. Furthermore, strategies which are designed to foster positive e-learning adoption should also be tailored to accommodate diverse learner profiles by taking the moderating factors of gender, cultural backgrounds, and economic disparities, ultimately leading to more equitable and inclusive e-learning in higher education.

Keywords E-learning · Higher education · Behavioral intention · UTAUT2 Model · COVID-19 pandemic · Meta-analytic review

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1 Introduction

The COVID-19 pandemic has precipitated an unprecedented shift towards e-learning in higher education globally. As traditional classrooms transitioned online, engagement with digital learning platforms surged, with Coursera (2021) reporting a doubling of enrollment in 2020 and a further 32% increase in 2021, reaching 189 million users. This shift led to a significant increase in publications on e-learning in higher education during the pandemic (Fauzi, 2022), covering a wide range of topics from student attitudes to online assessment and curriculum design (Brika et al., 2022).

The rapid adoption of e-learning during the pandemic has fundamentally transformed the landscape of higher education. E-learning offers unique advantages including flexibility in time and location, personalized learning paths, immediate feedback mechanisms, and enhanced accessibility to educational resources (Zheng et al., 2023). However, the successful implementation of e-learning systems depends heavily on user' acceptance and willingness to engage with these platforms (García-Morales et al., 2021). Therefore, understanding the factors influencing e-learning adoption particularly crucial for educational institutions and policymakers.

Central to this research is the concept of "behavioral intention" (BI) towards e-learning use. BI represents an individual's willingness to engage with e-learning systems (Alotumi, 2022) and should be distinguished from actual system use. While BI measures intent, actual use reflects observable engagement with these systems (Zacharis & Nikolopoulou, 2022). Research has consistently demonstrated that BI serves as a crucial predictor of technology adoption and sustained use, establishing it as a key indicator of user behavior in educational technology contexts (Prasetyo et al., 2021; Raza et al., 2021).

The theoretical foundation for understanding e-learning adoption has evolved significantly over the years. While earlier models such as the Technology Acceptance Model (TAM) provided valuable insights, they often failed to capture the complexity of modern technology adoption decisions (Liu et al., 2018), particularly in educational contexts (Islam et al., 2014). The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model, developed by Venkatesh et al. (2012), represents a more comprehensive framework that incorporates both utilitarian and hedonic aspects of technology use.

To understand the factors influencing e-learning adoption, many researchers have employed the UTAUT2 model as a theoretical framework. This model extends the original UTAUT by incorporating consumer-oriented constructs, making it particularly suitable for studying voluntary technology adoption contexts like e-learning. The UTAUT2 framework has demonstrated superior explanatory power compared to earlier models, accounting for up to 74% of the variance in BI to use technology (Venkatesh et al., 2012). The UTAUT2 incorporates seven key constructs: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit. These constructs are theorized to influence BI and/or use behavior, with age, gender, and experience may plan moderating roles between the various relationships in the model.

While the UTAUT2 has produced prolific research in BI towards using e-learning during COVID-19 pandemic (Meet et al., 2022; Prasetyo et al., 2021; Sitar-Taut & Mican, 2021; Bervell et al., 2022; Tseng et al., 2022; Goto & Munyai, 2022; Kosiba et al., 2022; Musa, 2022; Zacharis & Nikolopoulou, 2022), notable research gaps have also been identified. First, the rapid transition to e-learning during the pandemic has generated a substantial body of research with varying and sometimes contradictory findings. This inconsistency in results makes it challenging for stakeholders to make informed decisions about e-learning implementation. Studies have yielded inconclusive findings regarding the effect sizes and directions of various influencing factors (known as antecedents) on BI towards using e-learning. This inconsistency is partially attributed to variations in research samples, measurement instruments, and contextual differences across studies (Raza et al., 2022; Tandon et al., 2022). For instance, while some studies highlighted the pivotal role of Hedonic Motivation in BI towards using e-learning (Tandon et al., 2022), others only suggested a negligible impact (Raza et al., 2022).

Second, while individual studies have examined specific aspects of e-learning adoption, there is a lack of comprehensive synthesis of findings across different contexts and user groups. This gap is particularly significant given the global nature of the pandemic's impact on education. There has been limitations in moderation analysis to explore whether the association between various UTAUT2 constructs and the BI towards using e-learning varies by demographics, including gender (Welch et al., 2020), user type (Šumak et al., 2011), region (Paola Torres Maldonado et al., 2011), cultural orientation (Faqih, 2020; Tarhini et al., 2017a; Zhao et al., 2021), and income level (Cheng & Yuen, 2022).

Third, the unique circumstances of the pandemic have created a need to understand whether traditional technology acceptance models like UTAUT2 maintain their explanatory power in crisis situations. This understanding is crucial for developing more resilient educational systems that can adapt to future disruptions.

This meta-analysis aims to address these gaps by providing a comprehensive review of e-learning adoption factors during the COVID-19 pandemic and extending UTAUT2 application in e-learning by investigating moderating effects of key demographic and contextual factors. By employing meta-analytic techniques, this study synthesizes findings across multiple studies, accounts for different sample sizes and methodological variations, and provides more reliable estimates of the relationships between UTAUT2 constructs and BI. This approach not only helps resolve inconsistencies in previous findings but also offers a more nuanced understanding of how different contexts and user characteristics may influence e-learning adoption.

The insights gained will have implications for designing and implementing effective online learning strategies in higher education, contributing to a nuanced understanding of e-learning adoption in crisis situations and informing post-pandemic e-learning approaches.

2 Development of research questions

2.1 Antecedents

Performance Expectation Performance Expectation assesses the extent to which a user believes that utilizing a specific technology or e-system will enhance their work performance (Venkatesh et al., 2003). Even though many studies in the e-learning domain have reported a significant positive impact of Performance Expectation on BI (Esawe et al., 2023; Zacharis & Nikolopoulou, 2022; Zulfakar et al., 2022), a number of studies contested this result (Iftikhar et al., 2022; Reyes-Mercado et al., 2022). Consequently, we propose:

> **RQ1:** How does Performance Expectation influence BI towards using e-learning in higher education?

Effort Expectation Effort Expectation refers to the perceived level of effort required to use a technology or e-system (Venkatesh et al., 2003). In e-learning, Effort Expectation is concerned with platform usability and navigation simplicity (Alshehri et al., 2020; Nguyen et al., 2020; Tandon et al., 2022). While a few studies found a significant positive relationship between Effort Expectation and BI, suggesting that when users perceive the platform to be easier to use, they are more likely to adopt it (Abdekhoda et al., 2022; Esawe et al., 2023). Other research, however, reported that this relationship is not always significant (Prasetyo et al., 2021; Sangeeta & Tandon, 2021). This leads us to explore:

> **RQ2:** How does Effort Expectation influence BI towards using e-learning in higher education?

Social Influence Social Influence refers to the impact of the attitudes and behaviors the significant others of an individual towards a particular technology or e-system (Venkatesh et al., 2003). This may come from teachers' recommendations, positive evaluations from classmates or their friends (Arain et al., 2019; Chen et al., 2021). Some studies asserted that Social Influence positively affects an individual's BI towards using e-learning (Esawe et al., 2023; Garrido-Gutiérrez et al., 2023; Xu et al., 2022), whereas such results were not found in other studies (Abbad, 2021; Zulfakar et al., 2022). The research question developed with regard to Social Influence is:

> **RQ3:** How does Social Influence affect BI towards using e-learning in higher education?

Facilitating Conditions Facilitating Conditions is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003, p. 453). In the context of e-learning, Facilitating Conditions includes access to hardware, software tools, internet connectivity, and technical support (Abbad, 2021; Garrido-Gutiérrez et al., 2023).

Some studies highlighted that favorable Facilitating Conditions might reduce learning barriers, thereby boosting user acceptance and adoption (Hermita et al., 2023; Reyes-Mercado et al., 2022; Widjaja et al., 2020). Contradicts this claim, other research didn't find significant impact from Facilitating Conditions to acceptance and adoption (Esawe et al., 2023; Raza et al., 2021; Xu et al., 2022). Thus, we seek to understand:

RQ4: How does Facilitating Conditions influence BI towards using e-learning in higher education?

Hedonic Motivation Hedonic Motivation encompasses the intrinsic pleasure and satisfaction derived from the use of a technology or e-system (Venkatesh et al., 2012). In the realm of e-learning, Hedonic Motivation may be influenced by content, course materials, online design, and personalized learning experiences (Ng et al., 2022; Tandon et al., 2022; Udeozor et al., 2023). Studies found that when users reported higher Hedonic Motivation in the e-learning, their likelihood of continued usage also increased (Udeozor et al., 2023; Widjaja et al., 2020; Zacharis & Nikolopoulou, 2022). However, not all findings support the significant and positive influence of Hedonic Motivation on BI towards using e-learning (Qazi et al., 2020; Raza et al., 2022; Terblanche et al., 2023). Given these inconsistent research results, it is important to explore:

RQ5: How does Hedonic Motivation influence BI towards using e-learning in higher education?

