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A Comprehensive Meta-Analysis of Blended Learning Adoption and Technological Acceptance in Higher Education

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Abstract: Numerous facets of life are impacted by the efficient application of technologies. Education, like all other fields, is a major area where technology is used to teach and learn effectively. One of these technologies that instructors and educators have recently become interested in is blended learning. This article aims at identifying the main constructs that highly influence the adoption of blended learning in higher education through meta-analytic literature review and proposing new technology acceptance model that is suitable for digital education tools. About 32 quantitative studies published since 2007 in journals and conferences are selected for performing weight computation and meta-analysis of constructs with a total sample size of 8,168. Moreover, the study also conceptualises the new technology acceptance model for digital education tools, considering both students and instructors as end users. The descriptive statistics indicate that there has been an increase in the number of publications since the year 2020. The results show that perceived ease of use, attitude toward usage, and perceived usefulness on intention to use are good predictors concerning student respondents, while performance expectancy on behavioural intention is found to be a good predictor concerning instructors. The results of the meta-analysis highlight the significance of blended learning in government and educational institutions that prioritises student ease of use and instructor performance expectancy and facilitating conditions. The results prove the effectiveness of blended learning in enhancing student learning experiences while improving educational practises and outcomes. In addition to identifying key factors influencing blended learning adoption in higher education, the study also suggests a novel model for implementing digital education tools, considering both student and instructor perspectives, thereby addressing a critical need in educational technology research. It offers actionable recommendations for policymakers and educational institutions to enhance the quality of higher learning.

Index Terms: Blended learning adoption, technology acceptance, higher education, meta-analysis, digital education technology acceptance model.

1. Introduction

Blended learning, an education model of the 21st century, is a teaching-learning strategy that combines conventional face-to-face classroom learning with online educational opportunities for student engagement [1]. As it blends several education strategies, it takes advantage of a wide range of learning methodologies. Blended learning is widely acknowledged by experts from all over the globe since it has qualities that make it a great chance to bring about a paradigm shift in higher education [2, 3]. Blended learning has many benefits because it combines traditional teaching with e-learning and virtual learning. These benefits include making learning more accessible, being flexible, saving money, and making learning more interesting [4].

Due to the COVID-19 pandemic, schools and institutions have lately decided to use hybrid teaching learning method with conventional and online learning tools to allow students to take distance learning courses [5, 6]. Many governments, including Jordan, devised a strategy for higher education institutions to use blended learning based on feedback and suggestions collected during the pandemic [7]. As a result, several universities and higher education institutions are developing strategic plans and implementing a variety of initiatives to adopt and expand the use of blended learning techniques [3]. Furthermore, technological advancements compelled higher education institutions [8] and executive education institutions [9] to incorporate digital technologies into their teaching and learning processes [10].

While some students prefer online learning over conventional methods, the majority of them are comfortable with mixed learning [11]. However, it is quite challenging for the instructors to integrate modern technology into the teaching and learning process. So, the institutions are preparing their faculties with appropriate training to maximise the benefits from investments in modern technologies [12].

Though several studies focus on learning management systems [13, 14], e-learning [15, 16], and online learning [7, 17], only a few studies have been directly involved in the adoption of blended learning [18]. Moreover, many of these studies mainly focus on individual case studies that assess the intention to continue the tools used in blended learning by developing their own conceptual framework, while a few other studies focus on qualitative analysis [19]. In the case of comprehensive analysis, few studies exist with a simple systematic review that lacks quantitative analysis to prove the conclusion [20, 21]. Thus, despite the increasing popularity of blended learning in higher education and the availability of suitable solutions, there is a lack of systematic quantitative review on the topic. This is due to the fact that the majority of studies that have been conducted in the past have focused on isolated case studies or qualitative analysis. This paper fills the research gap of quantitative review in adopting blended learning among students and instructors of higher education. The study seeks to answer the following research questions concerning the adoption of blended learning in higher education, including the identification of significant factors and their relationship:

- RQ1. What are the acceptance models, variables, data collection, and statistical methods utilised in the selected articles on blended learning adoption?
- RQ2. What are the learning systems, countries, and publication years of the selected articles on acceptance of blended learning adoption?
- RQ3. What are the significant regression and correlation relationships assessed in the prior studies on the acceptance of blended learning adoption?
- RQ4. What are the constructs that influence students and instructors towards accepting blended learning adoption?
- RQ5. What constructs should be tested for technology adoption for digital tools that assessments students and instructors?

Thus, the main objective of this meta-analytic review is to identify the most significant constructs from the existing studies using weight analysis [15, 22] and meta-analysis to summarise information from major quantitative papers on blended learning adoption in higher education. Also, the existing models for evaluating technology acceptance are not appropriate for the technology used in the field of education since the digital technology tools are used by two type of end users, students and instructors. Thus, the study also conceptualises the new technology acceptance model for digital education tools used in teaching and learning process by considering both students and instructors as end users. The various relationships that exist in the research models from 32 articles published between 2007 and 2022 were examined. Though the selected studies utilise several research models to analyse the acceptance of blended learning in higher education, most of them were built on top of the technology acceptance model (TAM) [23, 24] or the unified theory of acceptance and use of technology (UTAUT) [25, 26].

Thus, the main contributions of this research are: 1) to highlight the inclinations and patterns in existing theoretical models and relationships; 2) to make it easier for theoretical advancement by identifying the research gap for future research; and 3) to propose a new digital education technology acceptance model (DETAM) that considers both students and instructors as its end users. The study indented to identify the trends in the adoption of blended learning systems, explore the perceptions of students and instructors regarding the implementation of blended learning, identify the most significant factors and promising predictors influencing the use of technology, develop a specialized digital education technology acceptance model (DETAM), and provide the quantitative insights into the relationships among key factors. The results of this study are expected to address research gaps and facilitate efficient implementation in the field of higher education.

The paper is structured as follows: Section 2 discusses the works related to the proposed review. Section 3 discusses the study background with key concepts related to the research. Section 4 presents the research methodology, which covers the criteria for the selection of studies, quality assessment and the process of extracting data and merging variables. Section 5 describes the results obtained from the analysis in two subsections: descriptive statistics and meta-analysis. Section 6 discusses the findings from the study along with the proposed DETAM model, the theoretical implications, the practical implications and limitations of the study. The work is concluded in Section 7 with suggestions for future research.

2. Related Works

Several researchers have assessed the technology acceptance of blended learning environment, and their contributions and insight are relevant to the objective of the proposed study. The study conducted by Lake (2020) defines blended learning as a multifaceted approach encompassing various forms of learning material, such as text, audio, video, forums, online discussions, online quizzes and assignments, as well as e-mails [27]. Deng et al. (2022) presented a model for evaluating the factors influencing blended learning in colleges and universities, highlighting its infancy and challenges in its development. The authors claimed that though blended learning is adopted by enterprises for staff training, it has gained popularity and recognition in the field of education only after the epidemic situation [28]. A study explored the efficacy of digital technology in teaching and learning, emphasising its necessity for widespread adoption and effective utilization. The result revealed that COVID-19 mandates the use of virtual technology in education, regardless of whether or not the necessary information and communication technology (ICT) infrastructure and support are in place [26]. With the help of various stakeholders, blended learning is being implemented through the use of several new digital technologies and learning platforms, such as Moodle [29, 30], collaborative and analytical tools [31], digital educational tools [32], webinar and web learning systems [33, 34], hybrid learning systems [35], interactive learning environments [36], massive open online courses (MOOC) platforms [37, 38], remote emergency learning [39], tablet PCs [40], virtual learning systems [41], and WhatsApp technology [42] in the teaching-learning process. These technological advancements and learning platforms serve as the foundation for the implementation of blended learning.

Further, the research objectives are aligned with those of previous studies that have utilised acceptance models to analyse the ways in which students and instructors accept and utilise blended learning systems. Some of the notable acceptance models in the existing research include the technology acceptance model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to study how students or teachers reach for and make use of blended learning environments. The TAM model considers the variables perceived ease of use (the technology is easy to use) and perceived usefulness (the technology boosts job performance) as independent variables that influence the attitude and intention of use [24, 43, 44]. On the other hand, the UTAUT model considers the independent variables performance expectancy (technology will improve performance), effort expectancy (ease of use), social factors or influence (others' belief in utilising technology), and facilitating conditions (infrastructure and facilities to support the technology) that influence behavioural intention and use behaviour [45, 46, 47]. Various other models studied include UTAUT2 [9] and TAM with the theory of planned behaviour [48].

However, a few studies in the existing literature delve into the specific domain of blended learning adoption and technological acceptance in higher education. Anthony et al. (2022) conducted a review with 94 articles and examined the factors influencing students, lecturers, and administration in higher education. The study highlighted the notions and elements toward embracing blended learning in higher education [20]. The study assessed the various implementation strategies but failed to assess the acceptance of technology or propose a suitable theoretical model. Further, Bervell and Umar (2017) reviewed previous research on faculty and student acceptance and adoption intentions of Learning Management System (LMS) technology in Sub-Saharan Africa over a decade. The study emphasised the significance of information and communication technology (ICT) infrastructure and LMS usage and insisted that top-level administrators at universities should devote more resources to improving their institutions' ICT infrastructure, LMS usage skills and training, LMS quality-related issues, support, and ICT policy formulation [49]. The various challenges faced in implementing blended learning were recognised by Ma'arop and Embi (2016) and revealed the critical role of training, support, and networking for personnel in addressing challenges [50]. Al-Nuaimi and Al-Emran (2021) conducted a similar study to determine the most influential theoretical models and external factors influencing LMS acceptance in higher education and uncovered the fact that TAM, UTAUT, and UTAUT2 have been the most prominent theoretical frameworks in LMS studies [51]. Al-Maroof et al. (2021) conducted a systematic review to examine the most prevalent theoretical models and external factors influencing the adoption of LMSs in higher educational institutions from 2005 to 2020. According to their findings, the TAM is the most effective model for predicting users' propensity to embrace blended learning [52]. Krismadinata et al. (2020) conducted a meta-analytic literature assessment on the effectiveness of the blended learning paradigm and found that it incorporates both face-to-face and online instruction [53]. However, the study focused only on vocational education.

Although various previous studies have performed systematic literature surveys and examined the existing body of research on the adoption of blended learning, very few of these studies have attempted quantitative meta-analysis in this specific context. The research seeks to significantly advance the field by filling this substantial gap in the literature. The purpose of this quantitative meta-analysis is to derive strong conclusions on the prevalence of blended learning in higher education by synthesising and aggregating data from a number of different research. Therefore, the goal of this research is to provide a more extensive and evidence-based understanding of the factors influencing the adoption of blended learning.

3. Background of the Study

This section presents a brief introduction to the key concepts related to the study, establishing its significance and relevance.

3.1. Blended Learning

By definition, blended learning, also called hybrid learning, integrates both online study resources and possibilities for student engagement with more conventional classroom-based practices. This dynamic educational technique is sometimes called technology-mediated, web-enhanced, or mixed-mode instruction [54]. It necessitates the physical presence of both the instructor and student and combines in-person and virtual learning for a more flexible, interactive, and individualised education. It allows students to access course materials online, engage with classmates and instructors, and attend classes as needed, enabling in-person interactions and self-paced learning with interactive media such as games, videos, tutorials, quizzes, etc. [55]. This versatile tool helps innovate, improves outcomes, and increases accessibility in a continuously changing educational environment. Research on blended learning found that it combines physical and online instruction, leading to higher student achievement compared to fully online or face-to-face learning [56].

The blended learning paradigms are face-to-face driver, rotation, flexible, laboratories, self-blend, and online driver [57]. Traditional teaching methods are combined with digital tools, offering consultation and support, and students can supplement physical learning with online course work or complete entire courses. A blended learning strategy includes instructor-delivered content, e-learning, webinars, conference calls, live sessions, and media events including Facebook, email, chat rooms, blogs, podcasting, Twitter, YouTube, Skype, and web forums. Though it has several advantages, it also has some drawbacks [58]. Compared to traditional examinations, e-learning platforms may cost instructors more time and money. Further, many students lack internet access, making network infrastructure essential for blended learning initiatives.

