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PAPER

A Bibliometric Analysis of the Literature on Mobile Learning Adoption and Continuance in the Field of Education

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ABSTRACT

This study examines mobile learning adoption and continuance in education literature through bibliometric methods. The metadata of 155 relevant publications was extracted from the Web of Science database and imported into "biblioshiny" for analysis. It was found that *Education and Information Technologies* has the highest publications, and *Computers & Education* is the most cited journal. Author analysis revealed that Shakeel Iqbal has the most articles fractionalized. Further, the most cited articles were published in the year 2012. The study revealed an exponential increase in research in the top producers, China and Turkey, since 2019. TAM was found to be the most popular theory among researchers. In addition, interest in self-determination theory has been growing recently. The studies examined limited subjects (language, mathematics, and science). The findings indicated several associated keywords, such as augmented reality, cyberloafing, and virtual reality. The thematic map revealed emerging (e.g., self-regulation), niche (e.g., literacy), motor (e.g., attitude), and basic (e.g., addiction) themes. Further, the conceptual structure map suggested the nuances of difference between the constructs of "intention" and "continuance intention."

KEYWORDS

bibliometric analysis, continuance intention, education, mobile learning, technology acceptance, technology adoption

1 INTRODUCTION

Mobile devices (e.g., laptops, smartphones, tablet PCs) have become ubiquitous and indispensable, and people globally are embracing their potential. The number of mobile devices operating worldwide is expected to be 18.22 billion by 2025 [1]. People are increasingly becoming dependent on mobile devices [2]. Many people use more than one mobile device. Further, 8.6 billion mobile phone subscriptions

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were reported worldwide in 2022, and their penetration is continuously rising [3, 4]. As of 2022, three-quarters of the world population aged 10 and over own a mobile phone. In addition, 66% of the world's population is using the internet. Accessing the internet using mobile devices is becoming affordable [5].

1.1 Mobile learning

Mobile learning (or m-learning) refers to the "use of mobile and handheld IT devices such as Personal Digital Assistants (PDAs), mobile telephones, laptops, and tablet PC technologies in teaching and learning" [6]. It is a form of e-learning that uses mobile devices to integrate with ubiquitous computing technologies for the teaching-learning process [7]. It involves "learning across multiple contexts, through social and content interactions, using personal electronic devices" [8]. Convenient, anytime, and anywhere learning provided by mobile devices facilitate communication, collaboration, and creativity among students [9, 67]. Contextualized and personalized learning enhances students' achievements [10]. M-learning is a relatively new tool that allows students to access learning contents (e.g., learning materials, tests, dictionaries) and conduct personalized curriculum sequencing according to their learning needs [7, 66]. Mobile technology is constantly upgraded with new features and applications. It allows adaptive assistance and instant social interaction platforms [11].

The research community has examined this growing field of m-learning with various research topics and methods [12]. M-learning enhances students' field trips and field work experiences through increased interaction, collaboration, and engagement [13]. It facilitates anytime and anywhere access to high quality educational content [14]. Further, it allows the learners to convert their dead time while in transit to productive activity. However, the flexibility of learning anytime and anywhere may lead to interaction and information overload [15]. Moreover, the benefits of m-learning are based on learner's motivation [14]. A meta-analysis of m-learning studies indicated that most studies focus on system design and effectiveness [16]. Further, a systematic review hinted at fragmented and idiosyncratic m-learning research [17]. Another study found that the research has focused more on learners' higher-order thinking performance and learning behaviors [11]. An investigation of m-learning research in PK-12 education indicated a focus on core subject areas: literacy, mathematics, and, particularly, science [10].

1.2 Technology adoption and continuance

Technology adoption and continuance have emerged as separate streams of research. Technology adoption refers to the acceptance or the first use of an emerged technology or product [18]. However, continuance intention describes the user's decision to continue using the technology. It refers to post-adoptive IT usage and describes behavioral patterns reflecting continued use [19].

Technology adoption is an extensively researched area. [18] reviewed literature and listed 21 theories employed by researchers in IT adoption studies. The most prominent theories are the Technology acceptance model (TAM), Diffusion of innovation (DOI), Unified theory of acceptance and use of technology (UTAUT), and Theory of planned behavior (TPB). Another literature review revealed that several factors, including perceived usefulness, perceived ease of use, perceived enjoyment, culture, attitude, subjective norms, and system and information inhibitors, contribute to the adoption of technology [20].

The success of a technology depends on its continued use [21]. The users may not continue using the technology after initial acceptance [22]. Retaining learners and facilitating their continuance is critical for m-learning providers and educators [23]. Researchers have used several theoretical models or extensions to examine continuance intention. The most widely used models are TAM, TPB, and expectancy confirmation theory (ECT) [22]. A recent study integrated the three models to examine m-learning continuance intention [24]. Antecedents of continuance intention include satisfaction, attitude, perceived enjoyment, trust, perceived usefulness, perceived ease of use, subjective norm, perceived critical mass, and habit [22].

M-learning adoption and continuance is an active area of research and has gained enormous interest among researchers during the COVID-19 period [25, 26, 27, 28].

1.3 Related researches

Scholars in the past have reviewed different aspects of mobile learning adoption and continuance in education (MACE) research area. [11] reviewed the top 100 highly cited m-learning studies from 2000 to 2016 and suggested that the focus of m-learning studies is shifting to examining issues of integrating new technologies. A meta-analysis of 164 m-learning studies from 2003 to 2010 found that mobile phones and PDA are the most widely used devices for m-learning [16]. A systemic review of m-learning in PK-12 education examined 131 articles published during the period 2010–15 in educational technology journals [10]. Further, [29] reviewed 87 research articles published on the TAM model in the m-learning context from 2006 to 2018 and revealed that m-learning studies had witnessed an enormous attraction among researchers. A systematic review analyzed m-learning adoption literature published from 2009 to 2017 and suggested that research in this area is expanding [9]. Further, [30] conducted bibliometric mapping of all publications related to m-learning in the Web of Science database (query—“mobile Learning” OR “m-learning”) till September 2019. The analysis had a very broad context. Recently, another study examined the top-cited technology adoption literature published from 1997 to 2022 using bibliometric analysis methods [31].

M-learning is in the nascent stage and studies examining adoption and continuance are scarce [32]. It is a recent trend in educational technology research and warrants extensive research in learners’ m-learning perceptions [8, 33]. Further, m-learning adoption is an active area of research [9]. Continuous research analyzing m-learning is required [34]. In addition, limited studies have examined the continuance intention of m-learning [24]. Research about learners’ perceptions of m-learning has not kept pace with the rapid developments in m-learning technology [23, 35, 36].