Price Value Price Value assesses a user's evaluation of the cost–benefit ratio of a technology or e-system (Venkatesh et al., 2012). In the context of learning, it is often the time and effort are a matter of concern rather than monetary values (Mehta et al., 2019). Hence, Price Value is often referred to as "learning value" or "perceived value" (Ain et al., 2016; Azhar et al., 2021; Kosiba et al., 2022; Musa, 2022; Prasetyo et al., 2021). In the e-learning environment, Price Value may involve the cost of e-learning delivery, the quality and quantity of content provided, and the cost-effectiveness compared to traditional face-to-face learning (Osei et al., 2022). Inconsistent findings also reported for the impact of Price Value on BI towards using e-learning, with both significant (Ain et al., 2016; Azhar et al., 2021; Kosiba et al., 2022; Mehta et al., 2019; Prasetyo et al., 2021) and non-significant results (El-Masri & Tarhini, 2017; Tandon et al., 2022; Tarhini et al., 2017b; Terblanche et al., 2023). These inconsistencies led us to explore:

RQ6: How does Price Value influence BI towards using e-learning in higher education?

Habit Habit denotes the natural tendency to use a particular technology or e-system due to habitual behavior (Venkatesh et al., 2012). In e-learning, a habit may develop through frequent platform use, leading to a comfort level with e-learning (Terblanche et al., 2023). Both significant and non-significant results were found from Habit to BI (Mehta et al., 2019; Qazi et al., 2020; Widjaja et al., 2020; Xu et al., 2022), (Ain et al., 2016; Prasetyo et al., 2021).

RQ7: How does Habit influence BI towards using e-learning in higher education?

2.2 Moderators

2.2.1 Gender

As an important demographic variable, gender significantly moderated various relations in understanding and explaining technology acceptance and use in the UTAUT2 model (Venkatesh et al., 2012). In e-learning context, for instance, previous research has indicated that male users place more emphasis on the usefulness of new technology, whereas female users are more likely to be influenced by its ease of use (Ong & Lai, 2006; Venkatesh & Morris, 2000). Preliminary investigations on how gender moderate the impacts from antecedents to BI towards using e-learning. For instance, Wang et al., 2009 found gender moderated the impact of Social Influence on BI. There is a lack of systematic examination of the possible moderating role in the relations between the antecedents and BI in UTAUT2 model. Therefore, we propose the following research question:

> **RQ8:** How does gender moderate the relations between the antecedents and BI in the UTAUT2 model in higher education?

2.2.2 User type

User type may also be an important moderator in the UTAUT2 model. In a previous meta-analysis, Šumak et al. (2011) found that user type was a moderator in of e-learning acceptance. However, these studies were not targeted the UTAUT2 model, neither were they specific in higher education context. Hence, we propose the following research question:

> **RQ9:** How does user type (such as students, teachers) moderate the relations between the antecedents and BI in the UTAUT2 model in higher education?

2.2.3 Region, cultural orientation, and income level

Previous research has recommended to conduct systematic investigations on the possible moderating roles of region, cultural orientation, and income level in the UTAUT2 model. This recommendation was some preliminary evidence. For instance, research by Jang et al. (2021), Reyes-Mercado et al. (2022), and Taghizadeh et al. (2022) found that during the pandemic the perceptions and adoption of technology by learners from different regions varied.

> **RQ10:** How does region moderate the relations between the antecedents and BI in the UTAUT2 model in higher education?

Furthermore, El-Masri and Tarhini (2017) recommended to use Hofstede's cultural orientation (i.e., individualism/collectivism) to explore the possible moderating role of culture of the relations between the antecedents and BI towards e-learning use in UTAUT2 model.

RQ11: How does cultural orientation moderate the relations between the antecedents and BI in the UTAUT2 model in higher education?

With regard to income level, it seems to be reasonable to assume that compared to students in the developed countries, those in developing countries are more constrained in opportunities in using e-learning, which may affect the relations between the antecedents and BI. Indeed, El-Masri and Tarhini (2017) found that effort expectancy and Social Influence increased the adoption of e-learning systems among students in developing countries, which was not the case in developed countries. Therefore, we propose the following questions:

RQ12: How does income level moderate the relations between the antecedents and BI in the UTAUT2 model in higher education?

A visual representation of the conceptual framework is displayed in Fig. 1.

3 Method

3.1 Literature retrieval and screening

This study examined the literature on e-learning adoption in higher education from January 1, 2020 to March 18, 2023, focusing on the COVID-19 pandemic period. We chose the Web of Science Core Collection as our primary database due to its extensive coverage and cross-disciplinary nature (Singh et al., 2021).

The study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009), which involved multiple cycles of screening and selection for the articles to be included in the analysis (see Fig. 2).

The primary search was based on a review of titles and abstracts. The search string included key phrases focusing on the Unified Theory of Acceptance and Use of Technology (UTAUT) and e-learning: "Unified Theory of Acceptance and Use of Technology" AND "e-learning" OR "Unified Theory of Acceptance and Use of Technology" AND "online learning" OR "UTAUT" AND "e-learning" OR "UTAUT" AND "online learning". To ensure comprehensive coverage, we conducted a secondary search of reference lists and solicited additional studies from authors via email.The initial screening involved reading titles and abstracts to eliminate irrelevant studies. The remaining articles were then subjected to further inclusion criteria described in the following:

- The research must utilize or partially incorporate the UTAUT2 model as its theoretical framework.
- Only empirical studies were included, excluding review papers, theoretical analyses, and other non-empirical works.

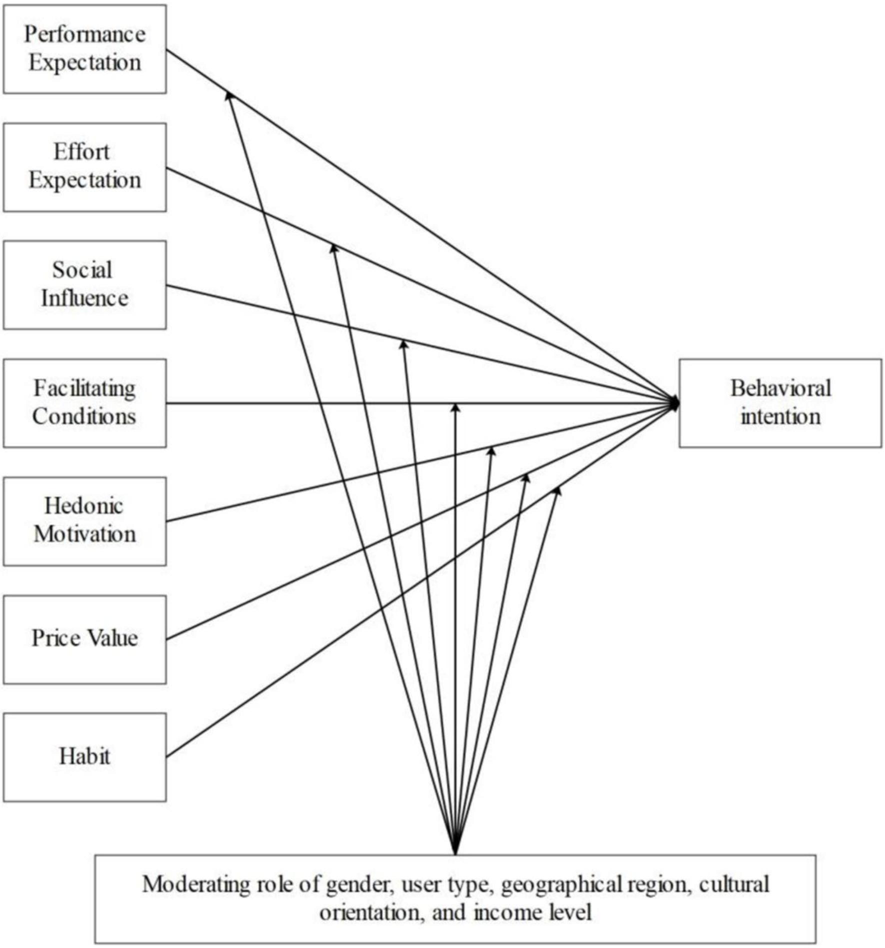

Fig. 1 Conceptual framework

- The studies must report sample size, correlation coefficients between independent variables, and BI towards using e-learning among higher education users during the COVID-19 pandemic, or provide other calculable data.
- The studies must represent independent research with distinct samples to avoid duplicated samples (e.g., journal articles and dissertations based on the same study).

Following the PRISMA process, a total of 91 articles met the requirements for inclusion in the final meta-analysis.