3.2. Technology Acceptance Models

With an emphasis on human behaviour and decision-making, acceptance models are used in psychology, sociology, and technology adoption to evaluate the elements that affect people's acceptance of novel ideas, practises, or technologies [59]. Users' motivations for accepting or rejecting new technologies are studied using acceptance models that take into account elements including perceived usefulness, ease of use, attitudes, social influence, facilitating conditionsand behavioural intentions. These models are crucial for researchers, businesses, and policymakers to better understand and predict human behaviour in innovation and change. There are several theoretical frameworks for understanding how people accept and utilise technology, including the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM). The Technology Acceptance Model (TAM), an influential framework for understanding and predicting user acceptance and use of new information technologies, was developed by Davis in 1989 [23]. TAM suggests that users' intention to use a technology is influenced by perceived ease of use and perceived usefulness. Perceived ease of use refers to a user's perception of a technology's ease of use, while perceived usefulness is user belief that the technology will enhance their performance or productivity.

UTAUT, developed by Venkatesh et al. (2003), is a widely used model in technology adoption and acceptance, provides a thorough knowledge of decision-making elements [25]. It integrates and extends TAM and the Theory of Reasoned Action to understand user behaviour. The model identifies several key constructs that significantly influence technology adoption. These constructs include performance expectancy (user perceptions of how the technology may enhance job performance), effort expectancy (users' views on the technology's usability and effort required), social influence (the impact of peers, coworkers, and supervisors on technology adoption and use), facilitating conditions (users' belief that they have the resources and assistance to use the technology), intention to use (intentions and willingness to utilise the technology are precursors to actual use), and behavioural use (actual technology usage by individuals). UTAUT recognises that age, gender, experience, and voluntariness of usage can affect these constructs and technology adoption.

Extended from the original UTAUT model, UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) incorporates factors for hedonic motivation and price value [60]. In the context of advanced technologies and consumer applications, it provides a comprehensive understanding of technology adoption and usage behavior. Further, Information system continuity intention (ISCI) is a model that measures the degree to which users intend to continue or end their use of an information system over time. On the other hand, the Task-Technology Fit (TTF) analysis determines how well a technology meets the needs of its users. Research in this area examines the connection between TTF and ISCI, focusing on how system fit with users' tasks influences their intention to continue using it, enhancing system design and user satisfaction [33]. The Theory of Planned Behavior (TPB) is a psychological model to examine human behaviour by considering three key factors such as attitude, subjective norm, and perceived behavioural control [48]. According to TPB, these elements have a role in influencing a person's choice to act in a certain way. Further, Technological, Pedagogical, and Content Knowledge (TPACK) is a pedagogical approach that unites different forms of knowledge and skill in the classroom [67]. By integrating these three bodies of information (technology, pedagogy, and content knowledge), TPACK enables educators to more effectively plan and deliver instructions. It is essential for modern classrooms as it allows instructors to make better use of technology in the classroom.

In this research study, these models are widely used by the existing literature for which an analysis is carried out to evaluate the adoption of blended learning technologies in higher education.

4. Methods

This research makes use of a meta-analytic strategy to examine the existing literature. Every research study begins with articulating a research problem. Thus, the main objective of the current research is to examine the relationships between independent and dependent variables by using technological acceptance models to analyse the adoption of blended learning in higher education over the past 15 years. This time frame was chosen in order to analyse the influence of blended learning once it became more definite with the publication of the first Handbook of Blended Learning in the year 2006 [61] and grown into a prominent educational trend around the world. Consequently, the study looks at the wide range of variables that the authors of other related studies have pointed out. The research used multiple operationism, which compares and aggregates many measurements related to similar theoretical constricts across various studies [62]. So, the research methodology uses a number of variables and variations of certain variables found in individual research studies.

This chosen research methodology, a meta-analytic approach, plays a crucial role in achieving the research objectives for several reasons. It enables the synthesis of a large body of research, including several studies spanning the past 15 years, facilitating the discovery of patterns, trends, and important relationships often overlooked in individual studies. Furthermore, it enhances the reliability and generalizability of findings by pooling data from multiple sources to understand the influential factors, thereby minimising the impact of individual study limitations and improving the quality of the analysis. Thus, the proposed methodology achieves the research objective by providing comprehensive, reliable, and generalizable insights into factors influencing blended learning adoption in higher education.

The study aims to minimise biases and ensure robust and trustworthy findings on blended learning adoption and technological acceptance in higher education, adhering to rigorous procedures. The research utilises reputable electronic databases to thoroughly identify the broad range of relevant articles. It strictly follows standard data selection and inclusion criteria to ensure the reliability of its findings by filtering out potentially biassed or low-quality studies. To further ensure reliability, a quality assessment of selected articles is conducted, evaluating each against specific criteria and only including those meeting a predefined quality cutoff in the analysis. Statistical techniques are employed to analyse the data from selected studies and measure the strength of relationships between variables, and publication bias analysis is used to assess whether the likelihood of studies with statistically significant results being published has influenced the overall outcomes of a study. Finally, the peer-review process involves all authors critically assessing methodology, analysis, and interpretations to identify potential flaws and enhance the accuracy and reliability of conclusions. The specific steps of the technique are broken down into the following subsections for discussion.

4.1. Selection of Studies

To carry out the review process, study selection plays a significant role, for which the search terms are identified as an initial step. Electronic databases like Scopus, Web of Science, Google Scholar, Emerald, and Science Direct are searched for articles and publications that are relevant for the current research. The advanced search option that these databases offer is used in a structured way that combines different keywords with logical operators (AND/OR). The keywords for the search are structured in three parts using logical operators: 1) keywords referring to the context of the study, such as "blended learning" or "blended e-learning"; 2) keywords stating the technology acceptance model used in the studies, such as "acceptance of technology," "use of technology," and "technology acceptance"; and 3) keywords referring to the event of participation, such as "higher education," "higher education institutions," and "universities." The papers with these search phrases in the title, keywords, and abstract were originally chosen. Moreover, the articles written in English and published after 2006 are identified. Also, articles that use quantitative analysis, like regression or correlation analysis, are taken into consideration when selecting the articles for review.

The suggested research used PRISMA standards to conduct an open, systematic assessment of the literature that was evidence-based when examining the articles for selection [63]. Initially, 729 articles were extracted from the databases, and after removing the 272 duplicate publications extracted from more than one database, 457 articles were screened. Further, 115 publications are selected in the initial screening after removing 342 articles that are written in languages other than English, abstracts only, review articles, non-relevant topics, and non-quantitative analysis. In the exclusion step, 85 articles that are not relevant to the study, have irrelevant or missing statistics, or do not contain data of interest are eliminated, leaving 30 articles. Furthermore, the reference lists of the selected articles are reviewed in order to identify relevant articles, from which two are included in the study. With these studies, Lazar et al. (2020) utilised two different datasets with respondents from different countries [64], and Nadlifatin et al. (2020) utilised two different datasets with respondents from the same country [65]. Finally, 32 publications with 34 different datasets of respondents are included in the current study. Fig.1 describes the workflow and phases of the study selection.

4.2. Quality Assessment

Before extracting the quantitative data from the selected studies, a quality assessment has been made by the reviewers on the selected studies to ensure reliable results, findings, and outcomes. The quality checklist proposed by Kitchenham and Charters (2007) [65] was adopted for article quality evaluation with little modification as presented by Awladthani et al. (2023) [66] and shown in Table 1. Each quality criterion is scored on a three-point scale, with 1 representing "yes," 0 representing "no," and 0.5 representing "partial." For analysis, only the articles with scores greater than a cutoff of 5 are chosen, and apparently, all of the articles meet the standards for quality.

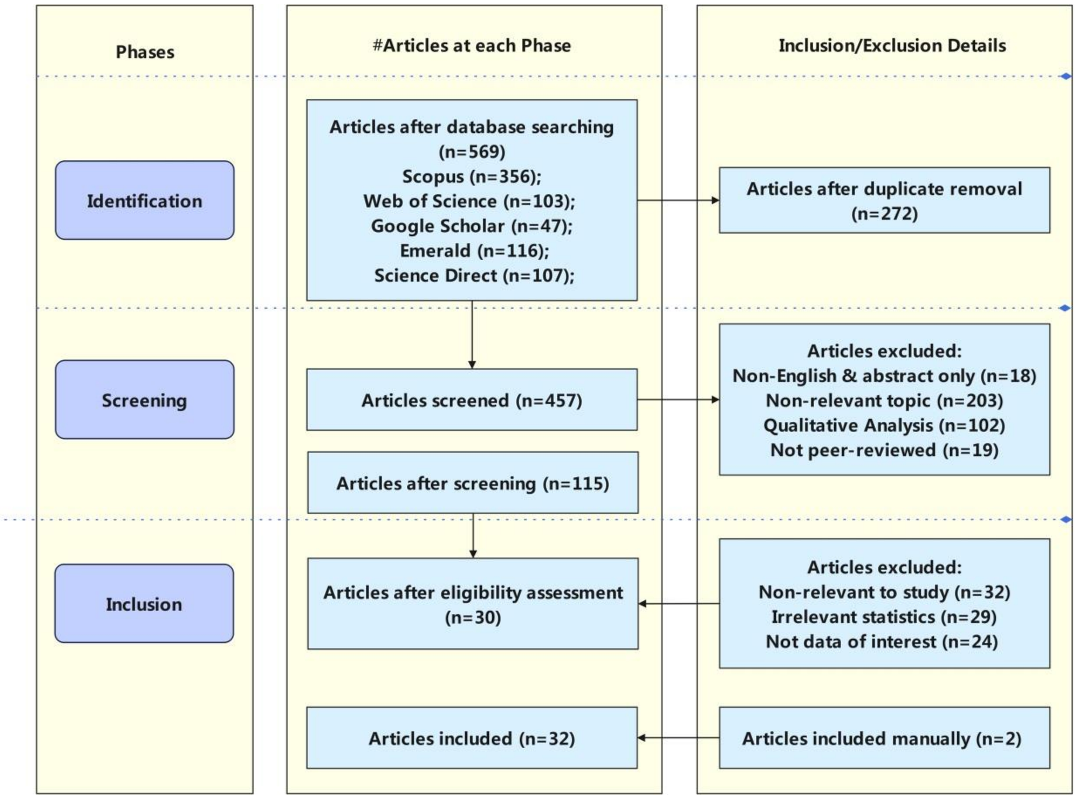


Fig.1. Overview of the study selection process (Source: Authors).

Table 1. Quality assessment criteria

No.	Quality Criteria for Selecting Articles
1	Is the research objective clearly stated?
2	Is the research aimed at achieving its goals?
3	Do the research findings adequately describe the research objective?
4	Has the research process been sufficiently documented?
5	Does the research study properly describe the data collection process?
6	Does the paper include details about the validity and dependability of the variables?
7	Are the findings and interpretations made clear?
8	Do the authors address the research's implications and limitations?

4.3. Data Extraction

Details such as the article title, year and source of publication, abstract, keywords, document type, type of learning technologies analysed, number of samples and country of origin, type of respondents, technology acceptance model used for the analysis, statistical methods used for quantitative analysis, independent and dependent variables, correlation coefficient, regression coefficient, and its significance are extracted for each selected article. Table 2 depicts the details of the selected literature.