Mobile technologies evolve rapidly. Therefore, a regular literature review is required to analyze the research trend [12]. Further, huge money is spent on developing m-learning technologies. Therefore, understanding the factors that drive the adoption and continuation intention is crucial [20]. Past review studies mostly had a broad scope (e.g., m-learning, technology adoption). In addition, hardly any review study has focused on m-leaning adoption and continuance. To the best of our knowledge, MACE literature has not been examined through bibliometric analysis. A review of MACE will enrich the literature by uncovering major themes, trends, and intellectual structures. The variables such as authors, citations, countries, keywords, publications, universities, and journals are analyzed in our study.

1.4 Research questions

In the field of mobile learning adoption and continuance in education:

- RQ1: What is the status of publications?
- RQ2: Which are the most influential journals?
- RQ3: Which are the most influential articles?
- RQ4: Who are the most productive authors?
- RQ5: Which are the most influential countries?
- RQ6: Which are the most cited references?
- RQ7: What is the trend of keywords?
- RQ8: What are the emerging, niche, motor, and basic themes?
- RQ9: What are the conceptual structures?

2 METHODOLOGY

2.1 Data collection

The data for this study were collected from the Web of Science (WoS) Core Collection. The database is a comprehensive international multidisciplinary bibliographic data source [37]. It provides detailed and reliable data about research publications [38]. The database indicated 151,768 documents related to mobile technologies. The search query was refined to include only research pertaining to adoption and continuance. The following query was executed on August 21, 2022, to obtain 4,109 documents:

((TI=((m-learning OR mobile learning OR mobile device OR laptop OR smartphone OR personal digital assistant OR PDA OR personal electronic device OR PED OR mobile phone OR mobile telephone OR tab* OR mobile technology OR mobile app* OR mobile software) AND (adopt* OR accept* OR usage OR success OR ((intention OR behaviour) AND (continue OR continuance OR use)))) OR KP=((m-learning OR mobile learning OR mobile device OR laptop OR smartphone OR personal digital assistant OR PDA OR personal electronic device OR PED OR mobile phone OR mobile telephone OR tab* OR mobile technology OR mobile app* OR mobile software) AND (adopt* OR accept* OR usage OR success OR ((intention OR behaviour) AND (continue OR continuance OR use))))) OR AK=((m-learning OR mobile learning OR mobile device OR laptop OR smartphone OR personal digital assistant OR PDA OR personal electronic device OR PED OR mobile phone OR mobile telephone OR tab* OR mobile technology OR mobile app* OR mobile software) AND (adopt* OR accept* OR usage OR success OR ((intention OR behaviour) AND (continue OR continuance OR use)))).

The research area filter of "Education Educational Research" provided by the WoS database was applied to the search query results to obtain 264 documents. The database filter was used as the current study is in the context of education. Further, seven records categorized as book chapters, proceeding papers, correction, meeting abstracts, and retraction documents were excluded from the study. Only high-quality peer-reviewed research work i.e., articles (review or original) were included [38]. Next, the title and abstract of the documents were examined to exclude 102 records that were not directly related to the topic or were duplicates. Finally, the metadata of 155 documents was extracted for analysis. The data included abstract, authors, citations, keywords, publication year, and title of articles. A timeframe was not specified in the search/extraction. The records till the date of execution of the search query were included. The final records were from 2006 to 2022. The process of identification, screening, and inclusion of records for analysis is transparently reported following the PRISMA guidance [39, 40]. Figure 1 depicts the procedure for bibliometric data collection.

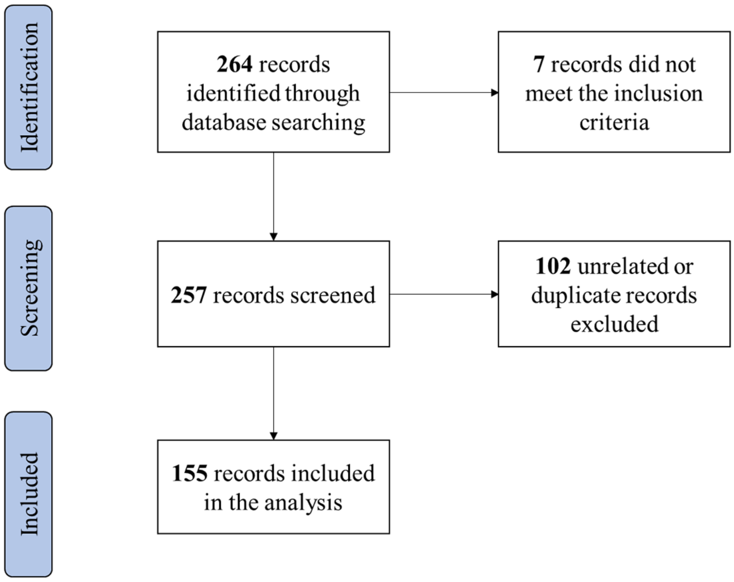


Fig. 1. Prisma flowchart

2.2 Data analysis

The metadata of the publications was exported from the WoS database as plain text and imported into "biblioshiny: the shiny app for bibliometrix" (an R-tool for comprehensive science mapping analysis) [40] for analysis.

A bibliometric performance analysis was conducted to determine the annual growth rate of publications, total and average citations per document, nature of authorship, and distribution of publications among authors, countries, and journals of MACE research over the years [41]. The bibliometric analysis captures a field's evolutionary nuances and emerging trends. It offers unique opportunities to contribute to theory and practice [42]. It uses mathematical and statistical techniques to analyze academic publications and citations [43]. Further, science mapping was performed to reveal the intellectual interactions and structural connections of MACE research [44]. The main techniques of science mapping used in this study include co-authorship analysis, bibliographic coupling, citation and co-citation analysis, and co-word analysis. Collaboration networks of authors and countries were generated, and the isolated nodes were removed. Further, a co-citation network of sources was created with 25 nodes.

In addition, research trends were examined using "Keywords Plus" keywords. Further, the Author keyword frequencies were analyzed to determine the most popular keywords. The WoS dataset records have two types of keywords i.e., Keywords Plus, and Author keywords. The Keywords Plus terms are extracted from titles of cited references by automatic computer algorithms and provide an in-depth understanding of the article's content. In contrast, Author keywords are terms that authors believe represent the content of their paper. The researchers have used Keyword Plus terms to identify research trends [45, 46].