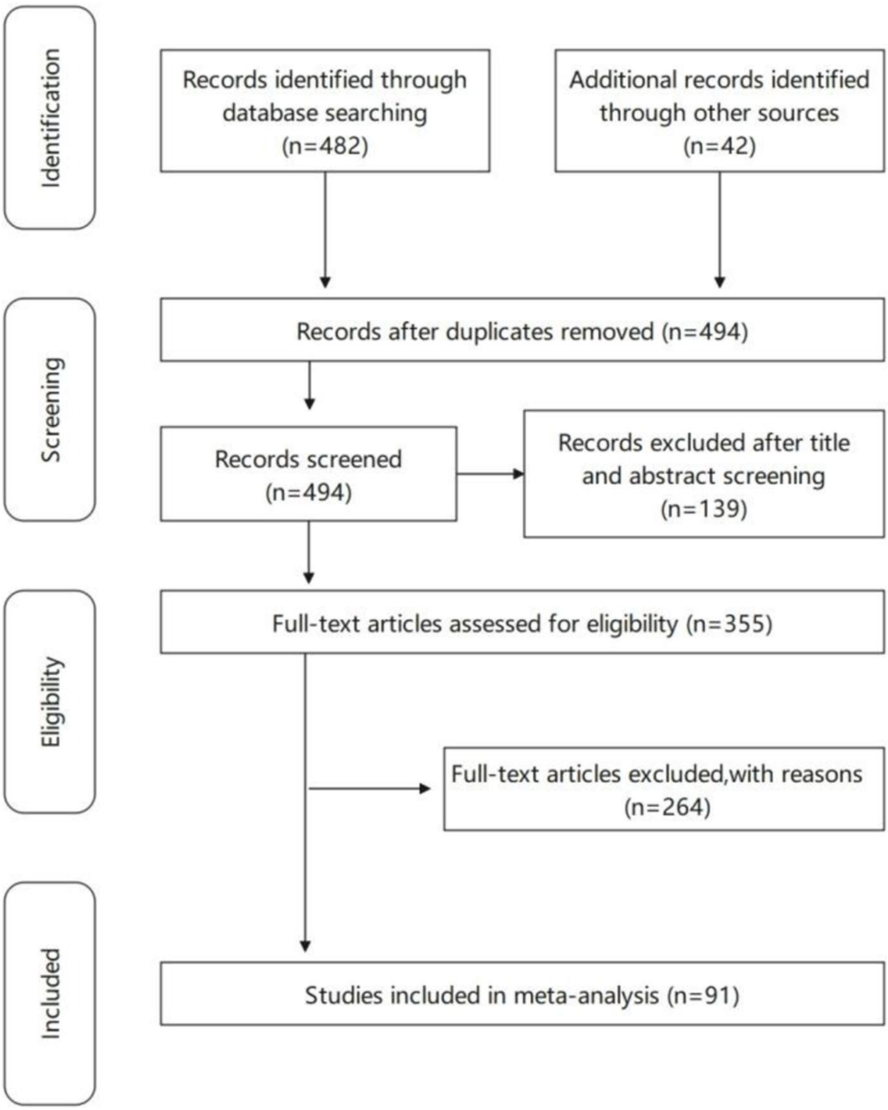

Fig. 2 Procedure of article retrieval and selection

3.2 Literature coding

Information related to the research theme was extracted and coded from the existing literature, including the first author, publication year, sample size, influencing factors, user type, region, cultural orientation, and income group, and correlation coefficients. The coding of the articles included in the analysis is detailed in Appendix A.

The 91 studies had a cumulative sample size of 37,910, spanning six regions: Africa, Asia–pacific, Europe, Middle East, North America, and South/Latin America. The user type were university students, faculty, or a combination of both. Data collection methods were predominantly self-reported surveys.

In terms of income level, the studies were categorized according to the World Bank's standards for country income groups: countries of high income, upper-middle income, lower-middle income and low income (World Bank, 2023).

Cultural orientation used Hofstede Insights' Country Comparison Tool (Hofstede Insights, 2023) to classify the countries or regions into collectivism and individualism culture according to the cultural attributes.

4 Analysis and results

4.1 Calculation of the effect sizes

We used Comprehensive Meta-Analysis (CMA) V3 software to calculate effect sizes either directly from the correlation coefficients or indirectly from path coefficients, Directly the correlation coefficients $_r$ were transformed into the z-values via Fisher's transformation as the effect size. Indirectly when the study provided β-values but not r-values, the β-values were converted into r-values first using the formula $r = .98\beta + .05\lambda$ ($\lambda = 1$ when $\beta \geq 0$; $\lambda = 0$ when $\beta < 0$), and then transformed into the effect sizes (Peterson & Brown, 2005).

4.2 Heterogeneity test

In empirical research, the presence of sampling errors often introduces discrepancies between the true effect sizes and the observed ones (Huedo-Medina et al., 2006). Furthermore, variations in research subjects, settings, and methodological approaches across studies may add additional differences in effect sizes. Hence, to ensure heterogeneity of the effect sizes across studies, we employed Q tests and I^2 statistics.

The Q-value is a statistical measure derived from the Q-test and assesses whether the observed heterogeneity among studies is greater than what would be expected by chance alone (Ruppar, 2020). A significant Q-value indicates that the observed differences in effect sizes across studies are unlikely to be due to random variation, suggesting the presence of true heterogeneity. Conversely, a non-significant Q-value suggests that the observed variation is likely to be attributable to chance and may not reflect genuine differences. The I^2 statistics quantify the proportion of variability in the effect sizes that can be attributed to heterogeneity. To interpret the I^2 values, we used the following criteria: 0% = no heterogeneity, 0–40% = mild heterogeneity, 40–60% = moderate heterogeneity, 50–90% = substantial heterogeneity, and 75–100% = significant heterogeneity (Higgins et al., 2003).

Table 1 presents the results of Q tests and I^2 statistics. All Q-values were statistically significant ($p < .001$), and I^2 statistics for all variables exceeded 75%, indicating

Table 1 Heterogeneity test results

variable	k	*N*	Q-value	df	*p*	I^2	Tau^2	Tau
Performance Expectation	76	33048	3266.517	75	***	97.704	.099	.315
Effort Expectation	77	34475	5120.091	76	***	98.516	.150	.388
Social Influence	77	32970	3699.839	76	***	97.946	.114	.338
Facilitating Conditions	83	34935	3469.831	82	***	97.637	.100	.316
Hedonic Motivation	38	17063	1191.377	37	***	96.894	.071	.267
Price Value	18	9551	698.920	17	***	97.568	.079	.280
Habit	19	11,531	1662.827	18	***	98.918	.155	.394

k number of studies, *N* the total sample size of the *k* studies

***$p < .001$

considerable heterogeneity in the effect sizes. Given the significant heterogeneity, we opted for a random-effects model in our meta-analysis (Deeks et al., 2019; Riley et al., 2011).

4.3 Publication bias analysis

Publication bias is a phenomenon where studies yielding statistically significant results are more likely to be published, potentially skewing the overall reliability of research findings (Dowdy et al., 2022). To address this issue, we used the following methods. First, we consulted funnel plots (Figs. 3, 4, 5, 6, 7, 8 and 9),