Table 2. Details of the selected studies

Authors	Learning Technologies Analysed	Country/Region	Sample Size	Model Used
Zhou et al. (2022) [26]	Virtual Learning	Zimbabwe	301	UTAUT
Almutawa (2022) [30]	Blended Distance Learning (Moodle)	Kuwait	273	TAM/BLAM
Esawe et al. (2022) [35]	Hybrid Learning	Egypt	803	UTAUT
Anthony et al. (2021) [67]	Blended Learning	Malaysia	544	UTAUT/TPACK
Gunasinghe & Nanayakkara, (2021) [41]	Virtual Learning Environment	Sri Lanka	219	UTAUT
Lazar et al. (2020) [64]	Digital Educational Tool	Romania	572	TAM
Hina et al. (2020) [31]	Collaborative and Analytical Tools	Malaysia	139	TAM
Virani et al. (2020) [24]	Massive Open Online Courses	India	286	TAM
Razami & Ibrahim (2020) [68]	Massive Open Online Courses	Malaysia	111	TAM
Dakduk et al. (2018) [9]	Executive Education	Colombia	307	UTAUT2
Radovan & Kristl, (2017) [46]	Learning Management Systems/Virtual Classroom	Slovenia	326	UTAUT
Vogelsang et al. (2017) [10]	Digital Technologies	Germany	68	TAM
Pardamean et al. (2013) [44]	Graph Theory in LMS	Indonesia	97	TAM
Lin (2012) [33]	Web Learning Performance	The Taiwan Region	165	IS/TTF
Nadlifatin et al. (2020) [48]	Blended Learning System	The Taiwan Region	167	TAM/TPB
Nadlifatin et al. (2020) [48]	Blended Learning System	Indonesia	150	TAM/TPB
Al-Azawei et al. (2017) [69]	Blended E-learning Technology	Iraq	210	TAM
Olivier (2016) [36]	Interactive Learning Environment	South Africa	82	TAM
Alhramelah & Alshahrani, (2020) [70]	Blended Learning Course	Saudi Arabia	167	UTAUT
Chen et al., (2022) [38]	MOOC Platforms	China	461	TAM/SET
Al-Harazneh et al., (2022) [71]	Blended E-learning Technology	Jordan	411	UTAUT
Aldekheel et al., (2022) [40]	Tablet PC	Kuwait	206	UTAUT
Han (2022) [47]	Online Teaching Community of Practice	China	204	UTAUT
Bamoallem and Altarteer, (2022) [39]	Remote Emergency Learning	Saudi Arabia	115	UTAUT
Kaur et al., (2021) [42]	WhatsApp for Language Learners' Lexical Competence	India	203	UTAUT
Al Murshidi (2020) [72]	Blended & Online Learning Technologies English Language Learners	United Arab Emirates	251	TAM
Tulinayo et al., (2018) [32]	Digital Technologies	Uganda	241	TAM
Prasad et al., (2018) [73]	Blended Learning	Sydney	95	UTAUT
Yeou, (2016) [74]	Blended Learning - Moodle	Morocco	47	TAM
Sarkam, (2019) [75]	Blended Learning System	Malaysia	201	UATUT
Khechine et al., (2014) [34]	Elluminate (Webinar System)	Canada	144	UTAUT
Tran (2016) [76]	Blended E-learning Technology	Vietnam	396	TAM
Okocha et al., (2017) [77]	Blended Learning	Nigeria	206	UATUT
Note: TAM – Technology Acceptance Model; BLAM- Blended Learning Acceptance Model; TPB - Theory of Planned Behavior; SET - Self-Efficacy Theory, UTAUT - Unified Theory of Acceptance and Use of Technology; TPACK - Technological, Pedagogical and Content Knowledge; IS/TTF - Information System Continuance Intention and Task-Technology Fit				

In these studies, some of the different variables are likely to have similar meanings. Thus, the variables having similar meanings are merged for the purposes of performing a meta-analysis. Variables such as 'Use Behavior of LMS', and 'Usage Behaviour' are merged as 'Use Behavior'; 'Behavioral Intention of LMS', 'Behavioral Intention of VLE', 'Continuance Intention' are merged as 'Behavioural Intention'; 'Computer Anxiety' and 'Technology Anxiety' as 'Technology Anxiety'; 'Perceived Impacts on Learning' as 'Perceived Usefulness'; 'Attitude towards usage', 'Attitude towards use' as 'Attitude'; 'Behavioural Intention to Use', 'Use Intention' as 'Intention to Use'; 'Perceived Satisfaction', 'User Satisfaction' as 'Satisfaction'.

5. Results

5.1. Descriptive Statistics

Among the 32 selected studies, the majority of the articles are published in journals, with a count of 31, and one paper is published in conference proceedings. For analysing the acceptance of blended learning, 15 articles utilised the Technology Acceptance Model (TAM) model, and 16 articles utilised the Unified Theory of Acceptance and Use of Technology (UTAUT) model as a base, along with additional self-developed models and variables. Additionaly, Lin (2012) used the information system (IS) continuance theory with the task-technology fit (TTF) model as a research model [33]. Thus, after merging the variables, a total of 80 variables were found in these 32 studies. The various variables used in these selected literature studies are shown in Fig.2. The various blended learning systems were evaluated in the existing studies, which included blended distance learning, Moodle, e-learning systems, different learning courses, collaborative and analytical tools, digital educational tools, webinar systems, executive education, hybrid learning, interactive learning environments, MOOC platforms, online teaching communities of practice, remote emergency learning, tablet PCs, virtual learning, web learning performance, and WhatsApp technology. The distribution of these learning environments after grouping is presented in Fig.3. Moreover, most of the authors used structural equation modelling (SEM) for performing statistical analysis with correlation analysis (CA) [44], whereas two studies used multiple linear regression (MLR) [70]. The total number of individual respondents across 34 datasets is 8,168 from 24 countries around the world, of which 5,875 are students, 1,986 are instructors, and 307 are senior and middle-ranking managers. Among all countries, Malaysia (995), Egypt (803), and China (665) have more respondents, and Sydney (95), South Africa (82), Germany (68), and Morocco (47) have the least number of respondents. The country distribution of respondents is shown in Fig.4. The descriptive statistics of the selected literature studies are presented in Table 3.

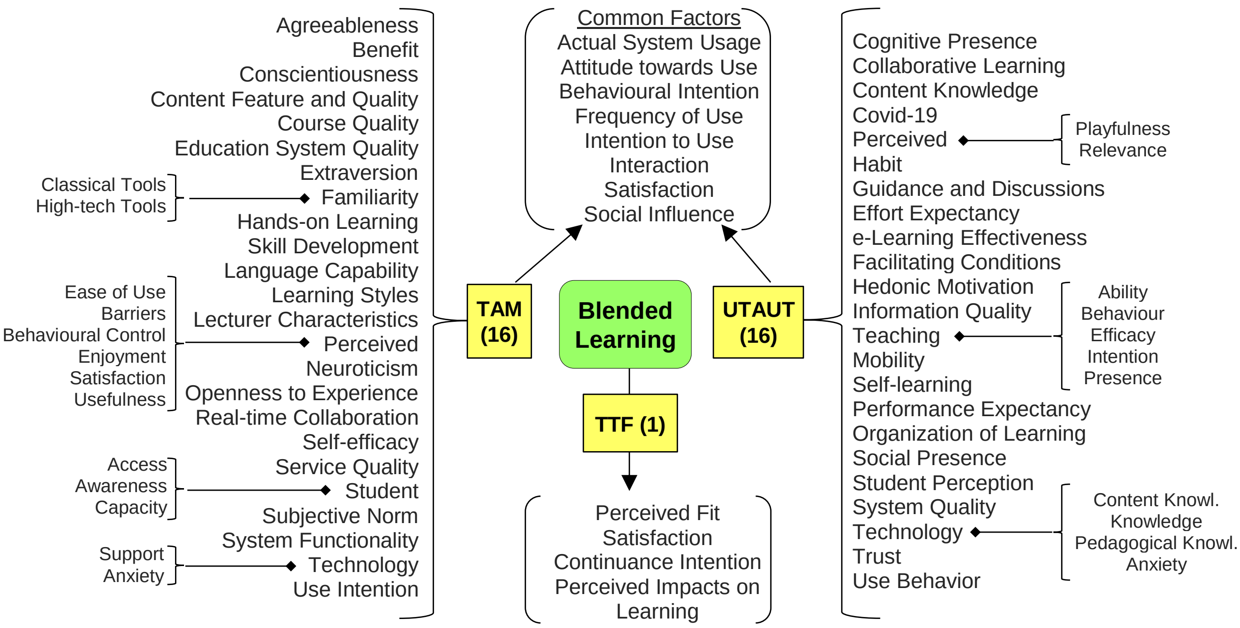


Fig.2. Variables used in the selected literature studies (Source: Authors).

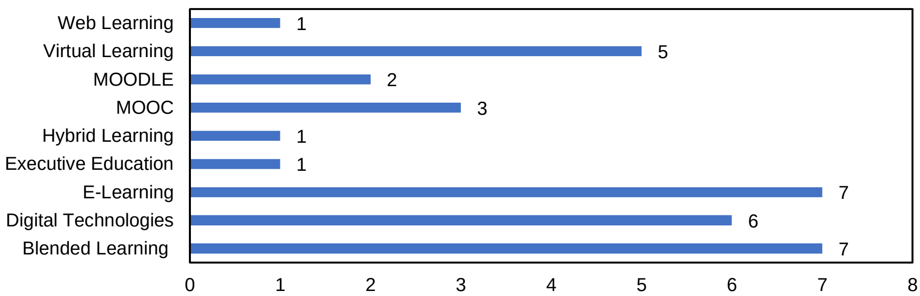


Fig.3. Various blended learning systems studied.

Table 3. Descriptive statistics

Model Used	Document Type	Statistical Methods	Respondents
TAM (15)	Article (31)	SEM (30)	Students (25)
UTAUT (16)	Conference (1)	MLR (1)	Instructors (7)
IS/TTF (1)		CA (1)	Senior Managers (1)

Though the study initially considered articles published between 2005 and 2022, no studies were found between 2005 and 2007 in an initial search. Moreover, after scrutinising the articles, the selected 32 articles range from 2012 to 2022. Though the use of the term 'blended learning' as formal terminology appeared in the late 1990s and became more concrete after 2006 [61], it has gained huge attention among educators and researchers during and after the COVID pandemic [26]. The distribution of the year of publication of selected literature is shown in Fig. 5.

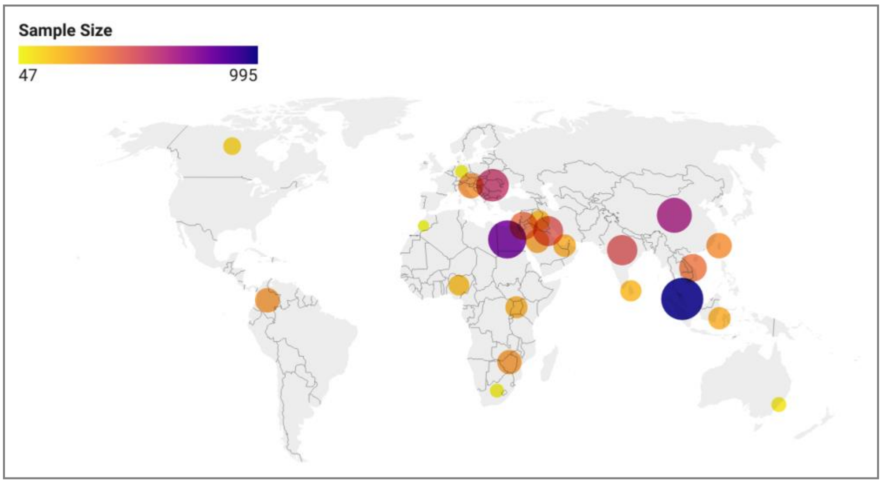


Fig.4. The country distribution of respondents.

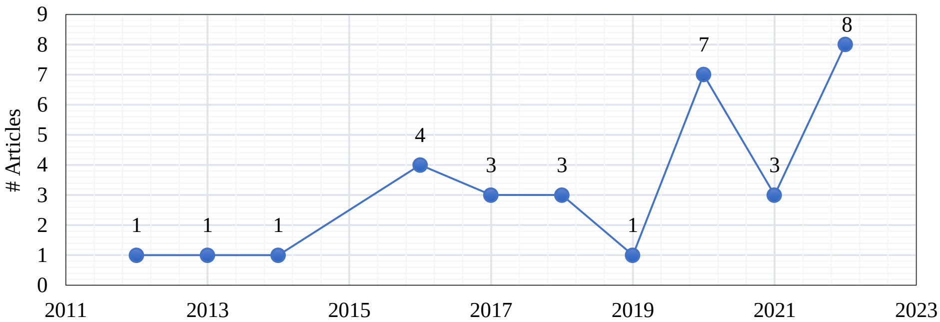


Fig.5. Distribution of year of publication.

The qualitative analysis is made for the titles of the selected articles, in which "blended learning," "acceptance," "technology acceptance model," "adoption," "higher education," "students," "theory of acceptance," "unified theory," and "learning management system" are the terms that have occurred frequently. The word cloud generated for the titles is shown in Fig.6. Moreover, the association of keywords among all 32 articles is also analysed using the VOSviewer tool, which indicates that blended learning is highly associated with UTAUT, teaching, e-learning, TAM, students, and learning systems, as shown in Fig.7.