Further, a Word Cloud of the Author keywords was created to examine the most frequently used keywords visually. Terms related to the search string, e.g., "mobile learning," "adoption," and "intention," were removed from the Word Cloud to enhance comprehensibility. Further, synonyms (e.g., "value," "perceived value," and "perceived mobile value") were treated as one term for calculating the frequency to develop an unambiguous understanding of the importance of terms. Accordingly, lists of terms to be removed and synonyms were uploaded to biblioshiny while preparing the Word Cloud. The lists were prepared by examining all Author keywords. Additionally, Author keywords were grouped manually into the following categories: a) theory/model/framework, b) methodology, c) factor, d) subject, e) country, and f) associated keywords (Figure 9). The grouping enhances the effectiveness of thematic analysis [38].

Next, bibliometric techniques of network analysis were performed. The thematic maps of Keyword Plus terms were created. The thematic maps or strategic diagrams plot themes into two-dimensional space based on their centrality and density rank values. Density represents the strength of the relationship between keywords within a theme, and centrality indicates the external relationships of the themes [38]. The themes or clusters of keywords are obtained through co-word analysis. The median and mean values of the two parameters of themes i.e., density and centrality, are used for the classification of themes into four groups, namely, motor, niche, emerging or declining, and basic [47, 48]. The themes are placed in four quadrants of the diagram. The upper right quadrant comprises strong centrality and high-density "motor" themes. These themes are well developed and most important for the research field. The upper left quadrant indicates highly developed and isolated "niche" themes. The niche themes are very specialized and peripheral. Further, the themes of the lower left quadrant have low density and centrality and are "emerging or declining" themes. The "basic" themes which are important for a research field but are not well developed are placed in the lower right quadrant.

Subsequently, multiple correspondence analysis (MCA) was performed to create a two-dimensional conceptual map of Keyword Plus terms. It was used for dimensionality reduction to identify underlying structures in the dataset [49]. K-means clustering was used to identify keywords that express common concepts [50]. The conceptual structure breaks down a research domain into clear "knowledge clusters" [51]. The keywords which are more similar in distribution are closely represented on the map.

3 RESULTS AND DISCUSSION

3.1 Publication status (RQ1)

The 155 publications examined in this study were spread across the years from 2006 to 2022 with an annual growth rate of 18%. The average citation per document was 30, and the references in the documents were 6163. Further, the number of Author keywords and Keywords Plus was 417 and 298, respectively. 97% (n=151/155) of the documents were articles, including early access, and the remaining (n=4/155) were review articles. Additionally, single-authored publications were 21, and 25% of the studies had international co-authorship. Further, 372 researchers with publications in 36 different journals examined MACE. Figure 2 shows that annual publications substantially increased to 23 articles in 2021 from 01 in 2006. Since 2018, the researchers have produced at least 14 publications each year. The results indicate growing interest among researchers in examining MACE. However, MACE research is merely 0.1% (n=155/151,768) of the work in the field of mobile technologies. Additionally, only 4% (n=155/4109) of the m-learning adoption and continuance studies are in the area of education.

3.2 The most influential journals (RQ2)

46% (n=71/155) of the research studies were published by four journals, namely: Education and Information Technologies, Computers & Education, Journal of Educational Computing Research, International Review of Research in Open and Distributed Learning (Figure 3). The distribution of publications seems to follow Bradford's law of diminishing returns and scattering, which claim that there are a few very productive periodicals for a given subject area [52]. The publications for three of the four journals have steadily increased over time. Interestingly, the growth has been exponential for Education and Information Technologies, which has published all 31 articles during the last five years (i.e., since 2018). The findings hint that in recent years, MACE has been one of the focus areas of the journal. Further, Computers & Education is the most cited journal (1488 citations) with a 14 h-index (Table 1). The journal contributed 38% (n=1488/3930) of the citations and 16% (n=17/108) of the documents of the top 9 journals.

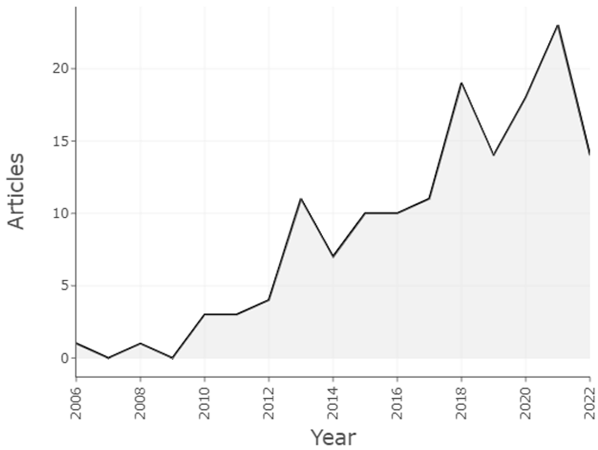


Fig. 2. Annual scientific production from 2006 to 2022

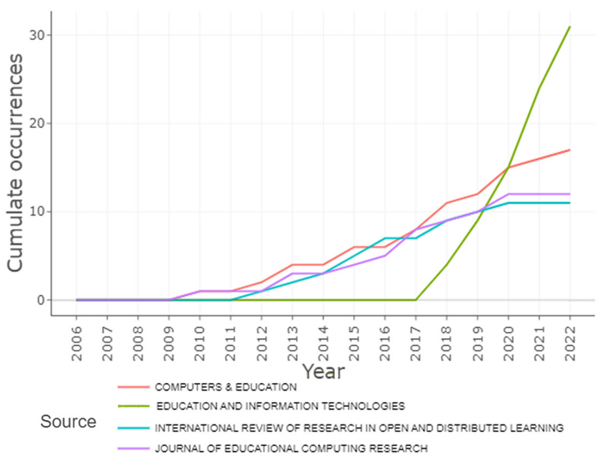


Fig. 3. Publication of top 4 sources from 2006 to 2022

Table 1. Top nine journals with the most publications

Journal	Documents	Citations	*h*-Index
Education and Information Technologies	31	451	13
Computers & Education	17	1488	14
Journal of Educational Computing Research	12	271	8
International Review of Research in Open and Distributed Learning	11	432	9
British Journal of Educational Technology	8	524	7
Educational Technology Research and Development	8	213	5
Interactive Learning Environments	8	93	4
Australasian Journal of Educational Technology	7	299	6
Educational Technology & Society	6	159	4

3.3 The most influential articles (RQ3)

The most influential articles are in Table 2. The top two most cited articles were published in 2012. The total citations of these articles in all the research areas were 442 and 336. Additionally, these articles of first authors Jongpil Cheon and Sung Youl Park were also the most cited publications in the research area of MACE. However, the LC/TC ratios of these articles were less than 12%. Interestingly, only one article among the top 10 had an LC/TC ratio of more than 20%. The results indicate that the articles are widely cited in other research areas. Further, five out of ten articles with the most citations were published in *Computers & Education.* Only one of the highly cited research works is a review-based study. The review study of the first author Mostafa Al-Emran was published in 2018. Further, yearly average citations peaked in 2012 and have been steadily increasing since 2014 (Figure 4).

