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Visualizing Contemporary Factors Affecting the Adoption of E-learning: A PRISMA Approach

Huong Thi Pham [1]

[1] *Digital Learning Data Development and Management Center, Vinh University, Vietnam*

***Abstract* – This study investigated the effects of factors that influence users' perceptions to adopt digital transformation. Eight hypotheses were proposed and tested employing the Structural Equation Modeling. 248 government personnel, instructors, and students were recruited to answer the questionnaires through Google Form. The experimental results indicated that facilitating conditions, policy, social influence, and knowledge all had a positive and significant impact on digital transformation adoption. Meanwhile, policy was found to have a positive effect on social influence. In turn, social influence positively affected knowledge. In addition, awareness was verified to be a reliable predictor of knowledge. The notable exception was that the awareness factor was shown to have no effect on digital transformation adoption. Thus, traditional reaching to citizens via television, news, broadcast needed to be re-examined. Overall, the model accounts for 52.5 percent of the variation in the data. Four recommendations were proposed for practitioners, and limitations were roughly discussed. Future study is called to reexamine the unexpected effect of awareness on digital transformation adoption.**

***Keywords* – Systematic review, factors, Theoretical models, Association rules mining, e-learning.**

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Corresponding author: Huong Thi Pham,
Digital Learning Data Development and Management Center, Vinh University, Vietnam.
Email: pthuong@vinhuni.edu.vn

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1. Introduction

In past decades, e-learning has been adopted by educators and lecturers for delivering courses in various domains [1], [2], [3] . E-learning has been shown to bring many benefits for teachers, learners and educators such as low cost, student friendliness, accessibility to current learning resources, flexibility, global reach, scalability, student autonomy, upskill, and retrain [4], [5]. However, several studies [5], [6], [7] have demonstrated the disadvantages of this educational method, including low motivation, technology dependence, legacy, content reliability, perceived isolation, commitments, limitations for impaired learners, ineffectiveness across classes, incomplete assignments and unsatisfactory learning outcomes, among others. There have been a lot of efforts put in to maintaining the merits while decreasing the negatives of e-learning from approaches, methods, case studies to factors analysis [4], [5], [7], [8] examined how traditional approaches to distance education may be adapted to today's highly interactive online classrooms. In this regard, learner abilities, traits, and preferred learning styles need to be taken into consideration across all online learning modalities, and instructor presence is still vital. For both the classroom and the industry, Chang [4] detailed five exemplary implementations of interactive learning, describing their pedagogical rationale and explaining how to integrate it effectively. Similar efforts were made by researchers to determine what factors of e-learning are most important to students and what components can be verified as having a significant impact on student satisfaction and performance. For example, Mtebe and Raphael [8] found that system quality, service quality, and instructor quality are reliable predictors on students' satisfaction with an e-learning system. Furthermore, Moorthy et al. [9] revealed that habit and hedonic incentive are the strongest determinants on learners' behaviours. Recently, Regmi and Jones [7] conducted a systematic review of factors affecting e-learning in health sciences education.

Their research showed that a number of important factors, including the learners' experience, learning outcomes, efficacy, motivation, satisfaction, expectation, training and support, collaboration, and integration of e-learning into current curricula, all play a role in the success of the e-learning model. What it means is that there are several potential factors influencing the adoption of e-learning.

Previous studies suggested that factor analysis in e-learning studies would be useful and might help researchers with evaluating both teachers and students. Despite the fact that there is variety of factors from which to consider, it may be challenging for inexperienced e-learning researchers to justify which ones are relevant and meaningful in their particular environment. Therefore, it is necessary to conduct a systematic review of the factors influencing e-learning adoption so that novices to the area may learn as effectively and efficiently as possible. Although there are many e-learning review studies available in the literature [5], [6], [10], [11] , none of them concentrate on this specific issue, that is the relationship among factors so, there is a need for this investigation and the current study fills a gap in the body of knowledge.

The current study aims to add to the factors in e-learning studies in two ways. First, it gives an overview of the important topics, theoretical models, factors, and their interconnections in e-learning research. The findings might be used to supplement existing e-learning review studies. Second, rather than narrative reports, the major findings in this study were displayed in a graphical style. The visualization outputs not only provide a full perspective of the contents under consideration [12], but also highlight structural knowledge of the most significant interactions of factors in e-learning study patterns [13] as well as help interested readers consume information faster. The following four major research questions lead this systematic literature review study:

RQ1. What were the most influential factors in the acceptance of e-learning? In what manner did these forces coexist?

RQ2. Which factors served as independent or predictive variables? Which factors were dependent ones?

RQ3. Which relationships (hypotheses/assumptions) between factors were validated? Which ones did not receive support?

For researchers in general and e-learning adopters, it is crucial to answer these research questions. First, it helps users of e-learning to obtain a thorough grasp of prevalent factors and their interrelationships, hence minimizing the amount of time necessary to study several researches.

Second, it permits researchers to corroborate their conceptual models (e.g., supported or rejected hypotheses) with evidence from earlier discoveries uncovered in this analysis. In addition, it aids both beginner and experienced researchers in remaining informed of the latest developments.

The remaining sections of this article are structured as follows: A brief survey of the literature pertinent to the current inquiry was conducted first. Next, the materials and methods sections were introduced, which outlined how data were acquired and analysed using the PRISMA approach. The results were then shown visually and scrutinized. At the end, implications were examined in relation to the findings.