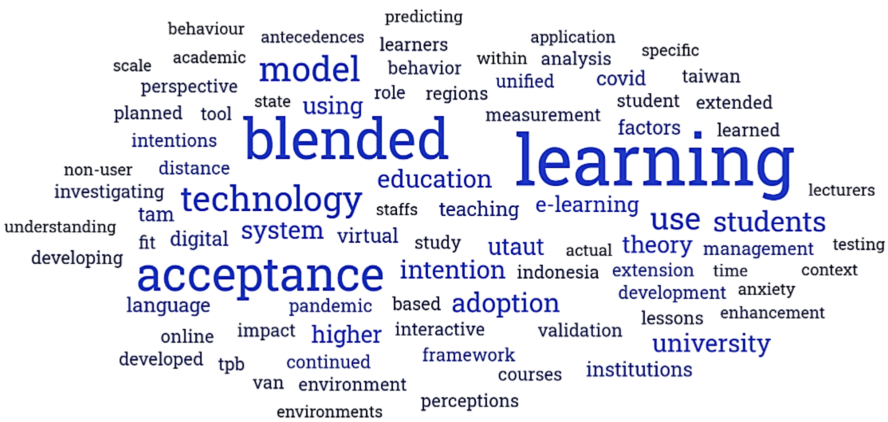


Fig.6. Word cloud generated for titles of the selected articles.

Within these selected studies, 282 useful relationships have been identified between independent and dependent variables, which have been reduced to 168 after aggregating the repeated relationships. Most of these relationships are measured for TAM or UTAUT models. To find out the significance of these relationships, the weights are calculated, which is a measure of the predicting ability of independent variables [22]. The weight is the ratio of the number of times the independent variables were tested as significant to the number of times they were examined in the selected studies [15]. The formula is given in Eq. (1).

$$weight = \frac{\#Significant\_constructs}{\#Studies\_having\_constructs} \quad (1)$$

The relationships that occurred more than once, with at least one being significant, are considered for computing the weights. The weights for the variables are presented in Table 4. The relationships with more weight are given in italics.

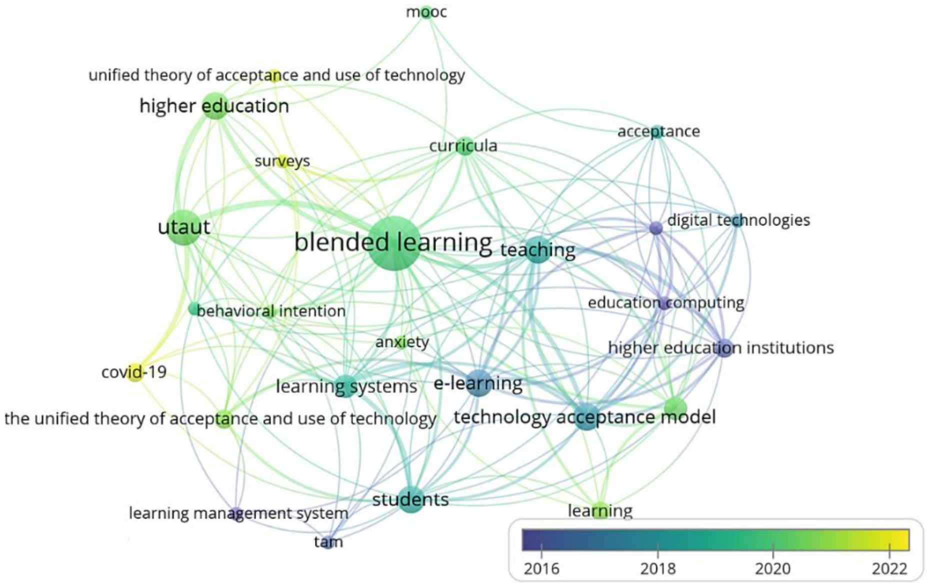


Fig.7. Association of keywords between selected articles.

Table 4. Weights for the relationship analyzed

Independent Variables	Dependent Variables	#Studies	#Sign.	#Non-sign.	Weight	Model
Social Influence	Behavioural Intention	12	6	6	0.50	UTAUT
Perceived Ease of Use	Perceived Usefulness	12	10	2	0.83	TAM/TPB/SET
Performance Expectancy	*Behavioural Intention*	11	10	1	0.91	UTAUT
Perceived Ease of Use	Attitude towards Usage	9	7	2	0.78	TAM/TPB
Effort Expectancy	Behavioural Intention	9	6	3	0.67	UTAUT/UTAUT2
Perceived Usefulness	Attitude towards Usage	8	7	1	0.88	TAM/TPB
Perceived Ease of Use	*Intention to Use*	8	8	0	1.00	TAM
Facilitating Conditions	Behavioural Intention	7	4	3	0.57	UTAUT
Perceived Usefulness	*Intention to Use*	7	7	0	1.00	TAM
Attitude towards Usage	*Intention to Use*	6	6	0	1.00	TAM
Self-efficacy	Perceived ease of use	4	4	0	1.00	TAM
Behavioural Intention	Use Behavior	4	4	0	1.00	UTAUT
Facilitating Conditions	Use Behavior	4	4	0	1.00	UTAUT
Technology Anxiety	Behavioural Intention	3	3	0	1.00	TAM/UTAUT
Technology Anxiety	Perceived Ease of Use	3	1	2	0.33	TAM
Intention to Use	Actual System Usage	2	2	0	1.00	TAM
Perceived Ease of Use	Actual System Usage	2	2	0	1.00	TAM
Perceived Usefulness	Actual System Usage	2	2	0	1.00	TAM
Self-efficacy	Attitude towards Usage	2	1	1	0.50	TAM
Hedonic Motivation	Behavioural Intention	2	2	0	1.00	UTAUT2
Social Influence	Effort Expectancy	2	2	0	1.00	UTAUT
Real-time Collaboration	Perceived Usefulness	2	1	1	0.50	TAM
Self-efficacy	Perceived Usefulness	2	2	0	1.00	TAM
Social Influence	Performance Expectancy	2	2	0	1.00	UTAUT
Perceived Usefulness	Satisfaction	2	2	0	1.00	TAM
Perceived Ease of Use	Self-efficacy	2	2	0	1.00	TAM/SET

In general, when the value of weight is 1, it indicates that the independent variable is a good predictor since it is significant in all the studies, and 0 indicates a poor predictor since it is not significant in any studies [15]. As a result of the analysis, *attitude, perceived usefulness,* and *perceived ease of use*, as well as *facilitating conditions* and *behavioural intention*, are good predictors of *intention to use* and *behavioural intention* since the relationships are significant in all studies. Moreover, performance expectancy is also considered a worthy predictor of behavioural intention, as it is significant in 10 studies out of 11. The significant relationships between dependent and independent variables of the UTAUT and TAM models that occurred in more than two articles are shown in Fig.8. The bold arrows represent the predictors with weight 1 considering at least 3 studies; the values in the arrows represent average beta values, and the values inside the brackets specify the weights.

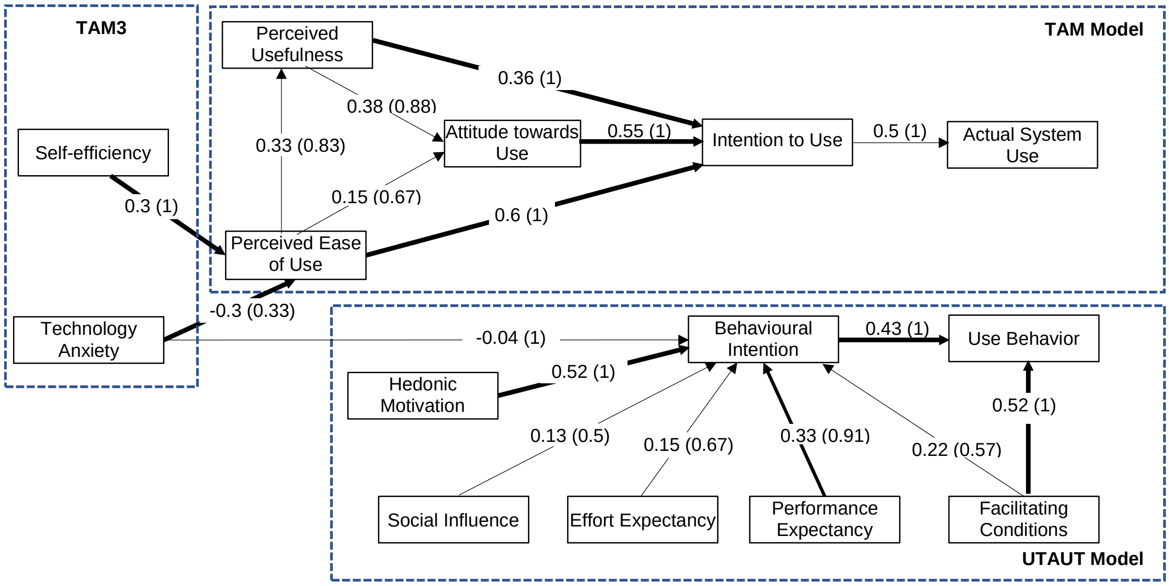


Fig.8. Significant relationships based on weights (Source: Authors).

5.2. Meta-analysis

A meta-analysis helps to integrate the quantitative results reported across the selected articles. These quantitative results can be correlation or regression coefficients as well as effect sizes [78]. Furthermore, it was demonstrated that the standardised regression coefficients and correlation coefficients are related in such a way that they can be used interchangeably [15, 79]. Thus, the standard regression coefficient (β) is used in the current study to analyse the relationship between variables, with the constraint that the relationship be examined in at least three studies [15]. Jeyaraj et al. (2006) suggested that variables tested more than five times can be considered "well-utilized" [22]. However, constructs tested fewer than five times can still be considered "promising" predictors [15]. Thus, the predictors identified in this meta-analysis can still seem promising. Thus, 15 relationships that occurred three or more times in the selected articles are considered for the analysis using random effects. The random effect models employed in the study are universally accepted [78]. Unlike the fixed effect model, which considers the variance within a study, random effect models have the ability to consider both variances within a study and variances between studies.

The R programming software is used to calculate average correlations for each construct using random effects. The standard error, p-value, standard normal deviations (Z-value), and the upper and lower confidence intervals (95%) are also computed. The results for the first 15 relationships given in Table 4 are presented in Table 5. The underlined values indicate relationships with a higher average beta value (estimates), and italics represent relationships with a weight of 1. Moreover, the heterogeneity for each relationship is also computed using I^2 statistics, which evaluate the percentage of the variance between studies [80].

From the values reported in Table 5, it can also be seen that the strength of the relationship between *technology anxiety* and *behavioural intention* is not significant, as the p-value (0.832) is greater than 0.05. On the other hand, the other relationships are found to be significant, and the beta values show the level of significance. Thus, the influence of *facilitating conditions on use behaviour* (beta = 0.677), *attitude toward usage on intention to use* (beta = 0.676), *behavioural intention on use behaviour* (beta = 0.573), and *perceived ease of use on intention to use* (beta = 0.565) seems to have the highest strength among the relationships under study. The I^2 statistics for each individual relationship are higher, indicating a higher level of heterogeneity.

Table 5. Meta-analysis on significant relationships.