Table 2. The ten articles with the highest citations

Document Title	TC	TC Per Year	LC	LC/TC Ratio %
An investigation of mobile learning readiness in higher education based on the theory of planned behavior	442	40.18	40	9.05
University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model	336	30.55	39	11.61
Factors driving the adoption of m-learning: An empirical study	264	20.31	24	9.09
Technology Acceptance Model in M-learning context: A systematic review	147	29.4	9	6.12
Factors influencing students' acceptance of m-learning: An investigation in higher education	146	14.6	15	10.27
Mobile-based assessment: Investigating the factors that influence behavioral intention to use	134	22.33	10	7.46
Perceived convenience in an extended technology acceptance model: Mobile technology and English learning for college students	115	10.45	14	12.17
Usage of a mobile social learning platform with virtual badges in a primary school	103	12.88	2	1.94
Schools going mobile: A study of the adoption of mobile handheld technologies in western Australian independent schools	99	9.9	4	4.04
M-learning adoption: A perspective from a developing country	92	8.36	20	21.74

Note: LC: Local citations, TC: Total citations.

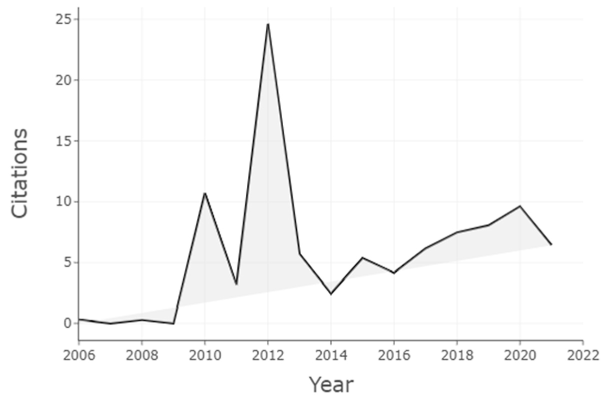


Fig. 4. Average citations per year from 2006 to 2022

3.4 The most productive authors (RQ4)

23% (n=36/155) of the articles were written by 11 authors (Table 3). The most productive authors were Mostafa Al-Emran, Shakeel Iqbal, and Yi-Shun Wang. All of them have published four articles each. However, Shakeel Iqbal has the most articles fractionalized. He has collaborated with Zeeshan Ahmed Bhatti in three of his four articles. Further, Mostafa Al-Emran has the highest citations. Four authors published all their articles during the period 2017–2021. Two authors (Chi-Cheng Chang, and Chi-Fang Yan) had their last publication in 2013. Interestingly, all authors (except Sung Youl Park) of the top three cited articles (Table 2) have contributed only one article in the area of study. Sung Youl Park has authored two articles. Shakeel Iqbal has consistently contributed to literature since 2012. Further, two authors (Adzhar Kamaludin and Vitaliy Mezhuyev) have published all their three articles together. The collaboration network of the authors is presented in Figure 5.

Table 3. Top 11 authors with the most publications

Author	Year (20XX)										TA	AF	TC
	12	13	14	15	16	17	18	19	20	21			
Mostafa Al-Emran							2		1	1	4	1.33	209
Shakeel Iqbal	1			1		1			1		4	2.00	149
Yi-Shun Wang						1		1	1	1	4	1.03	28
Vimala Balakrishnan			1		1	1					3	1.50	36
Zeeshan Ahmed Bhatti				1		1			1		3	1.50	57
Chi-Cheng Chang	1	2									3	0.83	169
Chin Lay Gan			1		1	1					3	1.50	36
Adzhar Kamaludin							2			1	3	1.00	171
Vitaliy Mezhuyev							2			1	3	1.00	171
Mohamed Sarrab					1	1	1				3	1.00	77
Chi-Fang Yan	1	2									3	0.83	169

Note: TA: Total number of articles of authors, AF: Articles fractionalized, TC: Total citations.