2. Literature Review

Almaiah et al. [6] interviewed 30 students and 31 e-learning system professionals across 6 institutions to investigate the key challenges and factors affecting the use of e-learning systems during the COVID-19 pandemic. The findings revealed that there were 15 factors influencing the adoption of e-learning system, and these factors were classified into four themes such as culture, trust, system quality and self-efficacy. Abdullah and Ward [14] proposed a unique framework that was based on the Delphi method in order to determine the most important factors that would lead to the successful implementation of an e-learning system in Saudi Arabia. Their findings highlighted eleven significant factors observed across four research areas (website quality, technological alternatives, top management support, and e-learning awareness). Nortvig et al. [15] conducted a literature review of factors influencing e-learning from Educational Resource Information Center (ERIC) and ProQuest databases. Results extracted from 44 articles showed that from 2014 to 2017, presence, interactions, materials, synchronous/asynchronous learning, realistic contents were the most prominent factors influencing e-learning. Regmi and Jones [7] conducted a systematic review on e-learning in health sciences education. After conducting research on 24 different articles that were published between 1980 and 2019, the authors came to the conclusion that the most critical factors of an effective e-learning environment include learner-facilitator interaction and collaboration, attention to learners' motivation and expectations, the use of intuitive technological tools, and making the students the focal point of the learning process. Muzaffar et al. [16] reviewed 53 studies from 2016 to 2020 in the topic of online exams solutions in e-learning, their findings discovered that network infrastructure, hardware requirements, implementation complexity and training requirements were important factors for online exam adoption.

In the midst of the COVID-19 outbreak, Naciri et al. [17] conducted a comprehensive review of e-learning in health professions education. During the pandemic, students' positive impressions of e-learning were attributed to a variety of factors, including ready access to technology, computer competency, the quality of online course materials, the quality of student-teacher interactions, and the students' ability to tailor their studies to their individual needs. However, concerns with internet connection, familiarity with online learning technologies, and the development of clinical competence are important obstacles to the broad adoption of e-learning. Furthermore, motivation and engagement were shown to be higher than in traditional education. The implementation of the DeLone and McLean Model (also known as the D&M model) in the field of e-learning was analyzed and discussed by Sabeh et al. [18]. In addition to the core success factors like system quality, information quality, use, user satisfaction, individual impact, and organizational impact, the authors discovered that many of the 92 studies either extended or modified the D&M model by integrating other factors self-efficacy, habits, ease of use, satisfaction, course quality, culture, computer anxiety, enjoyment, infrastructure, and net benefits.

To summarize, there is a growing number of e-learning evaluations, each of which is focused on a certain subject area (e.g., challenges, environment, technology). The present work is unique in comparison to earlier reviews because, in addition to focusing on factors, it also investigates the interconnections that exist between those many features. To the best of our knowledge, there has not been existing studies that has been published in the literature that directly focused on this issue.

3. Materials and Methods

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement was utilized since the current study involves a review of prior research on the application of factor analysis in e-learning studies [19]. The goal of the PRISMA statement is to offer researchers with recommendations for improving the reporting of scientific reviews and meta-analyses.

It is a fundamental collection of evidence-based components for systematic review reports, and its objective is to help systematic reviewers in properly articulating the review's purpose and the authors' objectives. It has been employed in the past to accomplish comparable research objectives [20], [21], and it is endorsed as a best practice in several the most prestigious publications.

3.1. Source selection

The corpus was compiled using titles, abstracts, and keywords from the Web of Science and Scopus databases. These two databases have proven as reliable resources for e-learning literature reviews in the past. In addition, these databases are acknowledged as vital and trustworthy sources of high-quality scientific and technical articles. In addition, the snowball approach was applied to assess prospective articles that may have been overlooked throughout the search effort. In this regard, each Web of Science and Scopus-obtained paper was exhaustively analyzed by examining each reference. This research analyzes the publication's title, abstract, objectives, methodology, findings, and conclusions to determine its relevancy to the current study.

3.2. Search criteria

To include articles in our corpus, both of the following prerequisites must be met: 1) e-learning search phrase: at least one e-learning term must occur in an article's title, abstract, or author keywords. 2) factors search term: at least one factor term must appear in an article's title, abstract, or author keywords. To focus on the factor analysis, the article's title, abstract, and keywords must contain at least one of the following terms: factor*, determinant*, effect*, behavior*, adopt*, acceptance, intention, and relationship. These keywords were obtained by following references to comparable research.

3.3. Eligibility evaluation

The first researcher personally assessed the entry criteria specified below by evaluating the titles and abstracts of the acquired publications to decide whether or not the obtained articles were acceptable for inclusion in the study. When it was determined that a definitive verdict could not be reached, the second and third authors were consulted to discuss the publication's other facets, notably the methodology and the factor analysis.

Only articles that can fulfil the following requirements are kept in the corpus: 1) The article was peer-reviewed for inclusion in the two indexing databases (Scopus and Web of Science). Due of the credibility of peer-reviewed journals and the rigorous peer-review processes, only publications from these databases are included in this study, 2) The topic of an article is relevant to factor analysis in e-learning in social sciences, 3) The article was written in English, 4) Publications were published between 2020 and 2022, and 4) Only journal article was evaluated.

The following criteria will be used to determine whether the article is retained in the database: Article in press, letter, note, brief survey, conference paper, review, book chapter. Secondly, the document was not written in English. Thirdly, research on e-learning that does not include factor analysis. Lastly, conference proceeding, report, trade journal, book in a series.