Independent Variables	Dependent Variables	# Studies	∑Sample size	Estimate	Std. error	Z value	p-value	Confidence Interval (95%)		I^2
								Lower limit	Upper Limit	
Social Influence	Behavioural Intention	12	3578	0.398**	0.124	3.197	0.001	0.154	0.641	97.97%
Performance Expectancy	Behavioural Intention	11	3372	0.398**	0.124	3.197	0.001	0.154	0.641	97.97%
Effort Expectancy	Behavioural Intention	9	2843	0.275**	0.098	2.795	0.005	0.082	0.467	96.05%
Perceived Ease of Use	Perceived Usefulness	12	2686	0.377***	0.101	3.718	0.0002	0.178	0.576	96.16%
Facilitating Conditions	Behavioural Intention	7	2280	0.217**	0.071	3.069	0.002	0.079	0.356	89.96%
Perceived Ease of Use	Attitude towards Usage	9	1910	0.437***	0.084	5.192	<0.0001	0.272	0.602	92.01%
Behavioural Intention	*Use Behavior*	*4*	*1643*	*0.573.*	*0.296*	*1.937*	*0.053*	*-0.007*	*1.154*	*99.17%*
Facilitating Conditions	*Use Behavior*	*4*	*1643*	*0.677***	*0.255*	*2.655*	*0.0079*	*0.177*	*1.177*	*98.87%*
Perceived Ease of Use	*Intention to Use*	*8*	*1571*	*0.565****	*0.077*	*7.288*	*<0.0001*	*0.412*	*.7151*	*88.08%*
Perceived Usefulness	Attitude towards Usage	8	1514	0.405***	0.079	5.097	<0.0001	0.249	0.560	88.58%
Perceived Usefulness	*Intention to Use*	*7*	*1259*	*0.470****	*0.0884*	*5.317*	*<0.0001*	*0.297*	*0.643*	*88.65%*
Attitude towards Usage	*Intention to Use*	*6*	*1197*	*0.676****	*0.111*	*5.734*	*<0.0001*	*0.419*	*0.854*	*92.46%*
Technology Anxiety	Behavioural Intention	3	791	-0.037	0.172	-0.212	0.832	-0.374	0.301	95.64%
Self-efficacy	Perceived Ease of Use	4	664	0.306*	0.128	2.401	0.016	0.056	0.556	87.18%
Technology Anxiety	Perceived Ease of Use	3	654	-0.297**	0.093	-3.195	0.001	-0.479	-0.115	79.34%
Significant codes: (***) p<0.001; (**) p<0.01; (*) p<0.05; (.) p<0.1;										

The graphical representation of the meta-analysis performed for the estimate and sample size given in Table 5 is shown in Fig.9. The graph is drawn with the estimated effect size on the x-axis, individual relationships on the y-axis, the average regression value in the form of a black square, and confidence intervals (CI) on the line across the square. The CI lines appear on the 0 value, indicating that the relationships are not significant. The CI lines that appear on the positive or negative sides indicate positive and negative significance, respectively. Thus, the influence of *technology anxiety on behavioural intention* is not statistically significant. Moreover, apart from the heterogeneity of individual relationships, an overall heterogeneity analysis has been performed, which indicates that the meta-analysis shows a high level of heterogeneity of 99.37%.

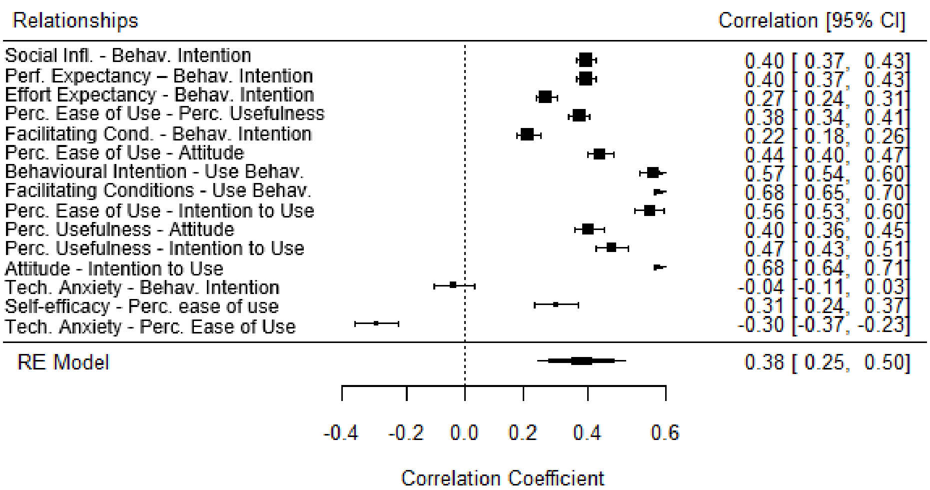


Fig.9. Forest Plot for the meta-analysis on relationships.

Few authors insist that blended learning has gained huge attention after the COVID-19 pandemic [81]. Thus, the most widely examined relationships, such as social influence and performance efficiency on behavioural intention, have been examined individually. As a result, the impact of these relationships is assessed with subgroups such as publications on or before 2020 and after 2020. The input for the two relationships is shown in Table 6. The regression coefficients and the number of samples are given as input for analysis, assuming a random effect model with a 95% confidence level, for which the free software tool Meta-Essentials is used [82, 83].

Table 6. Maximum examined relationships and the list of studies.

Social Influence on Behavioural Intention			**Performance Expectancy on Behavioural Intention**		
Author(s) (year)	**Beta**	**Sample Size**	**Author(s) (year)**	**Beta**	**Sample Size**
Dakduk et al. (2018) [9]	0.05	307	Dakduk et al. (2018) [9]	0.28	307
Radovan & Kristl (2017) [46]	0.24	326	Radovan & Kristl (2017) [46]	0.414	326
Alhramelah & Alshahrani (2020) [70]	0.039	167	Alhramelah & Alshahrani (2020) [70]	0.338	167
Prasad et al. (2018) [73]	0.083	95	Prasad et al. (2018) [73]	0.275	95
Sarkam (2019) [75]	0.025	201	Sarkam (2019) [75]	0.426	201
Okocha et al. (2017) [77]	0.027	206	Okocha et al. (2017) [77]	0.437	206
Zhou et al. (2022) [26]	0.265	301	Zhou et al., (2022) [26]	0.261	301
Esawe et al. (2022) [35]	0.169	803	Esawe et al., (2022) [35]	0.143	803
Anthony et al. (2021) [67]	0.733	544	Anthony et al., (2021) [67]	0.905	544
Gunasinghe & Nanayakkara (2021) [41]	0.03	219	Gunasinghe & Nanayakkara (2021) [41]	0.32	219
Aldekheel et al. (2022) [40]	0.646	206			
Kaur et al. (2021) [42]	0.274	203	Kaur et al., (2021) [42]	-0.171	203

The results obtained are presented in Fig.10 and Fig.11. The blue dots indicate the size of the effect for the individual studies on the relationship between *social influence and behavioural intention.* The red circles indicate the effect size of each subgroup, and the green circle indicates the combined effect size.

Study name / Subgroup name	Correlation	CI Lower limit	CI Upper limit
Zhou et al., (2022)	0.27	0.16	0.37
Esawe et al., (2022)	0.17	0.10	0.24
Anthony et al., (2022)	0.73	0.69	0.77
Gunasinghe & Nanayakkara (2021)	0.03	-0.10	0.16
Aldekheel et al., (2022)	0.65	0.56	0.72
Kaur et al., (2021)	0.27	0.14	0.40
After 2020	**0.39**	**0.03**	**0.66**
Dakduk et al. (2018)	0.05	-0.06	0.16
Radovan & Kristl (2017)	0.24	0.13	0.34
Alhramelah & Alshahrani (2020)	0.04	-0.11	0.19
Prasad et al. (2018)	0.08	-0.12	0.28
Sarkam (2019)	0.03	-0.11	0.16
Okocha et al. (2016)	0.03	-0.11	0.16
On or Before 2020	**0.08**	**-0.01**	**0.17**
Combined effect size	**0.21**	**-0.14**	**0.52**

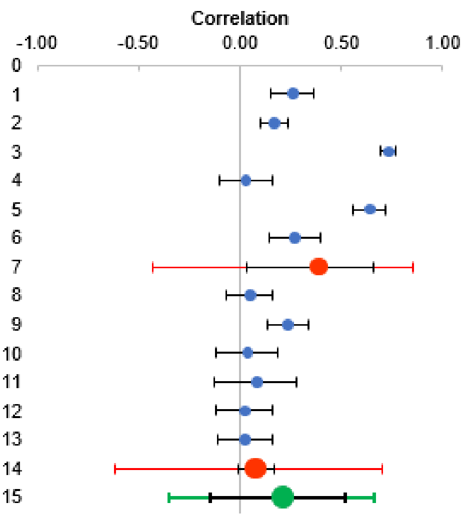


Fig.10. Forest plot for social influence on behavioural intention.

Study name / Subgroup name	Correlation	CI Lower limit	CI Upper limit
Zhou et al., (2022)	0.26	0.15	0.36
Esawe et al., (2022)	0.14	0.07	0.21
Anthony et al., (2022)	0.91	0.89	0.92
Gunasinghe & Nanayakkara (2021)	0.32	0.20	0.43
Kaur et al., (2021)	-0.17	-0.30	-0.03
After 2020	**0.47**	**0.42**	**0.51**
Dakduk et al. (2018)	0.28	0.17	0.38
Radovan & Kristl (2017)	0.41	0.32	0.50
Alhramelah & Alshahrani (2020)	0.34	0.20	0.47
Prasad et al. (2018)	0.28	0.08	0.45
Sarkam (2019)	0.43	0.30	0.53
Okocha et al. (2016)	0.44	0.32	0.54
On or Before 2020	**0.37**	**0.31**	**0.43**
Combined effect size	**0.42**	**0.31**	**0.52**

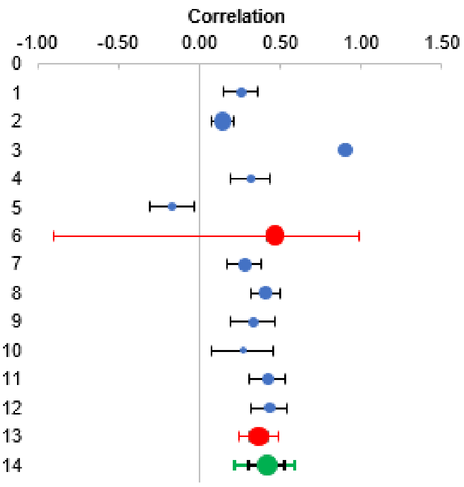
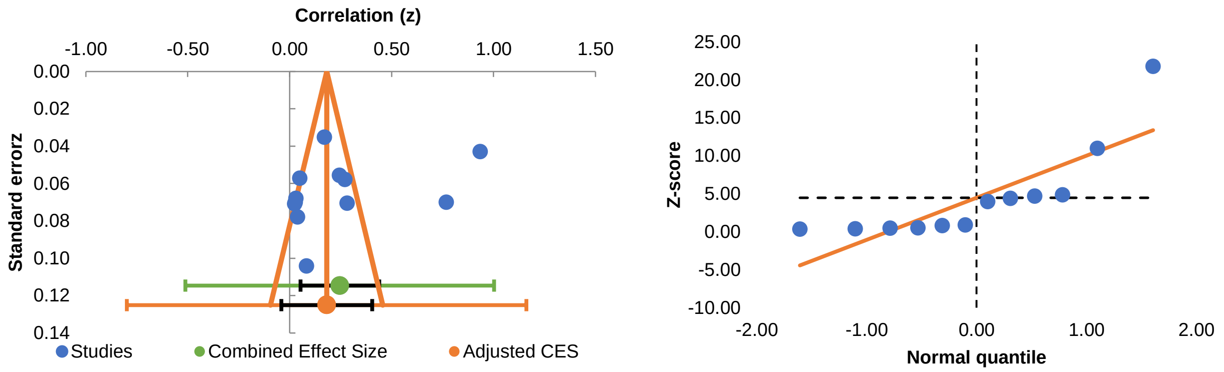


Fig.11. Forest plot for performance expectancy on behavioural intention.

From Fig.10, it can be seen that the correlation between social *influence and behavioural intention* on or before 2020 is 0.08 (I^2 = 98.09%), which has increased after 2020 to 0.39 (I^2 = 81.40%). This indicates that there is a huge change in the impact of *social influence on behavioural intention* when adopting blended learning. Moreover, the I^2 statistics for each subgroup remain high, with 96.93% for the combined effect size, indicating a higher level of heterogeneity. Fig.11 indicates that the correlation between *performance expectancy and behavioural intention* on or before 2020 is 0.37 (I^2 = 72.39%), which has increased after 2020 to 0.47 (I^2 = 99.47%). This shows that there is also a change in the influence of *performance expectancy and behavioural intention* in adopting blended learning. Moreover, the I^2 statistics for each subgroup remain high, with 98.71% for the combined effect size, indicating a higher level of heterogeneity.

As given in Table 5, in some articles some of the relationships are significant, whereas in other articles they seem to be non-significant. Thus, if there is a publication bias in the selected articles, the same will be reflected in the meta-analysis and its outcome. Harrison et al. (2017) demonstrated that the single construct is the best way to test for bias in publication [84]. Thus, the relationship that was analysed more in the selected articles, *social influence → behavioural intention* is used for evaluating publication bias. In general, the funnel plot will be used to identify publication bias, with the symmetrical inverted funnel plotted across standard error and effect size indicating no bias [15, 85].