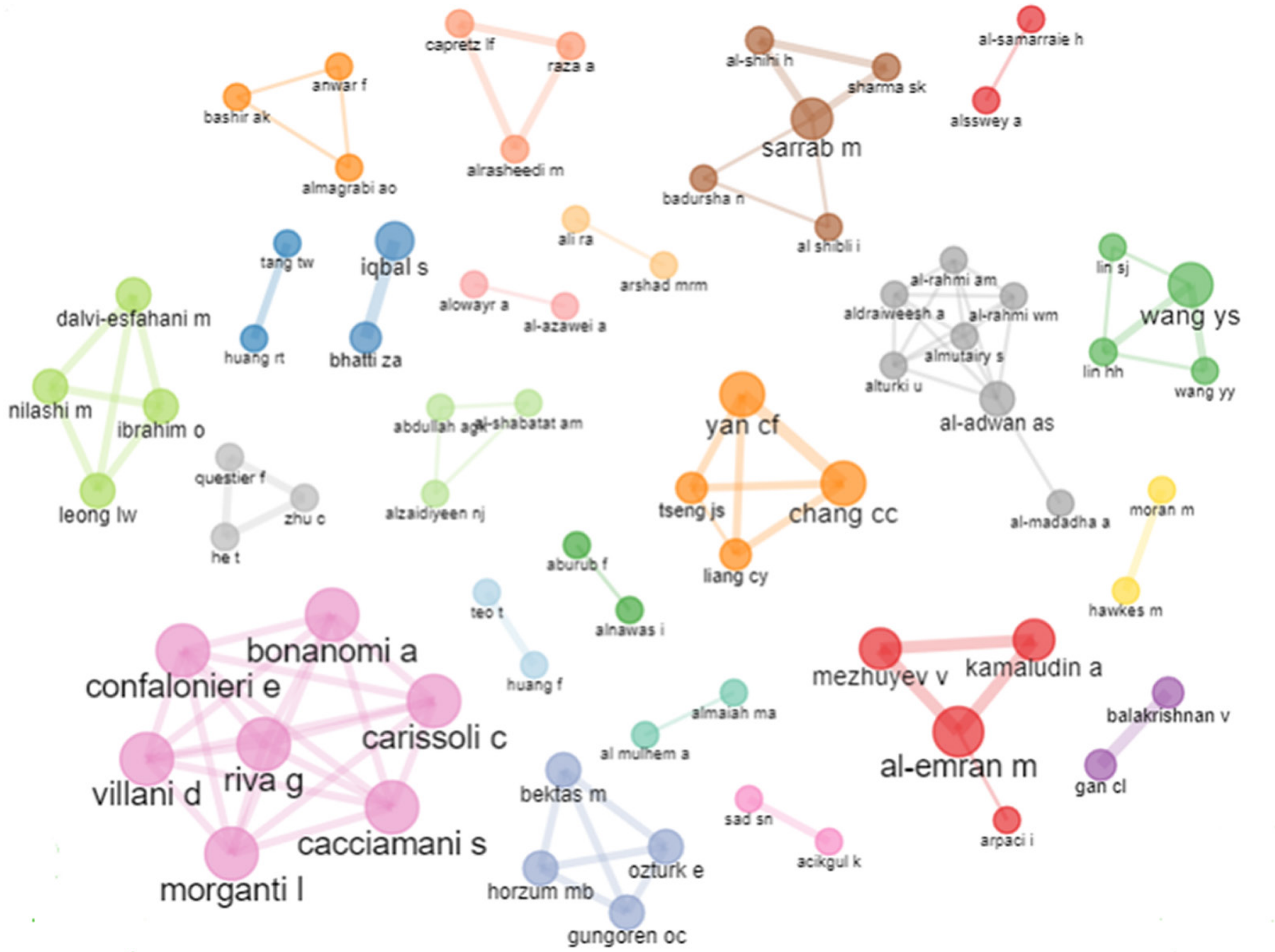


Fig. 5. Author collaboration network

3.5 The most influential countries (RQ5)

Figure 6 depicts a collaboration network of countries revealing a close association among the countries: China and USA; Saudi Arabia and Pakistan; Pakistan and United Kingdom; USA and Korea. Further, China has collaborated with the maximum number of countries (n=11). It is also the largest producer of articles (n=65), followed by Turkey (n=28) and the USA (n=27). Interestingly, Italy produced all 14 articles in 2018. Additionally, production increased by more than 100% in China and Turkey from 2019 to 2022 (Figure 7).

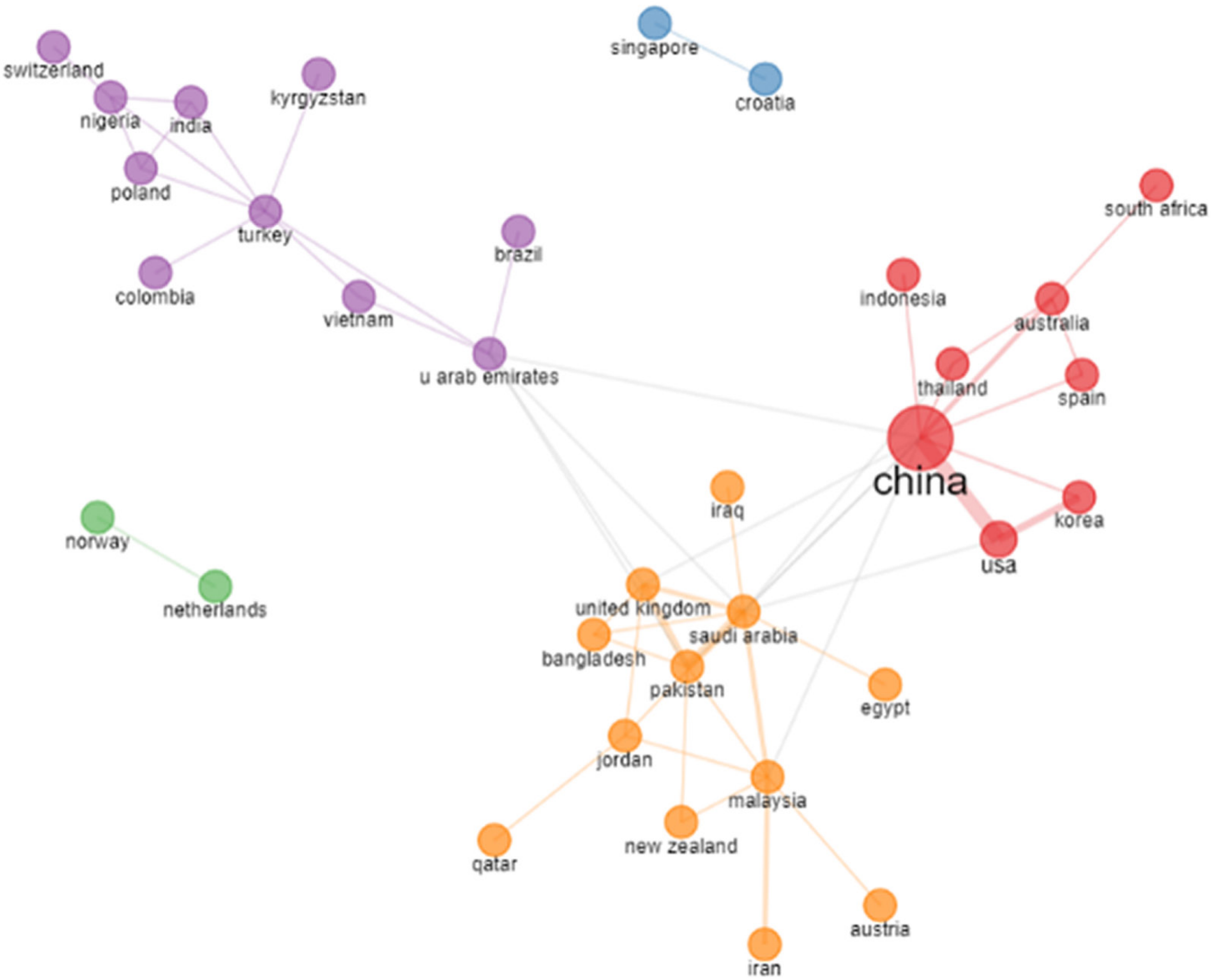


Fig. 6. Collaboration network of countries

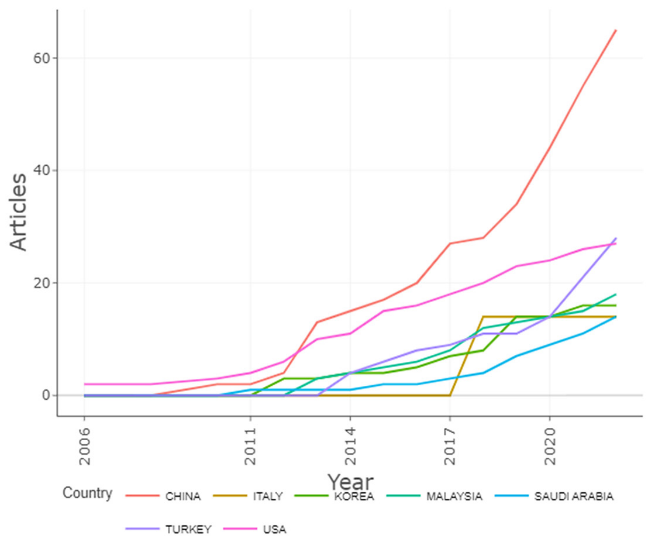


Fig. 7. Production of top 7 countries over time

3.6 The most cited references (RQ6)

An analysis of the references of the MACE research articles indicated that the research works of Fred D. Davis and Viswanath Venkatesh were the most cited references. The theoretical contributions of these two authors include the Technology acceptance model (TAM) and the Unified theory of acceptance and use of technology (UTAUT). The Word Cloud of the Author keywords also indicated the popularity of these two theories (Figure 8). Other highly cited theories were M. Fishbein and I. Ajzen's theory of reasoned action (TRA), and Icek Ajzen's Theory of planned behavior (TPB).