Figure 1. displays the systematic review's data collection and screening process using the PRISMA methodology. The inclusion and exclusion criteria from Scopus and Web of Science resulted in the identification of 559 publications. There were 283 duplicates that were removed from the list due to title and author similarities. 160 articles were eliminated for being off topic, leaving 116 publications suitable for the next step. Out of a total of 116 publications, only 98 were accessible for full-text extraction, while the remaining 18 were inaccessible. The remaining publications were thoroughly examined manually. In the end, 60 unique articles were considered for this research.

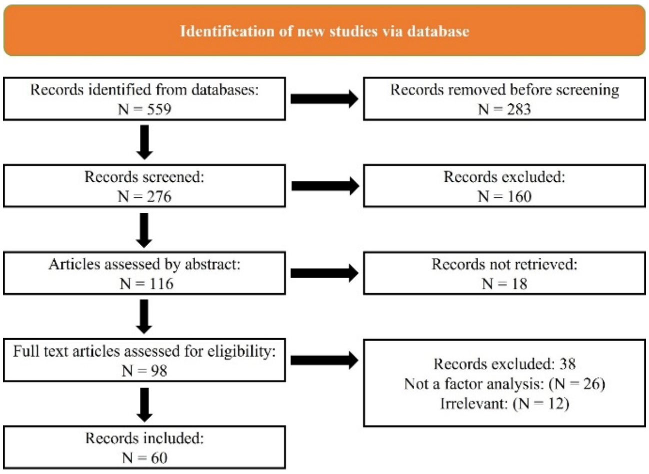

Figure 1. A PRISMA-compliant overview of the acquisition and processing of corpora for systematic research

3.4. Processing and data extraction

In order to carry out the analysis, the current study extracted relevant factors, theoretical frameworks, hypotheses that were supported, and hypotheses that were rejected. After the data were obtained, they were cleaned by either being changed to include synonym names or by having their abbreviations converted to their full names (e.g., TAM to Technology Acceptance Model). After that, each feature was parsed out into its own unique file format so that it could be imported into an appropriate visualization tool or program and examined using that application.

3.5. Data Distribution

Figure 2. depicts the distribution of publications concentrating on factors in e-learning research from 2020 to 2022. The graph's trend line revealed that interest in this subject had increased during the previous three years. The number of e-learning papers published in 2021 and 2022 was the same (24 articles), however in 2020, only 12 articles (20%) were published. Because this study was conducted in September 2022, and additional articles may be assigned to 2022 in the following months, the interpretation of 2022 may be unsatisfactory.

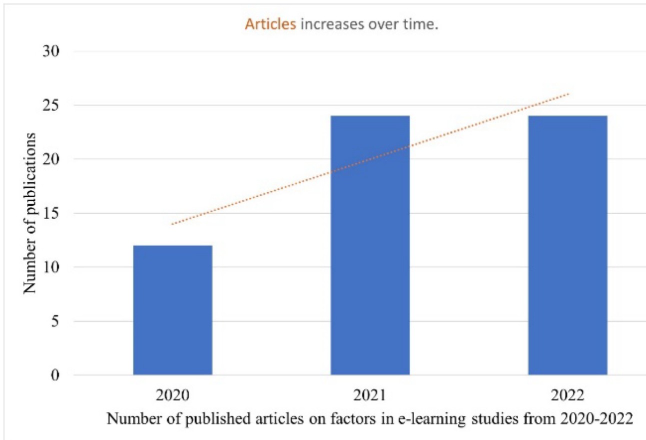

Figure 2. Number of published articles on factors in e-learning studies from 2020-2022

4. Results

4.1. What Were the Most Influential Factors in the Acceptance of E-learning? In What Manner Did These Forces Coexist?

There was a total of 463 factors studied in 60 e-learning papers between 2020 and 2022. Figure 3. highlights 136 unique factors extracted from that research. The size of each item is proportional to the number of times it appears in the studies.

As can be seen from the figure, behavioral intention, ease of use, usefulness, satisfaction, and attitude are the top five influential factors that have been adapted in many publications, with 49, 33, 33, 21, and 17 occurrences respectively. This phenomena is owed to the fact that behavioral intention was one of the primary objectives of the conceptual model and the Technology Acceptance Model (TAM), which integrates the aforementioned factors (e.g., behavioral intention, ease of use, usefulness, and attitude), was utilized in the great majority of e-learning research (30 studies as in Table 1).

This current study found that there was a total of 17 theoretical frameworks employed in 60 articles. In addition to TAM, the Unified Theory of Acceptance and Use of Technology [18], [20], [21], DeLone and Mclean [22], [23], Theory of Planned Behavior [24], [25], and Expectation Confirmation Model [26], [27] and Self-developed Model [28], [29] were among the theories that utilized the corpus at least three times (see Table 1). The current study's findings were consistent with a literature review conducted by Valverde-Berrocoso et al. [11], who indicated that TAM was primarily used, as were its variables.

Figure 3. Wordle of e-learning implementation factors used in 60 different studies.

Table 1. Theoretical models and Frameworks utilized in 60 e-learning publications.