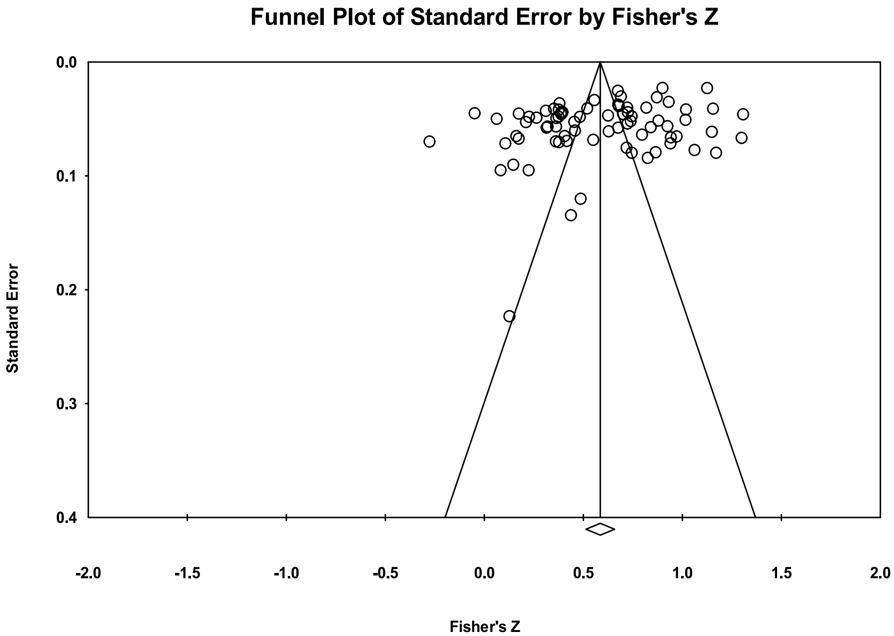

Fig. 3 Performance expectation funnel chart

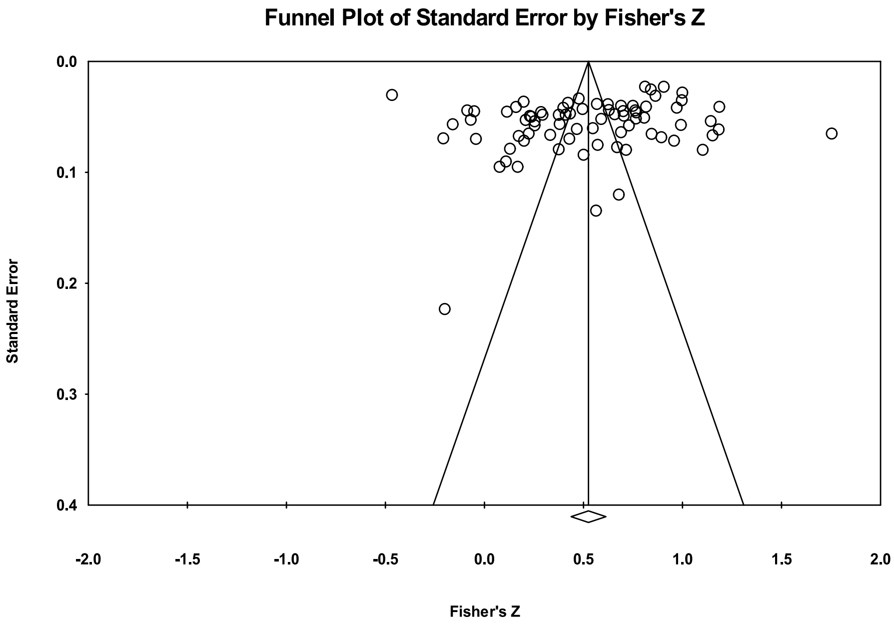

Fig. 4 Effort expectation funnel chart

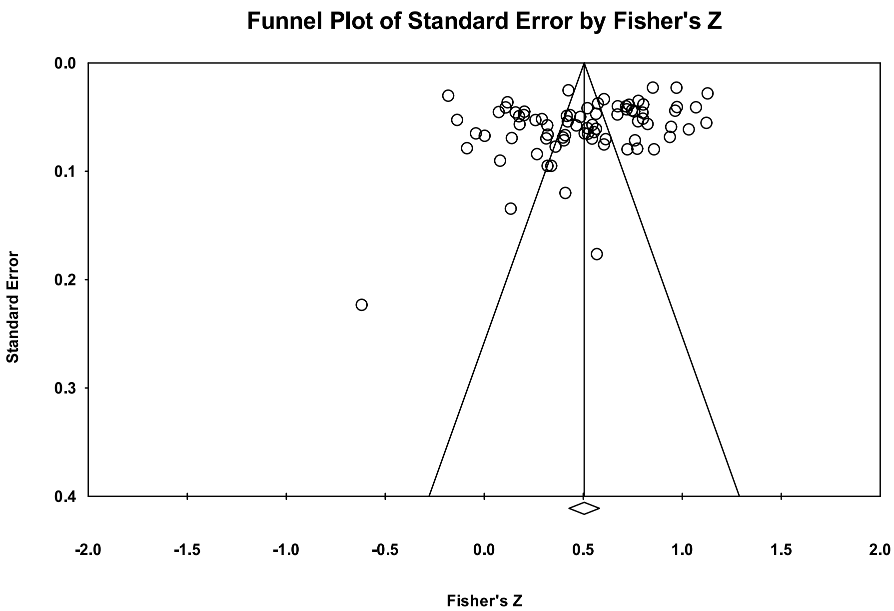

Fig. 5 Social influence funnel chart

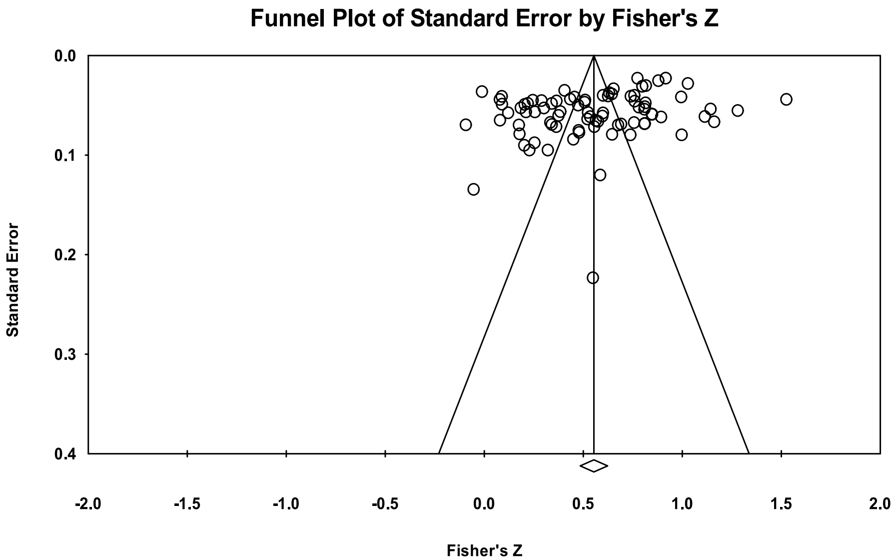

Fig. 6 Facilitating conditions funnel chart

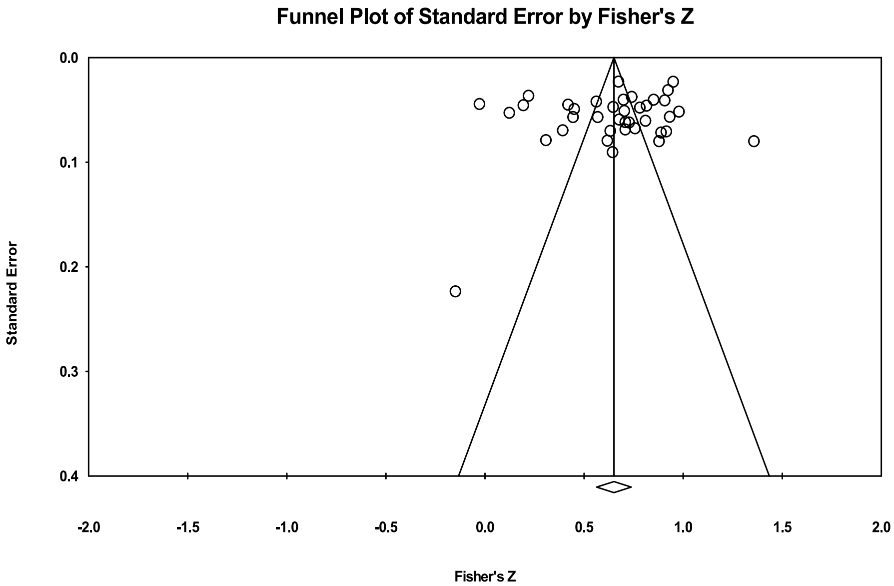

Fig. 7 Hedonic motivation funnel chart

which represent the distribution of effect sizes and their corresponding sample sizes, enabling the identification of any asymmetry that may indicate bias (Sterne & Egger, 2001). Second, we used the Fail-Safe N method, which estimates the number of unpublished studies with null results that would be necessary to negate the

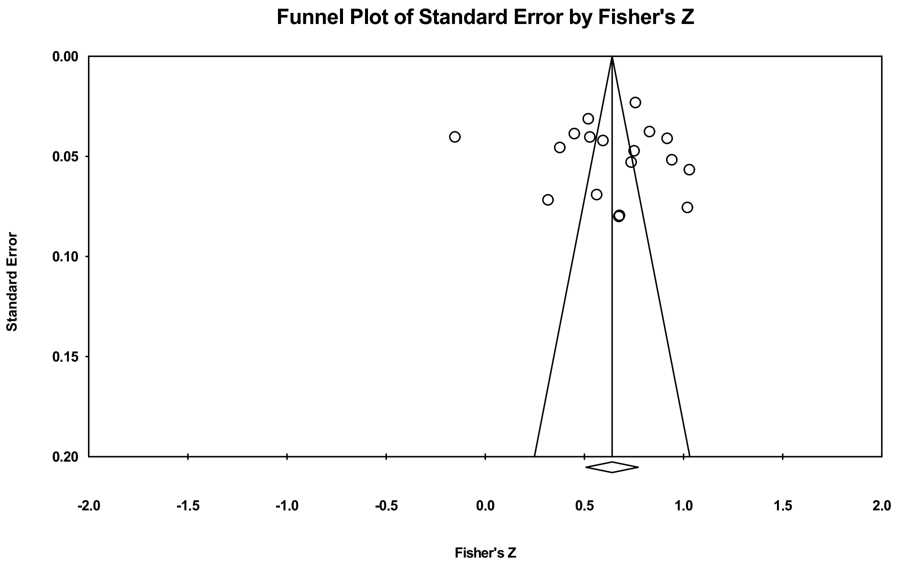

Fig. 8 Price value funnel chart

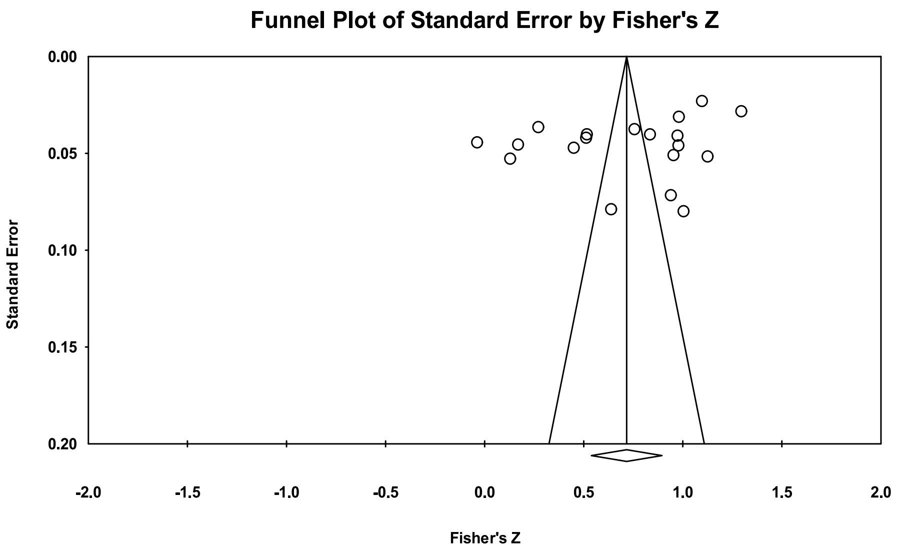

Fig. 9 Habit funnel chart

statistical significance of the meta-analytic effect size (Becker, 2005; Rosenthal, 1979). According to Thornton and Lee (2000), a high Fail-Safe N value indicates robustness against publication bias. The Fail-Safe N values are presented in Table 2, which all exceeded the commonly accepted threshold of 5 $k+10$, suggesting that inclusion of unpublished studies with null results would not alter the meta-analysis findings substantially (Rothstein, 2008).