Interestingly, an article evaluating structural equation models was also among the top 3 cited references (Table 4). The findings indicate that the statistical technique of structural equation modelling (SEM) is popular among MACE researchers. Further, the co-citation network of sources indicated that *Computers & Education, MIS Quarterly, Computers in Human Behavior,* and *British Journal of Educational Technology (BJET)* were the most cited journals (Figure 9).

Table 4. Top 9 most cited references

Document Title	Citations
Perceived usefulness, perceived ease of use, and user acceptance of information technology	93
User acceptance of information technology: Toward a unified view	72
Evaluating Structural Equation Models with Unobservable Variables and Measurement Error.	59
User Acceptance of Computer Technology: A Comparison of Two Theoretical Models	47
Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science	46
Investigating the determinants and age and gender differences in the acceptance of mobile learning	46
An investigation of mobile learning readiness in higher education based on the theory of planned behavior	40
University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model	39
The theory of planned behavior. Organizational Behavior and Human Decision Processes	38
Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research, Reading	28

Fig. 8. Word cloud of author keywords

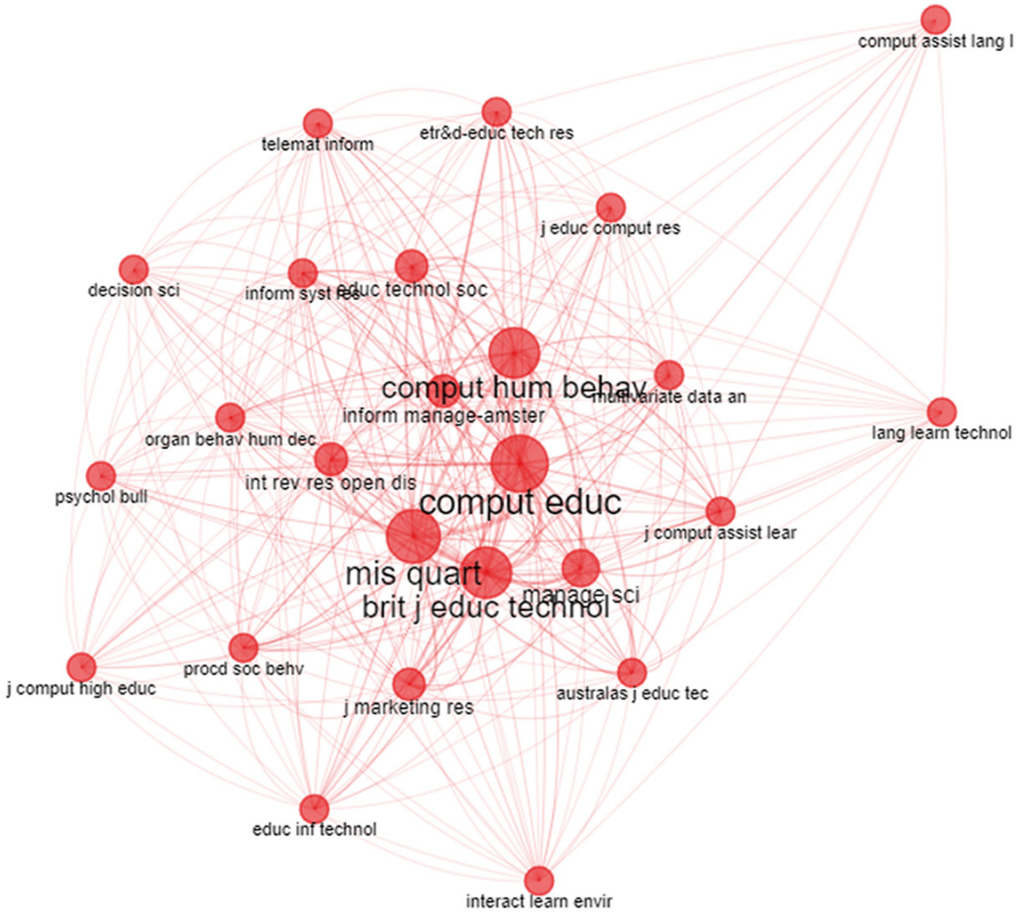


Fig. 9. Co-citation network of the sources

3.7 The trend of keywords (RQ7)

The Author keywords analysis revealed that researchers had used 18 theories/models/frameworks to examine MACE. TAM (including its extensions) is the most frequently mentioned model. The keywords divulge that the studies have investigated 47 factors influencing MACE. Further, it seems that SEM is the most frequently used technique for analysis. SEM is flexible and brings psychometric and econometric theory together in a unified manner, and is being increasingly used for theory building and model testing [53]. Interestingly, only three academic subjects: language, mathematics, and science were used as keywords. The research in m-learning has mostly focused on "science" [54]. In addition, m-learning studies usually do not specify subjects [55]. Further, nine countries, including China, India, Oman, and Saudi Arabia were indicated. Moreover, the results hint at several associated keywords such as e-learning, mobile social media, strategies, mobile library, mobile learning management system (m-lms), bring your own device (BYOD), messaging, and technology integration (Figure 10).