No	Theoretical Models and Frameworks	Freq.	Percent
1	(extended) Technology Acceptance Model (TAM)	30	46.15
2	(extended) Unified Theory of Acceptance and Use of Technology (UTAUT)	8	12.31
3	DeLone and Mclean (D&M)	5	7.69
4	Self-developed Model	5	7.69
5	Theory of Planned Behavior (TPB)	3	4.62
6	Expectation Confirmation Model (ECM)	3	4.62
7	(extended) Theory of Reasoned Action (TRA)	1	1.54
8	Technological Pedagogical Content Knowledge (TPACK)	1	1.54
9	Stimulus–Organism–Response (SOR)	1	1.54
10	GETAMEL	1	1.54
11	Distance Education Learning Environments Survey (DELES)	1	1.54
12	Self-Determination Theory (SDT)	1	1.54
13	SERVQUAL	1	1.54
14	Value-Based Adoption Model (VAM)	1	1.54
15	Perceived Organizational Support (POS)	1	1.54
16	Big Five Personality Traits	1	1.54
17	Information System Success Model (ISSM)	1	1.54
Total		65	100

In order to study additional intriguing factors, Figure 4. was created by omitting leading factors (i.e., behavioral intention, ease of use, usefulness, satisfaction, and attitude) so that researchers interested in identifying emerging factors between 2020 and 2022 can examine the present 60 samples. The data shown in the graph indicates that self-efficacy, social influence, enjoyment, system quality, and performance stand out in comparison to the other factors.

This suggests that researchers are focusing more on these issues than on others. The first three influencing factors are related to user behavior (self-efficacy, social influence, enjoyment), while the latter two are related to the e-learning system (system quality, and performance).

Figure 4. Wordcloud of factors used in e-learning research, excluding top factors.

Figure 5 provides a thorough perspective of the interrelationships between the factors, or the frequency with which factors are studied in tandem. In this diagram, each factor is represented by a circle whose diameter corresponds to the frequency of occurrence. The VOSviewer program [30] created the color of a circle to represent a cluster formation (19 clusters). In general, the network is readable, however there are a few overlapping nodes, showing that various research employed different factors. If every node in this network is connected to every other node in this network, the network will seem cluttered and overlapping. The nodes will be further apart if there are fewer connections. Both the development of 19 clusters and the application of 17 theoretical frameworks contribute to the explanation of why specific nodes (factors) were grouped together. Clearly, behavioral intention is at the center of the network, suggesting its substantial relationship with several other factors. Few factors, including flow, competence, auditory, critical mass, and relatedness, are displaced from the center, indicating that these were seldom explored.

The large circles in the middle of each colour region demonstrate that course content, satisfaction, usefulness, actual usage, and motivation are intriguing factors that are frequently associated with other factors.

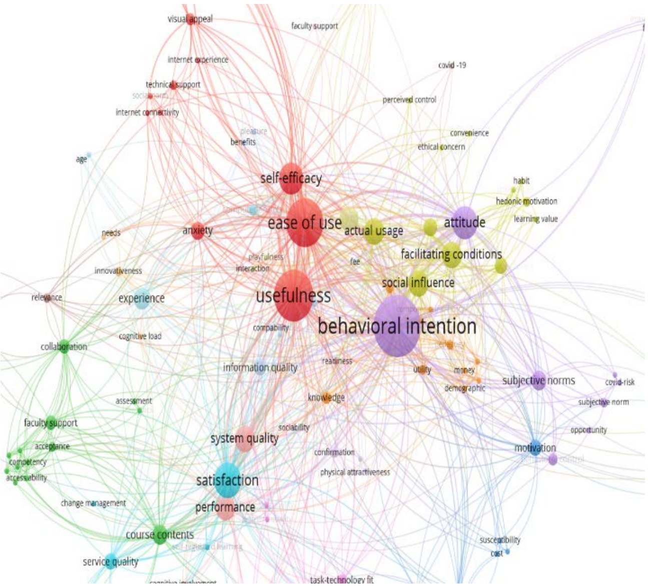

Figure 5. The associations among factors in e-learning studies

Figure 6. was produced without the TAM's factors in order to examine the interactions between growing factors other than those contained in the TAM.

Factors such as self-efficacy, satisfaction, system quality, social influence, subjective norms, course contents, information quality, instructor quality, enjoyment, experience, and service quality are readily evident in the network, and each serve as a hub joining other factors that are grouped in their respective sets. In addition to the knowledge obtained via the network, the diversity of 17 distinct theoretical frameworks helps us clarify that these are the external factors that are incorporated into the many existing theories (e.g., TAM, UTAUT, or D&M). In contrast, efficacy, competence, conscientiousness were addressed only once among the 60 publications [31].

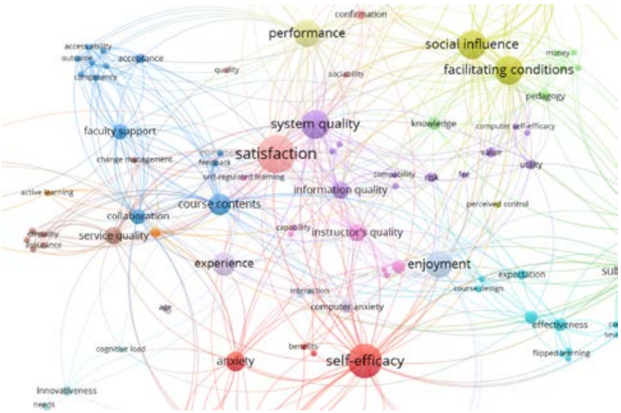

Figure 6 The association between factors in e-learning research without the TAM's variables

While Figure 5. and Figure 6. allow researchers to analyse the associations between factors in a chain or investigate the factors in clusters, these figures do not help researchers to determine which factors are frequently quantitatively investigated together. Thus, Table 2. reveals the principles of relationship between factors (arules package in R was used [32]). In this instance, the left and right sides of the arrow represent the probability that the factor(s) on the right will occur if the factor(s) on the left occur. Support for a factor-set X is defined as the proportion of corpus studies that include the factor-set [34]. For example, the factor set (ease of use) => (usefulness) has a support of 0.475 since it occurs in 47.5 of all e-learning studies. The confidence is the proportion of occurrences right hand side of the arrow in the studies with factors in the left hand side [34]. For example, the rule (ease of use) => (usefulness) has a confidence of 0.508 which suggests that the rule is valid in 50.8% of the studies including (ease of use). The lift indicates the interaction between the left and right sides of the arrow, with larger lift values suggesting stronger associations [32], [33].