Fig.12(a) depicts the funnel plot obtained from the Meta-Essentials software to investigate the relationship between *social influence → behavioural intention* in blended learning adoption from the selected articles. The result indicates that there is higher heterogeneity (I^2 = 98.32%) and no publication bias. For more accurate results of symmetry and publication analysis, Egger regression on a funnel plot [86] is used, and it indicates that the results are not significant for asymmetry (p = 0.35). The results are presented in Table 7. Moreover, the normality test is also used to verify the goodness-of-fit of the random effect model in the meta-analysis [87]. Fig.12(b) depicts the outcome of the normality test, which indicates that the data have a normal distribution since the majority of the points fall in a straight line with a slope of 1.



a) *Forest Plot*

b) *Normal Quantile Plot*

Fig.12. Plots for relationship social influence and behavioural intention.

Table 7. Egger regression for asymmetry analysis on publication bias.

Egger Regression	Estimate	Std. Error	Confidence Interval (95%)		Test results
			Lower Level	Upper Level	
Intercept	-5.78	5.93	-18.83	7.27	t test = -0.97
Slope	0.62	0.35	-0.14	1.38	p-value = 0.35

Additionally, the correlation values between various relationships reported in the articles for the TAM and UTAUT models are also examined. In general, 11 studies are selected for evaluating the variables *intention to use* (IU), *perceived usefulness* (PU), *perceived ease of use* (PEOU), and *attitude towards usage* under the TAM model, and 10 studies are selected for evaluating the variables *behavioural intention* (BI), *effort expectancy* (EE), *facilitating conditions* (FC), *performance expectancy* (PE), and *social influence* (SI) under the UTAUT model. Here, the variables are selected in such a way that they must be tested in at least three studies, and the studies are selected in a way that they must cover at least three of the variables in any of the models. The SEM meta-analysis is performed using the metaSEM package in R programming. The input for the confirmatory factor analysis (CFA) is given in Table 8.

The pooled correlation matrix for applying the random effect model is shown in Table 9. All of the correlation coefficients in this case are significant (p < 0.05). Moreover, the I^2 statistics of all the variables are higher, ranging from 88 to 98 percent for both model analyses.

Table 8. Input for confirmatory factor analysis.

TAM Model		UTAUT Model	
Author(s) (Year)	**Sample Size**	**Author(s) (Year)**	**Sample Size**
Hina et al., (2020)	139	Esawe et al., (2022)	803
Virani et al., (2020)	286	Anthony et al., (2021)	544
Razami & Ibrahim (2020)	111	Gunasinghe & Nanayakkara (2021)	219
Vogelsang et al., (2017)	68	Dakduk et al. (2018)	307
Pardamean et al., (2013)	97	Radovan & Kristl (2017)	326
Al-Azawei et al., (2017)	210	Alhramelah & Alshahrani (2020)	167
Olivier (2016)	82	Aldekheel et al., (2022)	206
Chen et al., (2022)	461	Kaur et al., (2021)	203
Al Murshidi (2020)	251	Prasad et al., (2018)	95
Tulinayo et al., (2018)	241	Sarkam (2019)	201
Yeou (2016)	47		

Table 9. Correlation coefficients of meta-analytic CFA.

	TAM Model					UTAUT Model				
	IU	**PU**	**PEOU**	**ATT**		**BI**	**EE**	**FC**	**PE**	**SI**
IU	1				**BI**	1				
PU	0.467	1			**EE**	0.375	1			
PEOU	0.518	0.500	1		**FC**	0.332	0.234	1		
ATT	0.366	0.328	0.367	1	**PE**	0.582	0.413	0.274	1	
					SI	0.477	0.353	0.306	0.411	1

Note: IU - intention to use; PU - perceived usefulness; PEOU - perceived ease of use; ATT - attitude towards usage; BI - behavioural intention; EE - effort expectancy; FC - facilitating conditions; PE - performance expectancy; SI - social influence

5.2.1. Students' Perspective on Blended Learning Adoption

The various relationships based on the students' responses are evaluated, for which the average correlation effect sizes using random effects are computed. Among the 217 relationships identified from the studies examined through student responses, 13 were chosen for analysis as they occurred in more than two studies after aggregation. The obtained results, such as standard error, p-value, standard normal deviations (Z-value), upper and lower confidence intervals (95%), and I^2 statistics for each relationship that occurred at least three times, are presented in Table 10. The results indicate that the influence of *facilitating conditions* on *behavioural intention* ($p > 0.05$) is not significant. On the other hand, all the remaining relationships are statistically significant. The relationships having higher beta values are formatted in italics. Moreover, the higher level of I^2 statistics for each individual relationship indicates a higher level of heterogeneity for all the relationships.

Table 10. Meta-analysis on significant relationships based on students' perception.

Independent Variables	Dependent Variables	No. of Studies	∑Sample size	Estimate	Std. error	Z value	P value	Confidence Interval (95%)		I^2
								Lower limit	Upper Limit	
Perceived Ease of Use	Perceived Usefulness	11	2400	0.404***	0.107	3.763	0.0002	0.193	0.614	96.14%
Performance Expectancy	Behavioural Intention	6	1775	0.221*	0.091	2.443	0.015	0.044	0.399	91.84%
Social Influence	Behavioural Intention	6	1775	0.155***	0.045	3.411	0.0006	0.066	0.244	76.25%
Perceived Ease of Use	*Attitude towards Usage*	*8*	*1624*	*0.441****	*0.096*	*4.619*	*<0.0001*	*0.254*	*0.628*	*92.62%*
Perceived Ease of Use	*Intention to Use*	*8*	*1574*	*0.564****	*0.077*	*7.288*	*<0.0001*	*0.412*	*0.715*	*88.08%*
Effort Expectancy	Behavioural Intention	5	1572	0.244**	0.084	2.903	0.004	0.079	0.408	88.70%
Facilitating Conditions	Behavioural Intention	*4*	*1454*	*0.093*	*0.058*	*1.598*	*0.11*	*-0.021*	*0.208*	*74.50%*
Perceived Usefulness	*Intention to Use*	*7*	*1259*	*0.470****	*0.088*	*5.317*	*<0.0001*	*0.297*	*0.643*	*88.65%*
Perceived Usefulness	*Attitude towards Usage*	*7*	*1228*	*0.477****	*0.043*	*44.059*	*<0.0001*	*0.393*	*0.562*	*70.81%*
Attitude towards Usage	*Intention to Use*	*5*	*911*	*0.668****	*0.132*	*5.046*	*<0.0001*	*0.408*	*0.926*	*92.77%*
Self-efficacy	Attitude towards Usage	3	784	0.193.	0.1001	1.923	0.054	-0.004	0.389	83.00%
Self-efficacy	Perceived Ease of Use	4	664	0.306*	0.128	2.4	0.016	0.056	0.556	87.18%
Technology Anxiety	Perceived Ease of Use	3	654	-0.297**	0.093	-3.195	0.001	-0.479	-0.115	79.34%
Significant codes: (***) p<0.001; (**) p<0.01; (*) p<0.05; (.) p<0.1;										

The graphical representation of the meta-analysis performed for the estimate and sample size for the adoption of blended learning among students for the values given in Table 10 is shown as a forest plot in Fig.13. The graph plot indicates that all the relationships are statistically significant except *facilitating conditions* on *behavioural intention*. Moreover, the I^2 statistics of the overall analysis are at 94.05%, which indicates a high level of heterogeneity between studies.

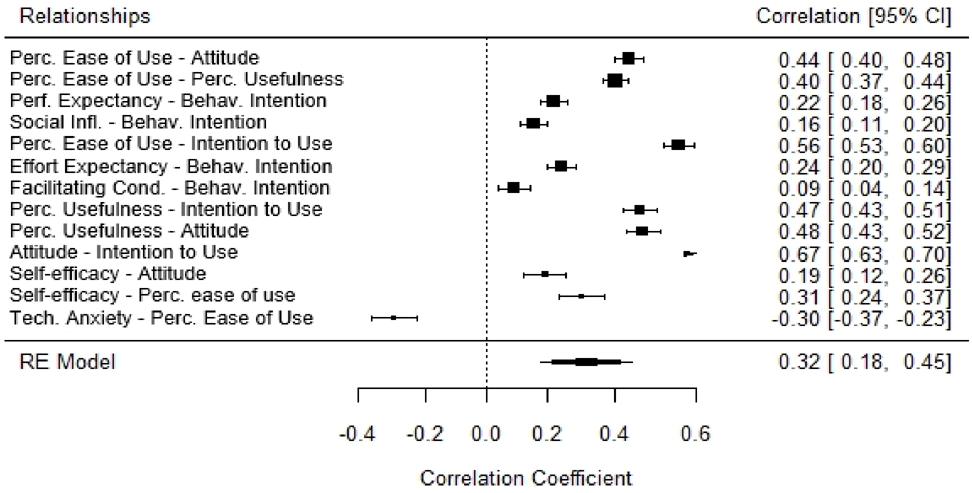


Fig.13. Forest plot for the relationships based on students' perception.

5.2.2. *Instructors' Perspective on Blended Learning Adoption*

The various relationships based on instructors' and educators' responses are evaluated, and the average correlations and effect sizes using random effects are computed. Since the total number of studies that analyse the instructors' perspective on blended learning is less (7 studies), the relationships that occurred in at least two of the studies are considered for the analysis. Thus, among 65 relationships between dependent and independent variables, after aggregation, six relationships are identified for analysis. The obtained results, such as standard error, p-value, standard normal deviations (Z-value), upper and lower confidence intervals (95%), and I^2 statistics for each relationship, are presented in Table 11. The results indicate that the influence of *effort expectancy* on *behavioural intention* is reported as insignificant ($p > 0.05$). On the other hand, all the remaining relationships are statistically significant. Moreover, the higher level of I^2 statistics for each individual relationship indicates a higher level of heterogeneity for all the relationships.

Table 11. Meta-analysis on significant relationships based on instructors' perception.

Independent Variables	**Dependent Variables**	**# Studies**	**∑Sample size**	**Estimate**	**Std. error**	**Z value**	**p-value**	**Confidence Interval (95%)**		**I^2**
								Lower limit	**Upper Limit**	
Social Influence	Behavioural Intention	6	1803	0.343*	0.166	2.064	0.039	0.017	0.669	97.90%
Performance Expectancy	Behavioural Intention	5	1597	0.604**	0.228	2.656	0.008	0.158	1.050	98.73%
Effort Expectancy	Behavioural Intention	4	1274	0.307	0.209	1.465	0.143	-0.1038	0.718	98.07%
Facilitating Conditions	Behavioural Intention	3	751	0.373***	0.083	4.510	<0.0001	0.211	0.535	79.73%
Behavioural Intention	Use Behavior	2	745	0.838*	0.580	1.444	0.015	-0.299	1.976	99.49%
Facilitating Conditions	Use Behavior	2	745	0.789***	0.153	7.136	<0.0001	0.7933	1.394	92.67%
Significant codes: (***) p<0.001; (**) p<0.01; (*) p<0.05; (.) p<0.1;										

The graphical representation of the meta-analysis performed for the estimate and sample size for the adoption of blended learning among instructors for the values given in Table 11 is shown as a forest plot in Fig.14. Since all the points on the graph fall on the positive side, the graph plot indicates that all the relationships are statistically significant except *effort expectancy* on *behavioural intention*. Moreover, the I^2 statistics of the overall analysis are 95.4%, which indicates a high level of heterogeneity between studies.

The resulting models built for the 13 relationships examined for blended learning based on students' perspectives from Table 10 and 6 relationships examined for blended learning based on instructors' perspectives from Table 11 are summarised in Fig.15. The bold arrow represents a strong relationship, and the dotted arrows represent weak or insignificant relationships.