Table 2 Publication bias test analysis results

variable	k	N	the fail-safe N
Performance Expectation	76	33048	213740
Effort Expectation	77	34475	181446
Social Influence	77	32970	160166
Facilitating Conditions	83	34935	222231
Hedonic Motivation	38	17063	63494
Price Value	18	9551	15754
Habit	19	11531	28644

k number of studies, *N* the total sample size of the *k* studies

4.4 Assessment of the overall effect

The overall impact was assessed using a random-effects model, and the results are presented in Table 3. We interpreted the correlation coefficient r following Cohen's (2013) guideline: .00 to .09 indicates no correlation, .10 to .29 suggests a weak correlation, .30 to .49 represents a moderate correlation, and .50 to 1.00 denotes a strong correlation (Cohen, 2013). As shown in Table 3, the following antecedents exhibited strong correlations with BI: Habit (r = .615), Hedonic Motivation (r = .572), Price Value (r = .565), Performance Expectation (r = .527), and Facilitating Conditions (r = .503). Effort Expectation (r = .482) and Social Influence (r = .466) showed moderate correlations with BI.

4.5 Analysis of the moderating effects

The analysis of moderating effects examined how various moderators (i.e., gender, user type, region, cultural orientation, and income level) influence the relationship between the antecedents of the UTAUT2 model and the BI towards using e-learning.

Table 3 Overall effect of the antecedents

variable	k	N	coefficient and 95% interval			z	*p*
			r	lower limit	upper limit		
PE	76	33048	.527	.472	.577	15.878	***
EE	77	34475	.482	.412	.546	11.728	***
SI	77	32970	.466	.404	.524	12.854	***
FC	83	34935	.503	.450	.553	15.657	***
HM	38	17063	.572	.511	.628	14.606	***
PV	18	9551	.565	.468	.648	9.509	***
HA	19	11531	.615	.492	.714	7.873	***

PE Performance Expectation, *EF* Effort Expectation, *SI* Social Influence, *FC* Facilitating Conditions, *HM* Hedonic Motivation, *PV* Price Value, *HA* Habit, *k* number of studies, *N* total sample size of the *k* studies

***p < .001

4.5.1 Gender as a moderator

Gender significantly moderated the relationships between Effort Expectancy, Price Value, and BI towards using e-learning (Table 4). The positive correlation between the proportion of males and Effort Expectancy suggests that platform usability had a stronger influence on males' BI. Conversely, the interaction between the proportion of males and Price Value showed a negative correlation.

4.5.2 User type as a moderator

User type primarily moderated the relationship between Habit and BI towards using e-learning (Table 5). This suggests that habitual use of e-learning platforms impacts various user groups differently.

4.5.3 Region as a moderator

Region significantly moderated the relations between most antecedents and BI towards using e-learning, except for Hedonic Motivation (Table 6). This suggests that the influence of these factors on e-learning adoption varies across different geographical areas, potentially due to differences in technological infrastructure, educational policies, or cultural norms.

4.5.4 Cultural orientation as a moderator

Cultural orientation significantly moderated the relationship between Hedonic Motivation and BI towards using e-learning (Table 7), suggesting that cultural factors play a role in how pleasure or enjoyment may shape an individual's decision to adopt e-learning systems.

Table 4 Gender as a moderator

variable	k	coefficient and 95% interval			z	*p*
		β	lower limit	upper limit		
Performance Expectation	71	.0012	−.0036	.0006	.50	.619
Effort Expectation	72	.0087	.0028	.0146	2.90	**
Social Influence	71	.0018	−.0034	.0071	.68	.497
Facilitating Conditions	77	.0009	−.0039	.0057	.36	.716
Hedonic Motivation	38	.0025	−.0033	.0083	.84	.402
Price Value	17	−.0104	−.0203	−.0005	−2.05	*
Habit	19	.0022	−.0173	.0218	.22	.825

K number of studies

$^{**}p<.01$, $^{*}p<.05$

Table 5 User type as a moderator

variable	user type	k	coefficient and 95% interval			test of null (2-tail)		Q_B	df	*p*
			r	lower limit	upper limit	z	*p*			
Performance Expectation	Stud	62	.510	.450	.565	14.168	.000	1.115	2	.573
	Fac	11	.600	.421	.734	5.559	.000			
	Stud. & Fac	3	.584	.136	.834	2.465	.014			
Effort Expectation	Stud	63	.469	.390	.541	10.234	.000	.662	2	.718
	Fac	11	.518	.334	.664	4.969	.000			
	Stud. & Fac	3	.603	.146	.848	2.484	.013			
Social Influence	Stud	61	.457	.384	.524	10.903	.000	.447	2	.800
	Fac	12	.494	.407	.571	9.765	.000			
	Stud. & Fac	3	.464	−.063	.789	1.741	.082			
Facilitating Conditions	Stud	68	.501	.441	.556	14.105	.000	.366	2	.833
	Fac	12	.493	.333	.626	5.457	.000			
	Stud. & Fac	3	.594	.241	.809	3.057	.002			
Hedonic Motivation	Stud	35	.560	.494	.619	13.714	.000	1.12	1	.290
	Fac	3	.703	.411	.864	3.926	.000			
	Stud. & Fac									
Price Value	Stud	16	.559	.451	.650	8.561	.000	1.454	1	.228
	Fac	2	.624	.573	.671	18.009	.000			
	Stud. & Fac									
Habit	Stud	18	.624	.498	.724	7.775	.000	7.075	1	**
	Fac	1	.423	.344	.496	9.542	.000			

k number of studies, *Stud.* university students, *Fac.* university faculty members, *Stud. & Fac.* both university students and faculty members

**$p < .01$

4.5.5 Income level as a moderator

Income level significantly moderated the relationships between Effort Expectancy, Social Influence, Hedonic Motivation, and Habit and BI towards using e-learning (Table 8). These results highlight the impact of economic conditions on how these antecedents may influence users' BI, emphasizing the need to consider economic disparities in the development of e-learning strategies.

5 Discussion

5.1 Influencing antecedents and intensity

The results of this study identified the main antecedents influencing the BI towards using e-learning. Habit ($r = .615$) emerged as the most influential factor, followed closely by Hedonic Motivation ($r = .572$), Price Value ($r = .565$), Performance Expectation ($r = .527$), and Facilitating Conditions ($r = .503$). Additionally, Effort Expectation ($r = .482$) and Social Influence ($r = .466$) were significant antecedents.

The primacy of Habit aligns with several prior studies. Zacharis and Nikolopoulou (2022) found that Habit was the strongest predictor of university students' BI to use e-learning platforms, noting that frequent use led to stronger automaticity in adopting these platforms for academic purposes. This finding was consistent with both pre-pandemic studies (El-Masri & Tarhini, 2017; Tarhini et al., 2017b) and pandemic-era research by Raman and Thannimalai (2021). The consistent evidence suggests that when users develop stable usage patterns through repeated interactions with e-learning systems, they are more likely to continue using them (El-Masri & Tarhini, 2017; Voicu & Muntean, 2023).

Hedonic motivation's strong influence aligns with Csikszentmihalyi's flow theory (1988), emphasizing enjoyment's role in sustained participation. For insance, Udeozor et al. (2023) found that Hedonic Motivation had the strongest positive influence on BI, explaining 52.9% of the variance in students' BI to use digital games for learning. Similarly, Tandon et al. (2022) and Kosiba et al. (2022) also found that Hedonic Motivation significantly influenced BI to use e-learning. These finding suggests that e-learning designers should incorporate interactive and gamification elements to enhance user engagement (Dichev & Dicheva, 2017; Saleem et al., 2022).

Price Value emerged as the third strongest predictor of BI. This construct was often conceptualized as "learning value" or "perceived value" in the e-learning context, rather than purely monetary considerations (Ain et al., 2016; Mehta et al., 2019). During the pandemic, several studies consistently found that learning value significantly influenced students' BI to use e-learning (Kosiba et al., 2022; Prasetyo et al., 2021; Zacharis & Nikolopoulou, 2022), suggesting that when students perceived that the value derived from e-learning outweighed the costs and effort invested, they were more likely to use these platforms. However, non-significant relationships between Price Value and BI were also reported (El-Masri & Tarhini, 2017; Tandon et al., 2022; Tarhini et al., 2017b; Terblanche et al., 2023). These inconsistent results see to indicated that the importance of Price Value vary across different contexts and user groups.