Table 2. Association rule mining of factors using the R package arules.

No	Rules	Support	Conf.	Lift
1	(subjective norms) => (behavioral intention)	0.115	0.115	1.356
2	(anxiety) => (ease of use)	0.115	0.115	1.968
3	(anxiety) => (usefulness)	0.115	0.115	1.848
4	(anxiety) => (behavioral intention)	0.115	0.115	1.356
5	(enjoyment) => (ease of use)	0.148	0.164	1.771
6	(enjoyment) => (usefulness)	0.131	0.164	1.479
7	(enjoyment) => (behavioral intention)	0.148	0.164	1.220
8	(actual usage) => (behavioral intention)	0.148	0.180	1.109
9	(social influence) => (behavioral intention)	0.164	0.180	1.232
10	(facilitating conditions) => (behavioral intention)	0.164	0.180	1.232
11	(attitude) => (behavioral intention)	0.246	0.262	1.271
12	(self-efficacy) => (ease of use)	0.197	0.246	1.574
13	(self-efficacy) => (usefulness)	0.213	0.246	1.602
14	(ease of use) => (usefulness)	0.475	0.508	1.729
15	(usefulness) => (ease of use)	0.475	0.541	1.729
16	(ease of use) => (behavioral intention)	0.443	0.508	1.181
17	(usefulness) => (behavioral intention)	0.459	0.541	1.150
18	(anxiety, ease of use) => (usefulness)	0.115	0.115	1.848
19	(anxiety, usefulness) => (ease of use)	0.115	0.115	1.968
20	(anxiety, ease of use) => (behavioral intention)	0.115	0.115	1.356
21	(anxiety, behavioral intention) => (ease of use)	0.115	0.115	1.968
22	(anxiety, usefulness) => (behavioral intention)	0.115	0.115	1.356
23	(anxiety, behavioral intention) => (usefulness)	0.115	0.115	1.848
24	(ease of use, enjoyment) => (usefulness)	0.131	0.148	1.643
25	(enjoyment, usefulness) => (ease of use)	0.131	0.131	1.968
26	(ease of use, enjoyment) => (behavioral intention)	0.148	0.148	1.356
27	(behavioral intention, enjoyment) => (ease of use)	0.148	0.148	1.968
28	(enjoyment, usefulness) => (behavioral intention)	0.131	0.131	1.356
29	(behavioral intention, enjoyment) => (usefulness)	0.131	0.148	1.643
30	(actual usage, ease of use) => (usefulness)	0.115	0.131	1.617
31	(actual usage, usefulness) => (ease of use)	0.115	0.131	1.722
32	(actual usage, ease of use) => (behavioral intention)	0.115	0.131	1.186
33	(facilitating conditions, social influence) => (behavioral intention)	0.115	0.115	1.356
34	(attitude, ease of use) => (usefulness)	0.180	0.180	1.848
35	(attitude, usefulness) => (ease of use)	0.180	0.180	1.968
36	(attitude, ease of use) => (behavioral intention)	0.164	0.180	1.232
37	(attitude, usefulness) => (behavioral intention)	0.164	0.180	1.232
38	(ease of use, self-efficacy) => (usefulness)	0.197	0.197	1.848
39	(self-efficacy, usefulness) => (ease of use)	0.197	0.213	1.816
40	(behavioral intention, self-efficacy) => (ease of use)	0.148	0.180	1.610
41	(behavioral intention, self-efficacy) => (usefulness)	0.164	0.180	1.680
42	(ease of use, usefulness) => (behavioral intention)	0.410	0.475	1.169
43	(behavioral intention, ease of use) => (usefulness)	0.410	0.443	1.712
44	(behavioral intention, usefulness) => (ease of use)	0.410	0.459	1.757
45	(anxiety, ease of use, usefulness) => (behavioral intention)	0.115	0.115	1.356
46	(anxiety, behavioral intention, ease of use) => (usefulness)	0.115	0.115	1.848
47	(anxiety, behavioral intention, usefulness) => (ease of use)	0.115	0.115	1.968
48	(ease of use, enjoyment, usefulness) => (behavioral intention)	0.131	0.131	1.356
49	(behavioral intention, ease of use, enjoyment) => (usefulness)	0.131	0.148	1.643
50	(behavioral intention, enjoyment, usefulness) => (ease of use)	0.131	0.131	1.968
51	(attitude, ease of use, usefulness) => (behavioral intention)	0.164	0.180	1.232
52	(attitude, behavioral intention, ease of use) => (usefulness)	0.164	0.164	1.848
53	(attitude, behavioral intention, usefulness) => (ease of use)	0.164	0.164	1.968
54	(behavioral intention, ease of use, self-efficacy) => (usefulness)	0.148	0.148	1.848
55	(behavioral intention, self-efficacy, usefulness) => (ease of use)	0.148	0.164	1.771