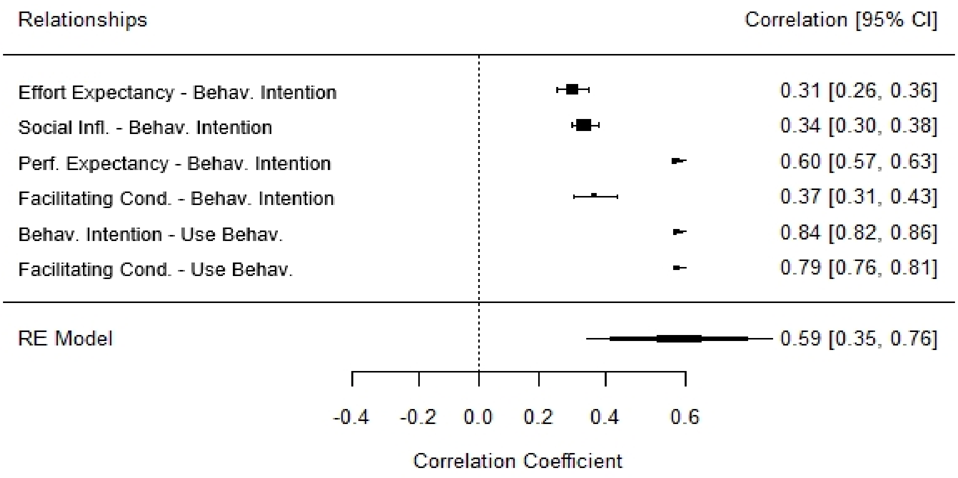
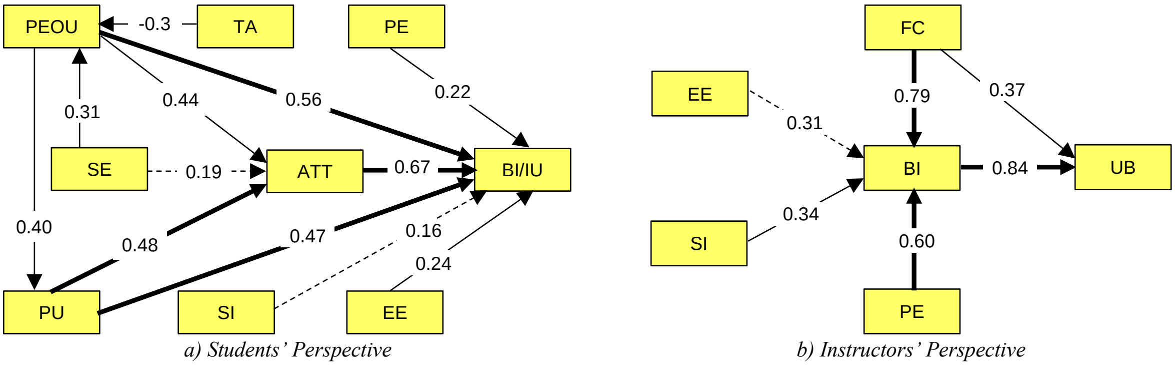


Fig.14. Forest plot for the relationships based on instructors' perception.



Note: IU - intention to use; BI - behavioural intention; EE - effort expectancy; PE - performance expectancy; ATT - attitude towards usage; TA – technology anxiety; SI - social influence; SE- self-efficacy; PU - perceived usefulness; PEOU - perceived ease of use; UB – use behaviour; FC - facilitating conditions.

Fig.15. Model built through meta-analysis.

The overall result based on student responses indicates that *perceived usefulness* has a strong relationship with *attitude towards usage*, whereas *perceived ease of use*, *attitude towards usage*, and *perceived usefulness* have a strong association with *intention to use*. However, *self-efficacy* has no significant relationship with *attitude towards usage*, and *social influence* has no significant relationship with *intention to use*. In the case of instructors' perspectives, *facilitating conditions* and *performance expectancy* have a strong association with *behavioural intention*, which in turn impacts use behaviour. However, *effort expectancy* has no significant relationship with *behavioural intention.*

6. Discussion

A nominal amount of research on the adoption of blended learning using a variety of theories and models was available in the literature [13, 30, 48]. Only a handful of these research followed an in-depth and methodical review of the existing literature on the adoption of blended learning [20, 50]. However, the importance of this research study is in the meta-analysis that was conducted to validate the findings of the review concerning the implementation of blended learning. Thus, a nominal amount of 32 such studies are used in this meta-analytic review, with 8,168 respondents, including 5,875 students and 2,293 instructors.

Most of the existing studies selected for the review are articles published in the journals than conferences and these studies utilise the UTAUT model developed by Venkatesh et al. (2003) [25] and TAM model developed by Davis (1989) [23] as a dominant acceptance models used to assess the use of blended learning. Other models include their combinations or variations [9], or self-developed models [30]. This goes against the findings of Al-Maroof et al. (2021), who found that the TAM model was the most commonly used in various studies. Further, around 80 variables were identified from these 32 studies (see Fig.2). However, the variables from UTAUT model such as behavioural intention, effort expectancy, facilitating conditions, performance expectancy, social influence and TAM models like behavioural intention, perceived usefulness, perceived ease of use, attitude towards use are frequently found in many studies. However, it was found that most of these studies performed empirical analysis to assess the adoption of blended learning. This finding is same as the findings of the existing review study by Anthony et al. (2022) [20]. Further, most of the empirical analysis were carried out on the data collected through survey in which students' perspective were studied more than the instructors' perspective. This finding is consistent with the findings of the prior literature conducted by Al-Maroof et al., (2022) [52] on adoption of blended learning. The statistical methods employed in almost all of the studies are structural equation modelling (SEM) and the result is consistent with Bervell and Umar (2017) [49] (see Table 3).

Most commonly, e-learning systems and general blended learning environment are studied more in existing studies on blended learning adoption. Other environments include virtual learning, digital technologies, MOOC and MOODLE are fairly studied (see Fig.3). This can also be visualized through keyword associations (see Fig.7). Though several literature reviews on blended learning were studied prior, no studies discussed about the various learning systems in blended learning adoptions. Further, with the countries involved in the article publications, Malaysia has a high number of 995 respondents covering 4 articles. Moreover, China, India, Kuwait, Saudi Arabia, and the Taiwan region publish two articles each (see Fig.4). This result findings are consistent to the results reported by Al-Maroof et al., (2021) [52] were the countries such as Malaysia, Turkey and the Taiwan region are the major contributors of blended learning. Though the studies were collected from the year 2005, the selected studies were published between 2012-2022. Also, it is observed that the number of articles published after COVID-19 is high in comparison with the other years (see Fig.4). This indicates that the use of blended learning has been elevated during and after the COVID pandemic and the result is consistent with the report published by Zhou et al. (2022) [26].

Within these studies, 168 individual relationships between the dependent and independent variables have been identified in TAM and UTAUT models. To know the more significant relationships, weight has been calculated for these constructs based on their significance in these studies, as suggested by Jeyaraj et al. (2006) [15]. Relationships that appear in at least five studies are more effective because relationships that are tested as significant in more studies carry more weight. Accordingly, *perceived ease of use* (8 studies), *perceived usefulness* (7 studies), and *attitude towards usage on intention to use* (6 studies) have the weight of 1, indicating that the construct is significant in all the studies (see Table 4). The construct, *Performance expectancy on behavioural intention* is also considered significant, with a weight of 0.93, indicating that 10 studies tested it as significant among 11 studies.

According to the findings of the meta-analysis after applying random effect model on variables that occur at least in 3 studies, *perceived ease of use, perceived usefulness, and attitude toward usage on intention to use*, which occurred in more than five studies with a higher average beta value and weight = 1, are identified as "well-utilized" predictors (see Table 4). Furthermore, *behavioural intention and facilitating conditions on use behaviour* are "good" predictors from four studies with a higher average beta value and weight = 1. On the other hand, low average beta values for eff*ort expectancy and facilitating conditions on behavioural intention* are found to be poor predictors. Also, *technology anxiety on behavioural intention* has a weight of 1 (significant in all three studies), and has lower negative beta value indicating it as a poor predictor (see Fig.9). However, more studies are required to conclude the constructs. The high value of I^2 statistics (99.37%) indicates that the meta-analysis has higher heterogeneity.

Because all studies consider the specific relationship as significant, the weight computed for the predictors will obviously be 1, and so the relationship will have a high average estimate. Thus, rather than choosing relationships with higher weights, the current study chooses relationships that have been studied more thoroughly in selected studies for analysis of publication bias. Thus, the two individual relationships between *social influence* (12 studies) and *performance expectancy* (11 studies) *on behavioural intention* are considered for deeper analysis. The relationships between these constructs are examined in two subgroups: those with beta values reported on or before 2020 and those with beta values reported after 2020. Surprisingly, the results indicate that there is a huge increase in the average beta values for relationships, *social influence* (0.08 to 0.39) and *performance expectancy* (0.37 to 0.47) *on behavioural intention* after 2020, given the high level of heterogeneity. This indicates that the factors of *social influence* and *performance expectancy* had a huge impact on *behavioural intention* which can also be seen as the adoption of blended learning has gained more attention, especially after COVID-19 and it supports the result reveled by Deng et al. (2022) [28].

To analyse the publication bias, the funnel plot is reported for the relationship between *social influence and behavioural intention* (see Fig.12a). Since the results are not conclusive, the Egger regression is applied, and the result indicates that there is no significance for asymmetry ($p = 0.35$). The random effect model built for the relationship is also verified for goodness-of-fit using a normal quantile plot, and the results show the normal distribution of data (see Fig.12b).

Apart from analysing regression coefficients, the correlation coefficients reported in the studies for TAM (11 studies) and UTAUT variables (10 studies) are also analysed (see Table 7 for studies included in this analysis). The variables that occurred in at least three studies are selected, and the studies having at least three selected variables are chosen for analysis. The variable *perceived ease of use* is highly correlated with the *intention to use* (0.52) and *perceived usefulness* (0.5) from the TAM model, and *performance expectancy* is highly positively correlated with *behavioural intention* (0.58) from the UTAUT model (see Table 8). Also, the *facilitating conditions* are poorly correlated with *performance expectancy* and *effort expectancy*.

There were very few studies that had conducted a review on the implementation of blended learning and identified the many factors that influence the adoption; however, there was not a single review study that focused on evaluating the relationship between those constructs. As a result, this study is unique in that it examines the relationship between the elements of the acceptance model in order to evaluate the adoption of blended learning in higher education.

Further, the perspectives of students and educators on the adoption of blended learning are assessed separately. The 13 relationships with student respondents that were examined in at least three studies have been identified for meta-analysis (see Table 10). The influence of *perceived ease of use on perceived usefulness* is most frequently examined in 11 studies. The results indicate that all the relationships are statistically significant except *facilitating conditions on behavioural intention*. More precisely, *perceived ease of use* (0.56), *attitude toward usage* (0.67), and *perceived usefulness* (0.47) are good predictors of *intention to use*, while *perceived ease of use* (0.44) and *perceived usefulness* (0.48) are good predictors of *attitude towards usage* with higher average beta values and 94% of heterogeneity (see Fig.13). Contradictorily, it was also found that the point for the relationship *technology anxiety* on *perceived ease of use* fall on the negative side indicating that the *technology anxiety on perceived ease of use* is negatively significant.

Moreover, for assessing the instructors' or educators' perceptions on blended learning adoption in higher education, the 6 relationships examined at least twice in the selected articles are used (see Table 11). The results indicate that all the relationships are statistically significant except *effort expectancy on behavioural intention*. Precisely, the *performance expectancy* (0.60) is found to be a good predictor of *behavioural intention* with 95% heterogeneity (see Fig.14). Though the relationships like *behavioural intention* (0.84) and *facilitating conditions* (0.79) on *use behaviour* have a high average beta value, they cannot be concluded to be good predictors since the relationships were analysed in only 2 studies. Finally, the models have been built through the meta-analysis results of the perspectives of students and instructors on blended learning (see Fig.14).

Though Anthony et al., (2022) [20] identified the factors and constructs that influence the adoption of blended learning in the perspective of students and educators, the study failed to perform the meta-analytic review to assess the relationship between the variables of acceptance models employed in the literature. This meta-analytic review fills the gap in the literature by assessing the relationship between the variables of acceptance models employed in assessing the use of blended learning in higher education. And the findings indicate that the *usage attitude* and *perceived usefulness* influence more on *intention to use* the blended learning for the students in higher education. On the other hand, *performance expectancy* and the *facilitating conditions* such as technical infrastructure and support from organization highly influence the *intention to use* the blended learning for the instructors in higher education. However, there are still several challenges exists in implementing blended learning such as continuous access to technologies, training for the learning environment, lack of support from the institutions, lack of technological experience, finding the right blend, and adaptability towards the learning environment and more which needs to be taken care before implementing blended learning [50].