Table 6 Region as a moderator

variable	region	k	coefficient and 95% interval			test of null (2-tail)		Q_B	df	*p*
			r	lower limit	upper limit	z	*p*			
Performance Expectation	AF	11	.572	.443	.678	7.278	.000	18.785	5	**
	AP	35	.447	.370	.519	10.107	.000			
	EU	9	.511	.301	.673	4.372	.000			
	ME	18	.642	.534	.729	9.037	.000			
	NA	1	.372	.292	.447	8.489	.000			
	SA									
Effort Expectation	AF	12	.588	.508	.658	11.557	.000	228.232	6	***
	AP	36	.414	.290	.524	6.094	.000			
	EU	7	.302	.068	.506	2.503	.135			
	ME	18	.587	.470	.684	8.082	.014			
	NA	1	.280	.195	.361	6.250	.000			
	SA	1	.762	.738	.784	35.162	.000			
Social Influence	AF	11	.554	.435	.654	7.711	.000	383.003	5	***
	AP	38	.461	.369	.544	8.777	.000			
	EU	7	.397	.158	.593	3.155	.002			
	ME	17	.432	.297	.550	5.802	.000			
	NA	1	.159	.070	.245	3.484	.000			
	SA	1	.811	.791	.829	39.693	.000			
Facilitating Conditions	AF	12	.530	.377	.656	5.955	.000	204.715	5	***
	AP	40	.512	.444	.574	12.577	.000			
	EU	9	.335	.144	.502	3.357	.001			
	ME	19	.546	.445	.634	8.927	.000			
	NA	1	.351	.270	.427	7.964	.000			
	SA	1	.774	.751	.795	36.190	.000			

Table 6 (continued)

variable	region	k	coefficient and 95% interval			test of null (2-tail)		Q_B	df	*p*
			r	lower limit	upper limit	z	*p*			
Hedonic Motivation	AF	7	.663	.588	.726	12.7	.000	5.798	3	.122
	AP	19	.532	.437	.616	9.283	.000			
	EU	7	.542	.375	.676	5.578	.000			
	ME	4	.606	.294	.802	3.443	.001			
	NA									
	SA									
Price Value	AF	6	.384	.146	.58	3.079	.002	31.979	3	***
	AP	10	.609	.532	.677	12.001	.000			
	EU	1	.774	.725	.815	18.168	.000			
	ME	1	.770	.702	.824	13.498	.000			
	NA									
	SA									
Habit	AF	5	.704	.586	.793	8.411	.000	47.345	3	***
	AP	10	.517	.315	.675	4.548	.000			
	EU	2	.555	−.067	.866	1.769	.077			
	ME									
	NA									
	SA	1	.861	.846	.875	45.568	.000			

k number of studies, *AP* Asia & Pacific, *ME* Middle East, *EU* Europe, *AF* Africa, *NA* North America, *SA* South/Latin America

***$p< .001$, **$p< .01$

Table 7 Cultural orientation as a moderator

variable	cultural orientation	k	coefficient and 95% interval			test of null (2-tail)		Q_B	df	*p*
			r	lower limit	upper limit	z	*p*			
Performance Expectation	Col	63	.521	.462	.575	14.565	.000	.705	1	.401
	Ind	4	.654	.301	.850	3.248	.001			
Effort Expectation	Col	63	.487	.409	.558	10.705	.000	.004	1	.952
	Ind	4	.481	.259	.654	3.971	.000			
Social Influence	Col	66	.472	.406	.534	12.239	.000	.042	1	.838
	Ind	4	.502	.182	.726	2.941	.003			
Facilitating Conditions	Col	70	.504	.450	.555	15.568	.000	.075	1	.785
	Ind	4	.480	.294	.631	4.654	.000			
Hedonic Motivation	Col	32	.579	.511	.640	13.334	.000	13.100	1	***
	Ind	1	.732	.676	.780	16.454	.000			

k number of studies, *Col.* Collectivism, *Ind.* Individualism

***$p < .001$

Table 8 Income level as a moderator

variable	income	k	coefficient and 95% interval			test of null (2-tail)		Q_B	df	*p*
			r	lower limit	upper limit	z	*p*			
Performance Expectation	H	26	.554	.451	.643	8.827	.000	5.284	3	.152
	UM	20	.475	.331	.598	5.852	.000			
	LM	24	.542	.471	.606	12.398	.000			
	L	1	.128	−.300	.513	.576	.565			
Effort Expectation	H	25	.446	.340	.541	7.483	.000	12.483	3	**
	UM	22	.466	.277	.620	4.484	.000			
	LM	25	.541	.446	.624	9.451	.000			
	L	1	−.196	−.563	.235	−.888	.375			
Social Influence	H	23	.438	.342	.525	8.139	.000	27.565	3	***
	UM	23	.458	.302	.591	5.277	.000			
	LM	25	.527	.443	.602	10.462	.000			
	L	1	−.549	−.784	−.177	−2.759	.006			
Facilitating Conditions	H	25	.452	.350	.544	7.839	.000	1.983	3	.576
	UM	24	.518	.404	.616	7.744	.000			
	LM	28	.536	.462	.603	11.920	.000			
	L	1	.501	.112	.757	2.463	.014			
Hedonic Motivation	H	10	.622	.500	.719	8.010	.000	14.000	3	**
	UM	10	.603	.498	.690	9.041	.000			
	LM	14	.546	.414	.655	6.996	.000			
	L	1	−.147	−.527	.282	−.662	.508			
Price Value	H	3	.692	.591	.772	9.629	.000	4.868	2	.088
	UM	6	.57	.465	.658	8.865	.000			
	LM	9	.515	.340	.656	5.186	.000			
	L									

Table 8 (continued)

variable	income	k	coefficient and 95% interval			test of null (2-tail)		Q_B	df	*p*
			r	lower limit	upper limit	z	*p*			
Habit	H	4	.629	.383	.792	4.307	.000	6.154	2	*
	UM	7	.739	.626	.822	8.679	.000			
	LM	8	.466	.221	.655	3.529	.000			
	L									

k number of studies, *H* High, *UM* Upper middle, *LM* Lower middle, *L* Low

***$p < .001$, **$p < .01$; *$p < .05$

The significant influence of Performance Expectation aligns with many existing studies included in our analysis (Esawe et al., 2023; Zacharis & Nikolopoulou, 2022; Zulfakar et al., 2022), exhibiting a consistent pattern across different cultural contexts and educational settings (Ahmed et al., 2022; Jang et al., 2021). For instance, Alshammari (2021) found that Performance Expectation substantially predicted BI (β=.473) in the context of virtual classrooms, suggesting that when users believe that e-learning will enhance their academic performance, they are more likely to adopt these systems.

The strong effect of Facilitating Conditions underscores the critical importance of technical and organizational support in e-learning adoption. During the pandemic, multiple studies demonstrated that adequate technical infrastructure and support significantly influenced BI to use e-learning systems (Abdekhoda et al., 2022; Hermita et al., 2023; Reyes-Mercado et al., 2022). For example, Abdekhoda et al.'s (2022) survey of Iranian faculty members revealed that Facilitating Conditions had a significant positive effect on technology adoption (β=.423). Similarly, Terblanche et al.'s (2023) research among South African university students demonstrated that Facilitating Conditions positively influenced BI (β=.096), highlighting the consistent importance of technical support across different educational contexts for both faculty and student population.

Effort Expectation showed a moderate but significant influence on BI as well, corroborating previous research. This finding suggested that the perceived ease of use becomes less critical as users gain experience with the technology (Venkatesh & Bala, 2008). For instance, studies by Abdekhoda et al. (2022) and Zhou et al. (2022) reported that significant positive relationships between Effort Expectation and BI during the pandemic (β=.464 and β=.204 respectively), indicating that user-friendly interfaces and easy-to-navigate platforms remain important factors in e-learning adoption.

Social Influence demonstrated interesting cultural patterns in its effects on BI. Studies in collectivist societies like Raza et al.'s (2021) research in Pakistan showed stronger effects (β=.321), while studies in more individualistic contexts like Antoniadis et al.'s (2022) research in Greece revealed weaker relationships (β=.139). This finding echoes El-Masri and Tarhini's (2017) cross-cultural comparative study, which found that Qatar, with its stronger collectivist culture, was more susceptible to social group influences in e-learning adoption and acceptance compared to the more individualistic United States.

5.2 Moderating effects

The examination of moderating effects revealed that gender, user type, region, cultural orientation, and income level explains some of the heterogeneity of the relations between various antecedents and users' BIs in previous studies.

While some studies suggested no significant gender differences in BI towards using e-learning (Coelho & Menon, 2024; Cuadrado-García et al., 2010), our meta-analysis shows that gender moderates the relations between two antecedents (i.e., Effort Expectation and Price Value) and BI towards using e-learning. Specifically, we observed a significant positive correlation between the proportion of males and effort expectancy, suggesting that the ease of use of the platform has a greater impact on males' BI towards using e-learning. However, this finding contrasts with some previous studies. For instance, Ong and Lai (2006) found that female users place more emphasis on the ease of use of e-learning systems, while male users are more influenced by their perceived usefulness. This discrepancy highlights the complexity of gender effects in e-learning adoption and suggests that these relationships may have evolved over time or may be context-dependent. These findings underscore the importance of considering gender differences in e-learning platform design, potentially necessitating different interface or feature emphases for users of different genders, while also recognizing that these differences may not be universal across all contexts.

The moderating effect of user type revealed non-significant variations for most antecedents on BI towards using e-learning. A notable exception was Habit, which exhibited a stronger influence on the student group than on the teacher group. This finding may reflect that in practical applications, students are more likely to develop habits of using specific e-learning platforms, while teachers may need more time to adapt and integrate new learning technologies into their daily teaching practices. For example, students might log into the learning management system daily to check assignments and course materials, thereby forming usage habits, whereas teachers might tend to use the system intermittently based on course requirements. This finding underscores the importance of considering the distinct habits and preferences of different user groups, alongside their adaptability to novel technologies in the design of e-learning platforms (Meet et al., 2022).

Region significantly moderates the relations between a number of antecedents (i.e., Performance Expectation, Effort Expectation, Social Influence, Facilitating Conditions, Price Value, and Babit) and users' BI towards using e-learning. For instance, Alzaidi and Shehawy (2022) compared students from Saudi Arabia, Egypt, and the UK, reporting that cultural differences influenced students' acceptance of e-learning systems. This suggests that when aiming to improve e-learning adoption for users in a specific region, e-learning providers may need to consider using different strategies.