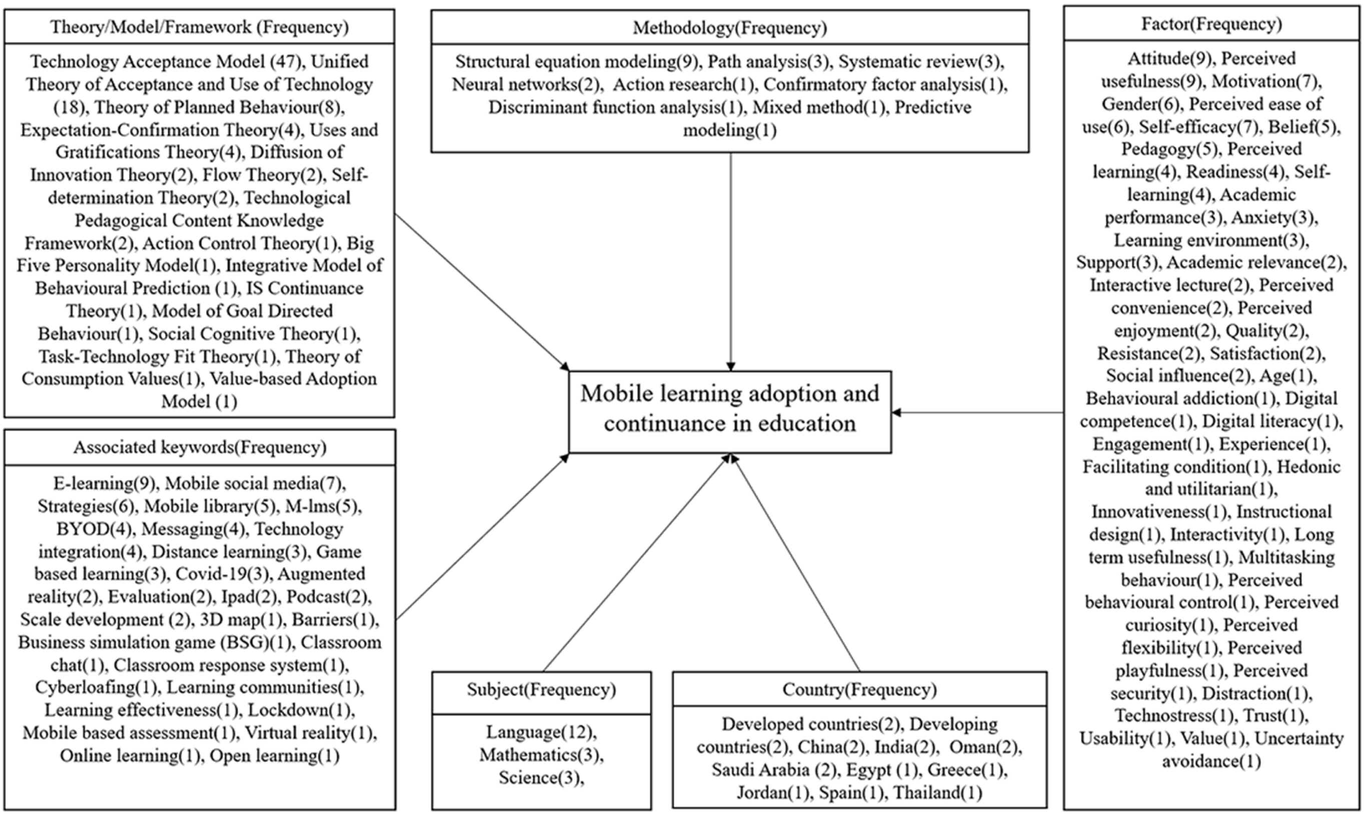


Fig. 10. Author keyword categorization

Further, the Keywords Plus trend from 2006 to 2022 indicated a higher frequency of "adoption" and "intention" as compared to "continuance intention" and "usage" (Figure 11). Additionally, "continuance intention" was stagnant during the period 2016 to 2020. However, the frequency of the keyword has doubled since 2020. The results indicate that m-learning adoption has been examined more than continuance [19]. It may be because m-learning is a relatively new field of study [56]. Additionally, continuance is a post-adoption stage. Further, the prevalence of "perceptions," "self-efficacy," and "motivation" has rapidly increased since 2019. In addition, "self-determination theory (SDT)" has become more prominent since 2020. SDT focuses on how people become self-motivated based on their perceptions of the surrounding environment. [57]. Further, the results indicate an incremental growth in "satisfaction". Several studies report a positive influence of "satisfaction" on continuance intention [22].

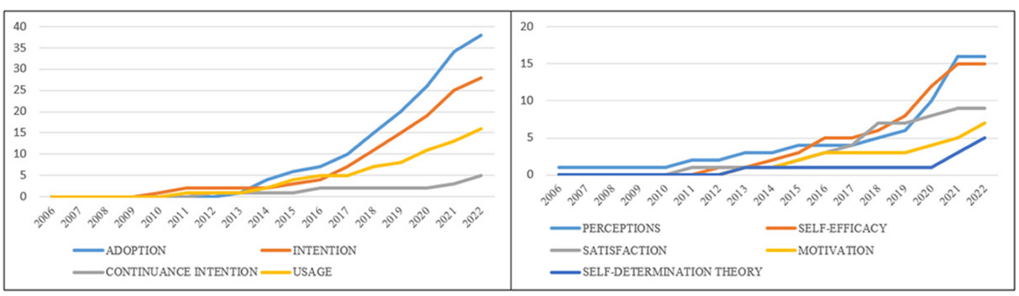
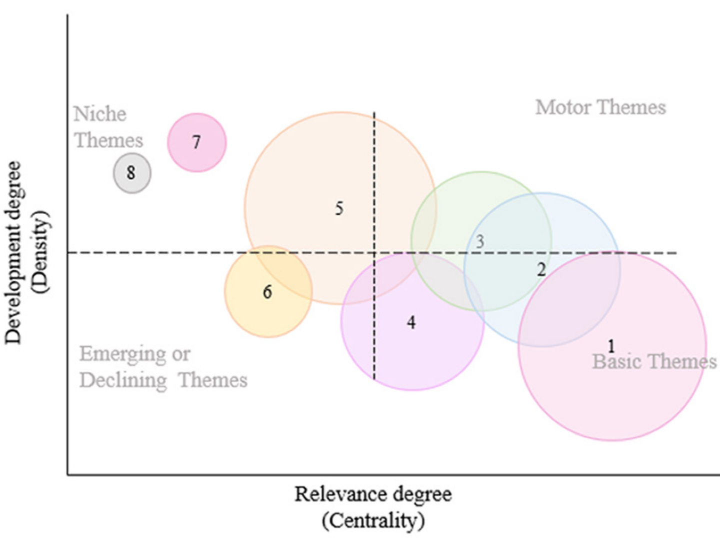


Fig. 11. Select keyword trends (Keyword Plus)