Overall, 55 rules about e-learning factors were extracted from 60 papers. Regarding the single component on the left, 17 rules were derived pertaining to 10 factors, including subjective norms, behavioral intention, anxiety, ease of use, usefulness, enjoyment, actual usage, social influence, facilitating situations, and self-efficacy. Notably, five of these ten factors are included in the TAM model (ease of use, usefulness, attitude, behavioral intention, actual usage), as are all factors on the right-hand side. Other intriguing results include subjective norms, anxiety, enjoyment, social influence, facilitating situations, and self-efficacy. In addition, behavioral intention is likely to be investigated along with factor such as subjective norms, anxiety, enjoyment, social influence, facilitating conditions. Furthermore, whether anxiety is studied, ease of use, usefulness and behavioral are often included. In terms of two factors in left hand side, 27 rules were found. In this regard, anxiety, ease of use, usefulness and behavioral intention were discovered too often occur together (rules 18 to 23). Similarly, enjoyment was considered when TAM model was evaluated (rules 24 to 29) [22], [35]. Notably, facilitating conditions and social influence (rule 33) are part of the UTAUT model which also includes behavioral intention. Self-efficacy, anxiety, and enjoyment are among the factors that primarily incorporated in the TAM's models in the three factors in left hand side.

4.2. Which Factors Served as Independent or Predictive Variables? Which Factors Were Dependent Ones?

In all, 129 factors serve as predictors or independent variables, whilst 39 factors serve as dependent variables. The network of predictors and outcomes is depicted in Figure 7. In this context, the arrow represents the direction of the influential factor. Behavioral intention is the primary topic of many studies, as seen by the numerous links leading to it in the figure. In addition, the thickness of ease of use and usefulness predicts behavioral intention. This is explained by the usage of the TAM model and the default setup of the model, which includes these assumptions. The network also reveals crucial information, such as the indirect relationship between factors or how a single factor predicts many factors. For example, openness factor is a predictor of privacy, which in turn is predictor of behavioral intention; hence, openness factor indirectly influences behavioral intention. Furthermore, competence is not just a predictor of digital literacy, and acceptance but also the outcomes of deep learning and surface learning.

Examining the nodes on the figure's perimeter that influence outcomes may yield more relevant information. Some nodes lack outbound linkages, suggesting that these factors, rather than behavioral intention, are the major focus of research (e.g., digital literacy [36], integration, reliability, assurance [37]). Overall, interested readers may uncover other intriguing patterns in the network that were not found in the study, or by analyzing information from Figure 7, e-learning researchers would have more alternatives for forming research hypotheses as opposed to depending on parsimonious models.

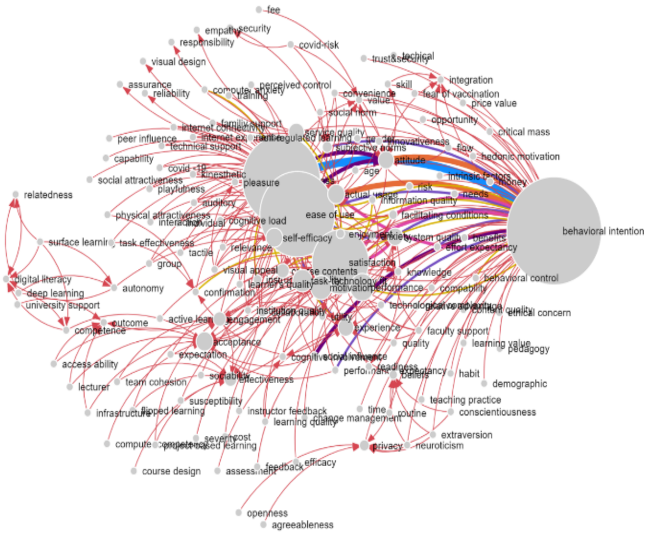

Figure 7. The network of predictors and dependent variables

Since the TAM model dominates the study as indicated in Table 1., it would be interesting to examine alternate interrelationships without taking into account the TAM model's assumptions; consequently, Figure 8 was updated for this purpose. Figure 8 demonstrates that satisfaction, performance, acceptance and motivation are the four most researched factors, as indicated by the size of their circles, indicating that these factors may be employed as outcomes or intermediate factors. Moreover, the plurality of network nodes remained connected, indicating that some components are included in numerous researches and that TAM's factors do not serve as bridges between these relations. The thickness of the link indicates that system quality has been assumed to influence satisfactions in numerous existing studies (8 times), followed by service quality, course contents, confirmation, and information quality. In addition to the top four factors (i.e., that satisfaction, performance, acceptance and motivation), the network also focuses on self-efficacy and effectiveness, for which there are more hypotheses than for the other factors.

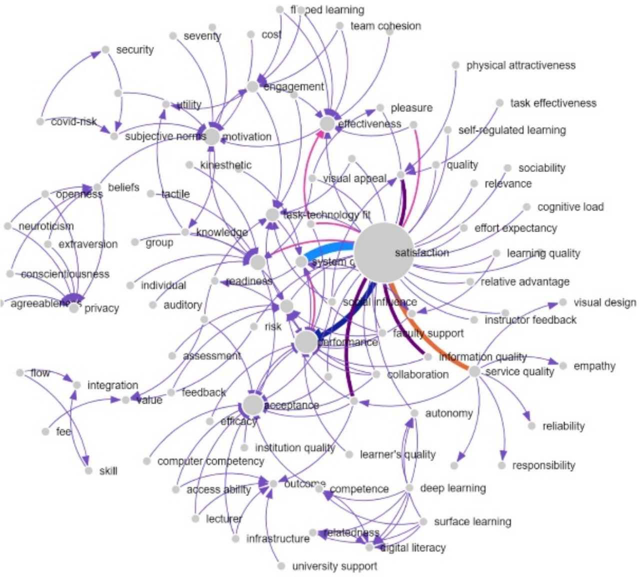

Figure 8. The network of predictors and results omitting the TAM's factors.