The individualism versus collectivism culture has a significant moderating effect on the relations between Hedonic Motivation and BI, indicating that the pleasure or enjoyment derived from using e-learning systems has a stronger influence on BI in individualistic cultures compared to collectivistic ones. This difference likely stems from the emphasis on personal satisfaction and achievement in individualistic cultures, leading individuals to prioritize the intrinsic fulfillment and personal interest offered by e-learning (Tarhini et al., 2017a). However, the limited number of studies from individualistic cultures in our sample calls for cautious interpretation and further investigation.

Lastly, income level demonstrated significant moderating effects on several UTAUT2 constructs, including Effort Expectancy, Social Influence, Hedonic Motivation, and Habit. Notably, the relationship between Effort Expectancy and BI was strongest in lower-middle income countries ($r = .541$), while Hedonic Motivation showed the strongest effect in high-income countries ($r = .622$). These findings echo the work of El-Masri and Tarhini (2017), who found that factors influencing e-learning adoption varied between developed and developing countries. Our results suggest that in lower-income contexts, practical considerations like ease of use may be more critical, while in higher-income settings, factors such as enjoyment, plays a more important role. However, the limited or absent data from low-income countries for most constructs highlights a significant gap in the existing research, calling for more studies in these contexts to fully understand e-learning adoption across diverse economic settings.

5.3 Applicability and generalizability of findings in post-pandemic "normal" situations

While this study focused on e-learning adoption during the COVID-19 pandemic, many of the findings may have applicability and generalizability in post-pandemic "normal" situations. Several key factors identified in this study are likely to have long-term relevance. The importance of habit and Hedonic Motivation as major influencing factors is likely to persist, as fostering positive e-learning habits and providing enjoyable learning experiences remain crucial even in regular educational environments (Deng et al., 2023; Ermilinda et al., 2024). Similarly, the impact of performance expectancy and Facilitating Conditions may remain stable, as users will always expect e-learning to enhance their learning effectiveness and require appropriate support (Rusman et al., 2024). The moderating effects of cultural orientation and income levels are also likely to continue, as these are deep-seated socioeconomic factors unlikely to change with the end of the pandemic.

However, some findings may need reassessment in the post-pandemic context. The importance of Price Value may shift, as e-learning may no longer be seen as a necessary alternative but as one of many options. The role of Social Influence might diminish in non-mandatory e-learning environments (Ermilinda et al., 2024), while the impact of effort expectancy might increase as users become more concerned with system usability when there are more options available (Miah et al., 2023).

Certain areas require further investigation. The moderating effects of gender and user type (students vs. faculty) may need reassessment in non-emergency situations to understand if these differences persist. The impact of regional differences might also need reexamination once global education systems return to normal, to determine if there are enduring region-specific patterns.

In the post-pandemic era, new factors may emerge that influence e-learning adoption. Blended learning models may become more prevalent, potentially introducing new influencing factors such as the degree of integration between face-to-face and online learning (Nikolopoulou & Zacharis, 2023). Emerging AI technologies, particularly large language models like ChatGPT, are revolutionizing e-learning by offering personalized, interactive experiences, potentially reshaping users' expectations and willingness to adopt these enhanced learning platforms (Halachev, 2024).

From a methodological perspective, the meta-analytic approach used in this study provides a robust framework that could be replicated in future "normal" situations to track the evolution of e-learning adoption factors. Longitudinal studies may become crucial tools for assessing how these factors transition from the pandemic period to the post-pandemic era.

It's important to note that the unprecedented nature of the pandemic may have accelerated certain trends in e-learning adoption that might have taken years to develop otherwise. As such, some of our findings may represent a 'new normal' rather than a temporary shift. Future research should focus on distinguishing between pandemic-induced changes that revert and those that become permanent fixtures in the educational technology landscape.

Overall, while the findings of this study stem from a pandemic context, many core insights are likely to have enduring relevance. However, educators and policymakers should recognize that the role and perception of e-learning may evolve as circumstances change. Therefore, ongoing monitoring and research into how these factors influence e-learning adoption in different contexts is crucial to ensure that e-learning strategies can effectively adapt to the changing educational landscape.

6 Conclusion

This meta-analysis examined the relations between the antecedents in the UTAUT2 model and the BI towards using e-learning among university students and faculties during the COVID-19 pandemic. Its results have some practical implications for e-learning providers and higher education institutions in order to foster e-learning adoption among users in higher education.

We found that habit, Hedonic Motivation, Price Value, Performance Expectation, and Facilitating Conditions are identified as highly influential antecedents on e-learning BI in higher education during emergent online learning and teaching in the pandemic. The strong correlation of these antecedents indicates e-learning providers should target one or more of these antecedents in order to enhance university users' BI towards using e-learning.

Furthermore, considering the moderating role of gender, user type, location, culture, and income level on users' BI towards using e-learning, the e-learning providers should take these multifaceted considerations into considerations when designing e-learning systems, platforms, and tools so that e-learning resources can be tailored to the distinct requirements of a diversity of groups. For instance, they may create the same platforms by using different contents to users from different cultural backgrounds. Or they may design e-learning platforms which have various levels of functionality by considering the income levels of the potential customers. Only in this way, more equitable access to e-learning resources can be achieved and the digital divide will be bridged and narrowed (Sims et al., 2008; Žmuk et al., 2023).

The study has several limitations and future directions. First, while this meta-analysis provides a comprehensive overview of e-learning adoption factors during the COVID-19 pandemic, it is limited by the timeframe and context of the included studies. Future research should examine how these factors evolve in post-pandemic settings where e-learning may be more of a choice than a necessity. Second, the study primarily focused on the UTAUT2 model; future studies could incorporate additional theoretical frameworks or emerging factors specific to e-learning contexts. Third, while the study identified several moderating variables, there may be other important moderators not captured in this analysis, such as specific institutional policies or national education systems. Future research could explore these potential moderators in more depth. Fourth, the quantitative nature of meta-analysis, while providing robust overall estimates, may not capture the nuanced contextual factors influencing e-learning adoption. Mixed-methods approaches in future studies could provide a more holistic understanding. Lastly, as technology rapidly evolves, particularly with the advancement of AI in education, future research should investigate how these new technologies impact the factors influencing e-learning adoption. Longitudinal studies tracking changes in adoption factors over time would also be valuable to understand the long-term trends in e-learning acceptance and use in higher education.

Appendix A

Table 9 Coded data

Study	N	country	% male	cult. orient	region	income	user type	PE-BI	EF-BI	SI-BI	FC-BI	HM-BI	PV-BI	HA-BI
Esawe et al., 2023	803	Egypt	47.8	Col	ME	LM	S	.732	.761	.653	.386			
Voicu & Muntean, 2023	474	Romania	34.6	Col	EU	H	S	.606				.673		.753
Udeozor et al., 2023	125	Europe	69.6		EU		S	.147	.11	.082	.201	.568		
Reyes-Mercado et al., 2023	587	Mexico Spain Malaysia	65.8		SA EU		S	.34	.16	.11	.09			
Terblanche et al., 2023	1864	South Africa	40.0	Col	AF	UM	S	.81	.72	.75	.65	.74	.64	.80
Zulfakar et al., 2022	209	Malaysia	30.6	Col	AP	UM	S	.396	-.203	.14	.33	.374		
Abdekhoda et al., 2022	143	Iran	49.0	Col	ME	LM	F	.679	.464	.262	.423			
Tandon et al., 2022	596	India	44.8	Col	AP	LM	S	.479	.674	.751	.556	.72	.725	.751
Raza et al., 2022	494	Pakistan	54.0	Col	AP	LM	S	.37	.606	.641	.471	.397		
Iftikhar et al., 2022	72	Spain	38.0	Ind	EU	H	S	.453	.592	.39	.528			
Zacharis & Nikolopoulou, 2022	314	Greece	10.8	Ind	EU	H	S	.729	.364	.679	.368	.732	.774	
Musa, 2022	376	Malaysia	48.8	Col	AP	UM	S	.707	.645	.666	.671	.753	.736	.81
Kaisara et al., 2022	415	Namibia	44.3	Col	AF	UM	S	.259	.608	.396	.091	.423		
Devisakti & Muftahu, 2022	411	Malaysia	48.4	Col	AP	UM	S	.35	.227	.176	.203			
Almogren, 2022	159	Saudi Arabia	30.2	Col	ME	H	F	.825	.802	.62	.761	.876		
Al-Rahmi et al., 2022	430	Malaysia	68.8	Col	AP	UM	S	.36	.39					
Osei et al., 2022	1024	Ghana	52.9	Col	AF	LM	S	.703	.699		.664	.728	.478	.754
Buabeng-Andoh, 2022	276	Ghana	83.0	Col	AF	LM	S	.43	.5	.48	.36	.67		
Antoniadis et al., 2022	471	Greece		Ind	EU	H	S	.864	.646	.665	.642			
Wut & Lee, 2022	113	Hong Kong	42.0	Col	AP	H	S	.222	.078	.328	.226			
Kosiba et al., 2022	616	Ghana	44.6	Col	AF	LM	S	.675	.636	.616	.641	.692	.484	.684

Table 9 (continued)