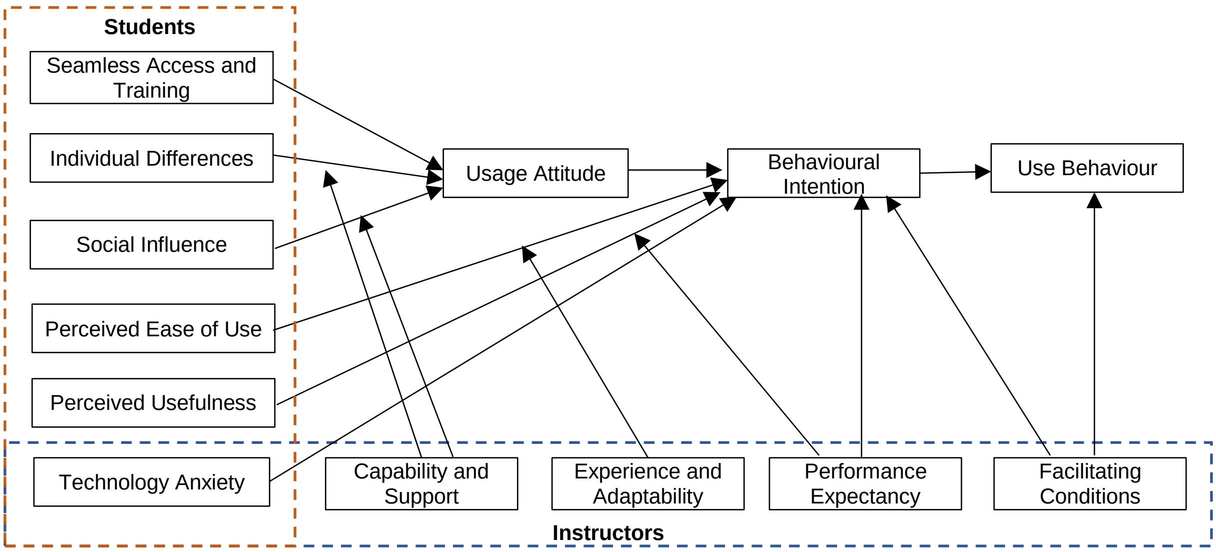


Fig.16. Proposed digital education technology acceptance model developed by authors (Source: Authors)

Finally, the general technology acceptance model such as TAM and UTAUT considers the single end users (either the students or the instructors). However, in the field of education, the primary technology users are both students and instructors. Thus, with the knowledge gained from this research study, a new technology acceptance model suitable for digital education tools has been proposed. The proposed novel digital education technology acceptance model (DETAM) that considers the various factors for both students and instructors are depicted in Fig.16. Specifically, for students, seamless access and training, individual differences (self-efficacy and passion towards learning with a new technology), and social influence create an impact on usage attitudes among students. Moreover, the instructor's capability and support moderate the relationship between individual differences and social influence on usage attitudes. Moreover, the students' perceived ease of use has a direct effect on behavioural intention, moderated by the instructor’s experience with and adaptability to new technology. The students' perceived usefulness influences their behavioural intention, moderated by the performance expectancy of the instructor. The technology anxiety of students and instructors directly influences behavioural intention. Moreover, the performance expectancy of the instructor to survive in the teaching field influence the behavioural intention to use digital technology. The facilitating conditions that cover sufficient resource availability, support from management and institutions, training, and an effective learning environment have a huge impact on the behavioural intention and actual use of the technology.

6.1. Implications for Theory

First, from the cumulative analysis of the relationships and their significance in the selected studies using weight computation, *perceived usefulness, perceived ease of use, attitude,* and *performance expectancy* influence more on *intention to use* or *behavioural intention*. Also, *social influence* and *facilitating conditions* have less impact on *behavioural intention*. Moreover, the impact of *technology anxiety* on *behavioural intention* seems to be negative, which needs to be researched further since only 3 articles are available on this relationship. The other variables, such as *real-time collaboration*, *self-efficacy*, and *hedonic motivation*, need to be analysed further in future research.

Second, with the meta-analysis performed, most of the constructs with weight = 1 seem to have a high average beta value. Moreover, *self-efficacy* and *technology anxiety* have an influence on *perceived ease of use*, which has to be researched further since the number of studies supporting the construct is small. The results of the meta-analytic CFA indicate that there is a strong correlation between the variables of the TAM and UTAUT models. Third, by performing the subgroup analysis with publication on or before 2020 and after 2020, the influence of independent variables (social influence and performance expectancy) on the dependent variables (behavioural intention) varies drastically. This indicates that the perception and need for blended learning have increased since COVID-19.

Fourth, from the perspective of students, *attitude, perceived ease of use,* and *perceived usefulness* have a greater influence on *intention to use.* Also, *technology anxiety* seems to negatively influence the *perceived ease of use*. The influence of *facilitating conditions on behavioural intention* is found to be insignificant, whereas *self-efficacy* and *social influence* are the poor predictors of *attitude towards usage* and *behavioural intention* respectively. Fifth, from the perspective of teachers, *performance expectancy* plays a huge role in *behavioural intention.* On the other hand, *effort expectancy* is a poor predictor of *behavioural intention.*

6.2. Implications for Practice

This meta-analytic research has some practical implications for educators as well as governments. The outcomes of *perceived usefulness, perceived ease of use, attitude,* and *performance expectancy* have a greater influence *on behavioural intention*. The results also proved the need for and perception of blended learning has increased, especially after the COVID pandemic. Thus, the government must give special attention to blended learning technologies and strategies that improve the attitude and perception of students and instructors in the long term.

The *self-efficiency* of the students and the influence of parents and mentors in using blended learning (*social influence*) have a moderate influence on blended learning adoption. So, the *perceived ease of use and usefulness* on the *attitude and intention* of students can be improved by choosing digital education tools that are simple yet effective. Since *technology anxiety* plays a negative role in *behaviour intention* among both students and instructors, more training must be provided by institutions and organisations to increase the *perceived usefulness and ease of use* when using digital tools and technologies for blended learning. More specifically, the instructors of the previous generation have difficulty using these advanced technologies, and so proper training must be provided for them separately to maximize the use of investment in technologies.

Moreover, the curriculum framed for traditional teaching methods cannot be used for blended learning. Some courses might have more difficulty than others, for which the curriculum and course structure have to be reframed in such a way that they suit blended learning. In the case of a traditional classroom environment, the instructor and the blackboard are the main resources. However, on the other hand, for blended learning, the appropriate technologies and resources are mandatory. Thus, institutions must provide appropriate, suitable, and quality resources, and the environment must be set up accordingly. Continuous improvement can be enhanced with constant feedback from the users of the technology.

During the transition phase of blended learning, there must be a temporary increase in the workload, so the instructors must be provided with proper support from the organization. Furthermore, both students and instructors exhibit a lack of motivation, which must be addressed. Maintaining the classroom and student progress is a challenging job for the instructors, since highly capable students might have less exposure to technology. Thus, providing flexibility and allowing them to work more helps them overcome technology anxiety. Possibly, the classroom materials are available online in a blended learning environment. Though it helps the students to learn whenever necessary, a few students may not be attentive during class due to the availability of teaching materials online, which can be overcome by using good tools to gamify the classes to engage the students.

6.3. Limitations of the Study

Like other studies, the current meta-analytic study has some limitations. The number of articles reviewed on the adoption of blended learning is merely 32. This is due to the fact that the analysis focuses only on the articles written in English and the adoption of blended learning in higher education. Also, though many articles focus on virtual learning or e-learning, the selected articles are confined to the term "blended learning" in the title and keyword list. The articles that performed the quantitative analysis with only SEM or regression with beta values have only been chosen for the analysis.

Like the selection process, the merging of constructs has a limitation in that a few variables, such as computer and technology, as well as perceived satisfaction and user satisfaction, have been merged together based on analogous meanings and not on the intended author's perspective. Also, this study mainly analyses only the direct relationships, even though some mediator and moderator variables influence the relationships between the dependent and independent variables. Though several new variables were reported in these selected studies that positively influence the adoption of blended learning, only the variables that were examined more are used for the analysis. Moreover, the result of the analysis of publication bias could not seem to be conclusive for asymmetry, since the number of studies tested for the individual relationships is minimal. The analysis of the constructs will be more effective if they have been tested in more than 20 studies.

7. Conclusion

With important implications for both teaching and learning, blended learning has evolved into a crucial educational model in the twenty-first century. Nevertheless, the current body of research lacks a comprehensive quantitative exploration of the factors influencing its implementation. Therefore, this study responds to the increased demand for evidence-based perspectives on the integration of digital tools and teaching methodologies. The research study achieves its objectives through a meta-analytic review of blended learning adoption and technological acceptance, particularly in higher education. Further, the results of the study can be used immediately in a workplace context by educators, administrators, and policymakers, guiding decisions about implementing technologies, changing pedagogical methods, and enhancing professional development for educators. This research empowers educational institutions to ensure that blended learning meets the requirements of students and improves instructor efficiency, allowing them to utilise the findings to their advantage.

By conducting a meta-analysis of 32 studies spanning from 2007 to 2022, involving a substantial sample size of 8,168, and assessing various relationships, this study has made a notable contribution to the existing body of knowledge on blended learning adoption in higher education. It extracted 282 useful constructs from research models for analysing the acceptance of blended learning. Additionally, a new digital education technology acceptance model (DETAM) has been conceptualized, considering both students and instructors as end-users. The analysis results indicate that the need for and positive perception of blended learning increased, especially after the COVID pandemic. The study identifies strong predictors, including perceived ease of use, perceived usefulness, attitude towards usage, intention to use, and performance expectancy. However, it differs for students and instructors. Specifically, among student respondents, perceived ease of use, attitude towards usage, and perceived usefulness of intention to use are the good predictors, and performance expectancy and facilitating conditions on behavioural intention is found to be the good predictor concerning instructors. Relationships such as effort expectancy and social influence on behavioural intention are discovered to be poor predictors. Furthermore, the impact of technology anxiety on behavioural intention, real-time collaboration, self-efficacy, and hedonic motivation needs to be analysed further in future research. Also, it is found that only six out of 32 articles are analysed with the instructors as the samples. Thus, more research work on blended learning from the instructors' perspective is necessary. The future study also aims at evaluating the proposed digital education technology acceptance model for the adoption of various learning methodologies in the field of education.

The study offers an understanding of factors influencing blended learning acceptability, establishing a solid foundation for efficient systems, and emphasising instructors' performance expectancy. This research study significantly advances the field of blended learning adoption in higher education by contributing significantly to existing knowledge. First, the study synthesises and quantitatively analyses the vast body of research, which not only supports previously reported tendencies but also reveals precise relationships and patterns that had been overlooked by other studies for both students and instructors. Second, the research addresses a significant need in the literature on technology acceptance models by proposing DETAM, which helps to accurately reflect and understand the educational technology adoption process. By introducing the DETAM, the research contributes to the empirical foundations of educational technology adoption and also serve as a foundation for more customised models that are adapted to certain educational contexts or disciplines. Researchers may modify and expand DETAM to examine technology acceptability in various learning contexts, enabling a deeper understanding of the various factors at higher education institutions.

Third, the findings identify promising directions for further study for the academic community to explore more deeply into important topics including technological anxiety, real-time collaboration, self-efficacy, and hedonic motivation. By identifying these areas, further research and development in the area of blended learning implementation is encouraged. In addition to this, the COVID-19 epidemic has increased the urgency of the need for successful blended learning techniques. This research highlights a pivotal point in education, proving the increasing demand for blended learning solutions. Thus, this study gains additional scientific relevance in this context as it addresses a real-world problem faced by universities and colleges worldwide. Finally, the research findings have important policy and practise implications for academic institutions. It is imperative to prioritise user-friendly solutions to improve student engagement and instructor performance, especially given the increased need for blended learning in the post-COVID era. These findings can help policymakers develop plans to increase the use of blended learning in higher education.

More specifically, the government and educational institutions must ensure they use the best tools that are easy to use for the students while considering instructor performance expectancy and facilitating conditions as a significant factor.

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