4.3. Which Relationships (Hypotheses/Assumptions) Between Factors Were Validated? Which Ones Did Not Receive Support?

There was a total of 603 hypotheses established across 60 e-learning studies, with an average of ten hypotheses per study. 498 of these assumptions were determined to be acceptable, whilst 105 were deemed insignificant.

Figure 9. depicts the validated hypotheses from the collected e-learning studies. The thickness and color of the link conveys the same information allowing scholars to rapidly discover associations with the same strength. Supported hypotheses may be divided into three categories: weakly supported (less than 5 times supported), intermediately supported (greater than/equal 5 times and less than 10 times supported), and strongly supported (greater or equal 10 times supported). Due to the overlapping of nodes, we list out some influencing relationships which are hardly seen in the figure. Strongly supported hypotheses include usefulness → behavioral intention (19 times), ease of use → usefulness (16 times), attitude → behavioral intention (14 times), ease of use → behavioral intention (13 times), ease of use → attitude (11 times), usefulness → attitude (11 times), and social influence → behavioral intention (10 times). Weakly supported hypotheses are depicted in Figure 9 indicated by thin arrows.

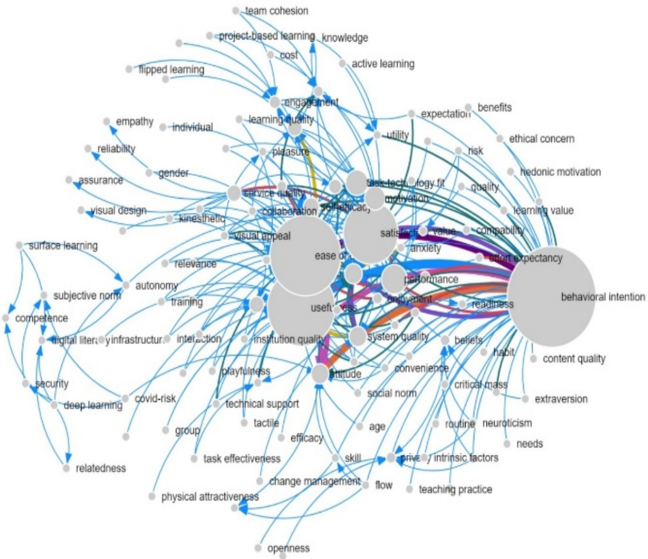

Figure 9. Supported hypotheses in e-learning studies.

Figure 10. illustrates the validated hypotheses that have been filtered from the collected e-learning research. Any hypothesis that has been supported more than ten times (or excluding the strongly supported hypotheses) or fewer than two times was eliminated. This representation is intended to give scholars with a picture of growing interactions that are neither too common nor too uncommon.

It can be seen from the figure that the assumptions of satisfaction → behavioral intention and self-efficacy → ease of use appear to be investigated in many e-learning studies (9 times each), followed by behavioral intention → actual usage (8 times), system quality → satisfaction (8 times). The hypotheses that anxiety → ease of use, experience → ease of use, and system quality → usefulness gain the same number of popularity (6 times). The five assumptions including effort expectancy → behavioral intention, facilitating conditions → behavioral intention, performance expectancy → behavioral intention, satisfaction → performance, self-efficacy → usefulness also show their significant effects in 60 publications as highlighted by yellow color. The remaining hypotheses indicated by thinner arrows are those appear four times.

Table 3. gives information on the supported and unsupported hypotheses. There are 21 hypotheses with contradictory experimental data. In general, a hypothesis is more likely to be confirmed by data evidence than to be rejected, as shown by the data in Table 3. The top five hypotheses were evidently derived from the TAM model; therefore, it is not surprising that the majority of findings were consistent with proved theory.

Six through twelve hypotheses are more supported than their opposing findings. 8 hypotheses generate an equal number of contradictory results (hypotheses 13 to 20). Only in one circumstance was a hypothesis rejected more often than it was accepted (i.e., information quality → satisfaction).

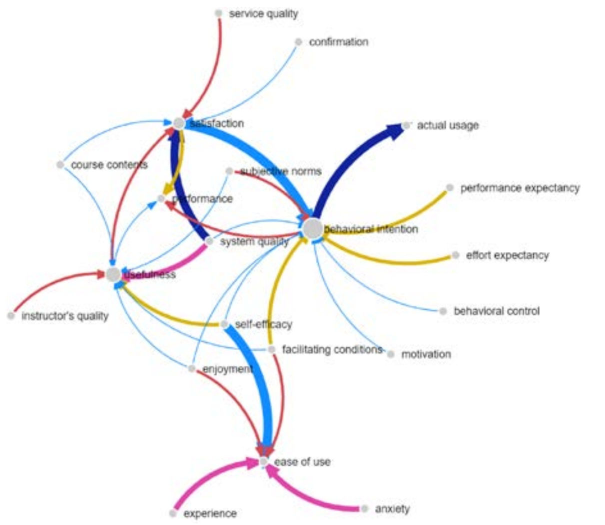

Figure 10. Supported hypotheses in e-learning research with the exclusion of prevalent and uncommon assumptions.

Table 3. Hypotheses that are both supported and rejected.