3.8 The emerging, niche, motor, and basic themes (RQ8)

Figure 12 is a thematic map of "Keyword Plus" keywords [48]. The keywords in clusters 1, 2, 3 and 4 were partially or entirely categorized as basic themes. Basic themes are transversal and general. They are important for a research field but not well developed. Further, motor themes comprise keywords from clusters 2, 3, and 5. These keywords represent themes that are well-developed and important for this study's research area. Most of cluster 5 and all keywords of clusters 7 and 8 were categorized as Niche themes (well-developed and isolated). Furthermore, keywords of cluster 6 and some keywords of clusters 4 and 5 were weakly developed and marginal (emerging or declining themes). Interestingly, most keywords belonged to the basic themes. Many clusters were overlapping. Therefore, the keywords representing themes in clusters were analyzed alongside the Author keyword frequencies in Figure 9. The results indicate that the keywords: "impact", "academic performance", "lectures", and "self-regulation" are emerging or declining areas in MACE research. The results conform to the recommendation of [11] to conduct further research on academic performance and learning behavior. Further, niche research themes include literacy and skills. Literacy is a common domain in m-learning research [10]. The themes represented by keywords attitude, gender, motivation, perceived ease, self-efficacy, structural equation models, and technology acceptance model are important and well developed in MACE research. Moreover, addiction, barriers, engagement, innovativeness, satisfaction, and usability represent important but not well-developed themes in MACE.



Cluster no.: Select keywords
1: information-technology, determinants, meta-analysis, age, internet
2: intention, technology acceptance model, attitudes, satisfaction, computer self-efficacy
3: gender-differences, intrinsic motivation, personal innovativeness, continuance intention
4: perceived ease, motivation, structural equation models, media, messaging services
5: addiction, barriers, engagement, game, learning-systems, usability
6: impact, academic-performance, lectures, self-regulation
7: confirmatory factor-analysis, Delone and McLean, models, moderating role
8: literacy, skills

Fig. 12. Thematic map (Keyword Plus)

3.9 The conceptual structures (RQ9)

The conceptual structure map revealed two clusters of keywords (Figure 13). The two dimensions after reduction using MCA account for roughly 40% of the total variability. Clusters represent discriminating profiles [47]. The blue cluster is on the positive side of both dimensions. It appears to deal with post-adoption and includes keywords such as "continuance intention", "experience", and "impact".

"Self-determination theory", "structural equation models", and "English" are also part of this cluster. The red cluster is larger and comprises keywords spread across all four map quadrants. The cluster seems to deal with the m-learning adoption ecosystem. The keywords of this cluster on the positive side of dimension 1 seem to deal with factors and models and comprise keywords such as "determinants", "age", "motivation", "behavior", "unified model", "acceptance model", "tam", "extension", "perceptions", "system", "services", and "model". Additionally, the keywords on the negative side appear to deal with facilitating conditions and social influence and comprises keywords such as "students", "University", "teachers", "system", "technologies", and "devices". The map reveals that "continuance intention" and "intention" are different constructs as "intention" is on the negative side and "continuance intention" is on the positive side of both dimensions.

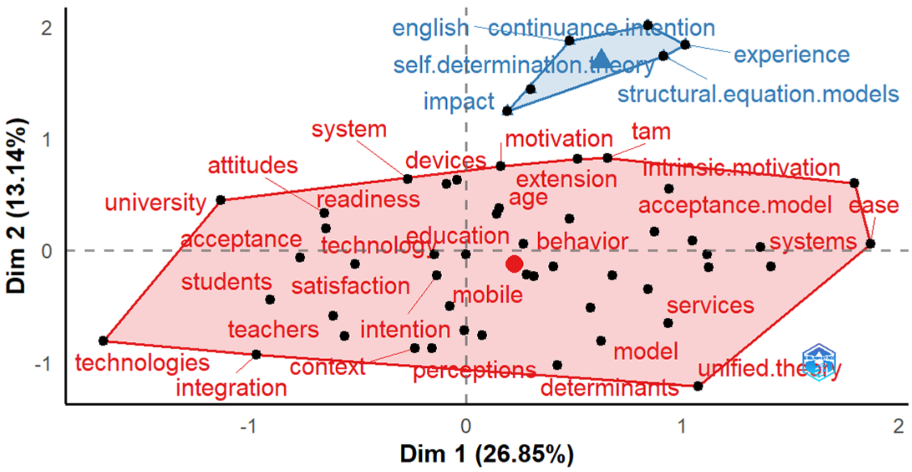


Fig. 13. Conceptual Structure Map (MCA method)

4 CONCLUSION

In this study, we used bibliometric analysis to identify core articles, authors, countries, institutions, and journals in the research area of mobile learning adoption and continuance in education. In addition, an evaluation of the existing 155 relevant articles obtained from the WoS database revealed knowledge flows and evolving research themes [58]. Although the study is limited by reliance on a single research database, it offers multiple conclusions for MACE research. Interest in the research area is rapidly increasing since 2006. However, its contribution to m-learning adoption and continuance, and overall research in mobile technologies is marginal. The MACE research is suggested to keep pace with the fast-changing landscape of mobile technologies. It is anticipated that the scholars would examine emerging technologies including augmented reality, social media, and virtual reality. In addition, factors influencing m-learning such as cyberloafing, mobile phone addiction, and learning communities may be explored. Further, the growing adoption of BYOD warrants more research in emerging fields of game-based learning, and mobile-based assessment [59, 60, 61, 68].

The study revealed that the researchers have applied several theories to MACE research. Generic technology adoption theories including TAM, UTAUT, TRA, and TPB are the most popular. There is no specific model for MACE research and the technology adoption theories are usually extended, modified, and integrated to examine this research area [17]. Additionally, hardly any study in MACE has examined technology integration frameworks in education such as technological pedagogical content knowledge (TPACK). The TPACK model suggests the development of different technological skills and seeks efficient ICT integration to improve teaching and learning [62]. Further, the references for self-determination theory have increased recently. SDT addresses the learning and motivation challenges of m-learning [63]. The studies suggest that motivation is a fundamental requirement for learning [64, 65]. However, learners' m-learning motivation has hardly evoked researchers' interest [23]. The findings indicated a close association between m-learning continuance and SDT. Hence, much research integrating TPACK and SDT is essential to enrich the MACE research area. Further, it seems that a higher number of publications examined adoption as compared to continuance. Therefore, future studies are suggested to focus more on m-learning continuance. Additionally, the scholars can analyze a broad and diverse range of subjects (e.g., history, geography, economics, fine arts, commerce), including lab-based courses. The existing literature seems to have a narrow focus on a few subjects.

To conclude, MACE is an emerging area of research. It is suggested to enrich this area with more studies. Future studies could suggest an integrated model for MACE research. Further, more studies can examine continuance intention, especially in the wake of forced adoption due to the COVID-19 pandemic. Additionally, emerging technologies and themes identified in this study may be explored by the researchers.

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