Study	N	country	% male	cult. orient	region	income	user type	PE-BI	EF-BI	SI-BI	FC-BI	HM-BI	PV-BI	HA-BI
Twum et al., 2022	617	Ghana	55.4	Col	AF	LM	S	.619	.599	.589	.538	.604	-.151	.476
Zhou et al., 2022	301	Zimbabwe	64.5		AF	LM	S	.306	.25	.31	.122			
Uchenna & Oluchukwu, 2022	358	Nigeria	50.8	Col	AF	LM	S	.209	.207	.255	.294			
Shaqrah & Almars, 2022	400	Taiwan	43.8	Col	AP	H	S	.064	.234	.452	.443			
Meet et al., 2022	483	India	49.7	Col	AP	LM	S	.174	.115	.075	.283	.192	.36	.169
Alotumi, 2022	23	Yemen	34.8		ME	L	S	.128	-.196	-.549	.501	-.147		
Zhang et al., 2022	287	Mainland China	29.2	Col	AP	UM	S			.738	.691			
Taghizadeh et al., 2022(a)	265	Oman	22.0		ME	H	S				.49	.61		
Taghizadeh et al., 2022(b)	214	Iran	38.0	Col	ME	LM	S				.67	.61		
Taghizadeh et al., 2022(c)	287	Bangladesh	55.0	Col	AP	LM	S				.69	.59		
Taghizadeh et al., 2022(d)	206	Romania	32.0	Col	EU	H	S				.59	.56		
Taghizadeh et al., 2022(e)	221	Malaysia	30.0	Col	AP	UM	S				.64	.64		
Tiwari et al., 2022	450	India	38.0	Col	AP	LM	F	.556	.409	.513	.469	.57	.636	.423
Goto & Munyai, 2022	197	South Africa	42.6	Col	AF	UM	S	.736	.744	.643	.506	.711	.307	.736
Shi-Hui et al., 2022	207	Malaysia	49.8	Col	AP	UM	S	.348	.406	.305	-.091			
Lutfi et al., 2022	428	Saudi Arabia	66.6	Col	ME	H	S	.45	.36	.41	.33			
Zou, 2022	438	Mainland China	56.0	Col	AP	UM	S	.633	.578	.588	.673	.654		
Zhang & Yu, 2022	1072	Mainland China	21.6	Col	AP	UM	S	.599	-.434	-.178	.674			
Wut et al., 2022	113	Hong Kong	42.0	Col	AP	H	S	.084	.168	.311	.312			
Abdullah et al., 2022	662	Pakistan	37.6	Col	AP	LM	S	.592	.555	.625	.569			
Batucan et al., 2022	880	Philippines	28.3	Col	AP	LM	S	.506	.445	.542	.575			
Xu et al., 2022	566	Mainland China	40.1	Col	AP	UM	S	.361	.38	.48	.428	.51	.533	.473
Tseng et al., 2022	161	Taiwan	63.5	Col	AP	H	F	.7	.36	.65	.57	.55	.59	

Table 9 (continued)

Study	N	country	% male	cult. orient	region	income	user type	PE-BI	EF-BI	SI-BI	FC-BI	HM-BI	PV-BI	HA-BI
Al-Adwan et al., 2022	590	Jordan	46.6	Col	ME	LM	S	.82	.83	.79	.63			
Humida et al., 2022	262	Bangladesh	71.8	Col	AP	LM	S				.714	.622		
Sakka, 2022	178	Jordan		Col	ME	LM	S	.617	.518	.542	.445		.770	
Mujalli et al., 2022	222	Saudi Arabia	41.9	Col	ME	H	S&F	.174	.173	.004	0.323			
Chang et al., 2022	707	Taiwan	53.0	Col	AP	H	S	.59	.4	.52	.56	.63	.68	.64
Malanga et al., 2022	1237	Brazil	34.0	Col	SA	UM	S		.762	.811	.774			.861
Kader et al., 2022	212	Malaysia	57.5	Col	AP	UM	S			.38	.6		.51	
Attuquayefio, 2022	671	Ghana	56.2	Col	AF	LM	S		.515	.667			.422	
Alghamdi, 2022	429	Saudi Arabia	35.3	Col	ME	H	S	.224	.287	.2	.218			
Smolinski et al., 2022	237	Poland	43.9	Col	EU	H	F	.386	.222	.469	.081			
Ng et al., 2022	270	Macao	40.0		AP	H	S	.558	.437	.513	.536			
Cao et al., 2022	569	United Arab Emirates	35.5	Col	ME	H	S	.77	.75		.76			
Bervell et al., 2022	163	Malaysia	18.4	Col	AP	UM	S		.13	-.085	.178	.299		.565
Ahmed et al., 2022	1875	Pakistan India South Korea Malaysia Bangladesh	47.8	Col	AP		S	.717	.671	.693	.725	.588		
Abbad, 2021	370	Jordan	41.6	Col	ME	LM	S	.63	.531	.285	.654			
Singh & Sharma, 2021	326	India		Col	AP	LM	S			.809	.857			
Alwahaishi, 2021	229	Saudi Arabia	59.8	Col	ME	H	S	.737	.322	.312	.52			
Alvi, 2021	305	India	84.3	Col	AP	LM	S	.687	.759	.499	.482			
Sitar-Taut & Mican, 2021	311	Europe	36.7		EU		S	.349			.252	.418		
Jang et al., 2021	386	South Korea Finland	43.8		AP EU	H	S	.769	.669			.607		.742
Abd Rahman et al., 2021	206	Malaysia		Col	AP	UM	F	-.268	-.041	.498	.175			
Sitar-Taut, 2021	311	Romania	36.7	Col	EU	H	S	.311	-.157	.179	.209	.515		

Table 9 (continued)

Study	N	country	% male	cult. orient	region	income	user type	PE-BI	EF-BI	SI-BI	FC-BI	HM-BI	PV-BI	HA-BI
Prasetyo et al., 2021	360	Philippines	26.7	Col	AP	LM	S	.427	-.067	-.134	.184	.123	.627	.130
Maican et al., 2021	748	Romania	30.9	Col	EU	H	S	.364	.197	.119	-.01	.217		.266
Sholikah et al., 2021	197	Indonesia	29.9	Col	AP	UM	S	.108	.199	.384	.35			
Raza et al., 2021	516	Pakistan	54.8	Col	AP	LM	S	.375	.558	.634	.41			
Rahman et al., 2021	300	Bangladesh	74.3	Col	AP	LM	S&F	.59	.624	.436	.538			
Yunus et al., 2021	169	Malaysia		Col	AP	UM	S	.787	.586	.347	.447			
Badwelan & Bahaddad, 2021	539	Saudi Arabia	53.6	Col	ME	H	S	.303	.46	.618				
Shameem & Sanjeetha, 2021	344	Sri Lanka	42.4	Col	AP	LM	S		.816	.652	.816			
Raman & Thannimalai, 2021	159	Malaysia	42.8	Col	AP	UM	S	.633	.615	.696	.629	.706	.588	0.764
Khalid et al., 2021	490	Thailand	41.0	Col	AP	UM	S	-.047	-.050	.202	.242			
Kaur et al., 2021	203	India	72.3	Col	AP	LM	S	.362		.548		.724		
Alshammari, 2021	235	Saudi Arabia	64.3	Col	ME	H	F	.75	.689	.482	.512			
Alowayr & Al-Azawei, 2021	246	Saudi Arabia	39.0	Col	ME	H	S	.663	.599	.505	.480			
Jere, 2020	132	South Africa	67.4	Col	AF	UM	F				.250			
Yudiatmaja et al., 2020	342	Indonesia	60.1	Col	AP	UM	F	.620	.250	.4	.670			
Qazi et al., 2020	508	Pakistan	51.4	Col	AP	LM	S	.377	-.085		.080	-.027		-.036
Kumar et al., 2020	35	Fiji	66.0	Col	AP	UM	F			.516				
Taamneh et al., 2022	226	United Arab Emirates Jordan	68.1	Col	ME		F	.862	.819	.389	.822			
Toh et al., 2023	215	Malaysia	34.7	Col	AP	UM	F	.502	.714	.735	.671			
Marandu et al., 2023	509	Botswana	40.5		AF	UM	S	.621	.643	.747	.91			

Table 9 (continued)

Study	N	country	% male	cult. orient	region	income	user type	PE-BI	EF-BI	SI-BI	FC-BI	HM-BI	PV-BI	HA-BI
Madani et al., 2023	58	Saudi Arabia		Col	ME	H	F	.413	.512	.135	-.052			
Li et al., 2022	237	Mainland China	75.9	Col	AP	UM	S	.162	.942	-.040				
Khechine et al., 2023	475	Canada	22.1	Ind	NA	H	S	.372	.280	.159	.351			
Edumadze et al., 2022	1527	Ghana	58.8	Col	AF	LM	S	.589	.687	.403	.707			
AL-Nuaimi et al., 2022	266	Oman	75.9		ME	H	S&F	.818	.829	.776	.806			

Col. Collectivism, *Ind.* Individualism, *AP* Asia & Pacific, *ME* Middle East, *EU* Europe, *AF* Africa, *NA* North America, *SA* South/Latin America, *H* High, *UM* Upper middle, *LM* Lower middle, *L* Low, *S* university students, *F* university faculties, *S&F* both university students and faculties, *PE* Performance Expectation, *EF* Effort Expectation, *SI* Social Influence, *FC* Facilitating Conditions, *HM* Hedonic Motivation, *PV* Price Value, *HA* Habit

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Declarations

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