No	Hypothesis	Supported	Rejected
1	usefulness → behavioral intention	19	5
2	ease of use → usefulness	16	2
3	attitude → behavioral intention	14	3
4	ease of use → behavioral intention	13	3
5	behavioral intention → actual usage	8	1
6	facilitating conditions → behavioral intention	5	3
7	effort expectancy → behavioral intention	5	1
8	performance expectancy → behavioral intention	5	1
9	subjective norms → behavioral intention	4	1
10	system quality → behavioral intention	3	2
11	enjoyment → behavioral intention	3	1
12	subjective norms → usefulness	3	1
13	facilitating conditions → actual usage	1	1
14	hedonic motivation → behavioral intention	1	1
15	information quality → behavioral intention	1	1
16	information quality → usefulness	1	1
17	self-efficacy → behavioral intention	1	1
18	beliefs → behavioral intention	1	1
19	confirmation → usefulness	1	1
20	technical support → usefulness	1	1
21	information quality → satisfaction	1	2

5. Discussion

When performing an e-learning experimental research with end-user assessment, it is a demanding endeavor for e-learning researchers to read each and every article to identify the relevant factor. Although there are several available theoretical frameworks and conceptual models, some factors may no longer be applicable in today's fast-paced world [38]. Others may evolve due to user preferences. Not only is it vital for new e-learning researchers to engage in the field, but also for experienced scientists to stay updated. The increasing number of systematic studies in e-learning from a variety of time frames or perspectives has revealed that e-learning plays a vital role in a wide variety of sectors, and this might assist interested readers stay up with the trend [4], [15], [16], [17].

Reviewing significant e-learning research factors would contribute to the body of knowledge. First, it focuses on the factors that are still prevalent, which might serve as a beginning point for new e-learning researchers, particularly social science scholars who intend to put their e-learning strategy in reality [39]. Second, experienced researchers may examine the less popular ones to see if they are obsolete or developing. As a result, conceptual models may incorporate new assumptions or reject traditional beliefs. Third, the interdependence of factors suggests that there may be an indirect influence from one factor to another, which the research community should investigate in more depth. Self-efficacy, satisfaction, system quality, social influence, subjective norms, course contents, information quality, instructor quality, enjoyment, experience, and service quality emphasized in the research suggest that while creating an e-learning model, educators should concentrate on how to create an engaging environment that provides learners with experience.

In terms of theoretical frameworks, the current finding was consistent with previous studies in which the authors found that TAM was the ideal solution for assisting evaluator assessment [11]. This phenomenon may be partially explained by the perception that TAM is a robust and feasible model, and the ubiquity of results across domains, which makes comparing them easier [38]. However, researchers are encouraged to be open-minded in order to study and apply other theories that may assist to explain users' behavior owing to additional factors.

In terms of supported and unsupported hypotheses, this study's findings have three implications. First, while performing evaluations with users, new e-learning researchers can use and incorporate verified assumptions into the proposed framework.

Second, for unsupported assumptions, there is a need for more research including more participants from varied groups, given that user preferences vary by region/country/culture. In addition, caution should be taken when adopting concepts that have been both accepted and rejected.

In conclusion, the current study adds to the body of knowledge in three ways: first, it provided a comprehensive overview of factors in evaluating an e-learning model, so new e-learning researchers can think about this approach as a complement evaluation to their study to enhance the likelihood of e-acceptance learning's in the society. Second, researchers in the field of e-learning who are interested in constructing e-learning models might benefit from the suggestion provided by the examination of influential factors and their interactions. Third, e-learning researchers might provide supporting evidence for their hypotheses before setting up the model based on the results of the experiments that confirm or refute them. Lastly, the new study goes farther than previous research on e-learning studies by allowing interested researchers to evaluate in depth e-learning factors of interest, as opposed to just naming and classifying them.

While the current study did provide some useful information on the topic of factor analysis in e-learning research, it was hampered by a number of issues. The biggest drawback is that there isn't as many indexing databases as possible, thus it could not be seen by other potentially useful publications. Thus, more investigation is required to broaden this study to other domains that make use of specialized databases (e.g., PubMed, ERIC, JSTOR). Second, the research only included journal publications, thus it is possible that important information from lecture notes, conference papers, and book chapters was left out. It is challenging for novice researchers to get an overview of the e-learning area because the current study did not analyze research trends, classification, or other content analysis. However, the plethora of e-learning reviews in the literature would enable scholars to investigate e-learning from several angles, thereby expanding their understanding. Finally, some publications might not have been uncovered because they lacked appropriate keywords in their titles, abstracts, or keywords that were used to search for and gather articles in this investigation. Because this investigation only covers the years 2020 and 2022, other publications that may be in press at the time may have been overlooked. Finally, our review only included articles that were freely accessible online; numerous subscription-only research was left out, potentially omitting significant factors.

6. Conclusion

This article provided a comprehensive evaluation of the use of factor analysis in e-learning research from 2020 to 2022. As a guideline, the PRISMA approach was utilized to extract corpora from Scopus and Web of Science. 60 publications were therefore included in the study. Clearly, behavioral intention, ease of use, usefulness, and attitude are among the most important factors being investigated. Anxiety, enjoyment, social influence, facilitating conditions, and self-efficacy are the most favourable external factors incorporated into existing theoretical models. There were identified 55 association rules that highlight the factors being investigated jointly. Of the 603 study hypotheses, 498 were confirmed, while 105 were disproved. Strong determinants of intention to utilize an e-learning model include usefulness, attitude, ease of use, facilitating conditions, and effort expectancy. The implications for new and experienced e-learning researchers in the field of e-learning were highlighted.

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