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EDUCATIONAL RECOMMENDER SYSTEMS: A BIBLIOMETRIC ANALYSIS FOR THE PERIOD 2002 – 2022

(Sistem Pengesyor Pendidikan: Analisis Bibliometrik untuk Tempoh 2002 – 2022)

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ABSTRACT

Recommender systems have been applied across various domains to address the challenge of information overload by furnishing users with a personalised and pertinent recommendations. The surge in educational resources, notably within the e-learning content realm, has spurred educational recommender systems' emergence. Numerous studies have delved into these systems, employing diverse approaches and techniques to enhance the accuracy of recommendations. Consequently, analysing scholarly work on educational recommender systems becomes pivotal, providing an overview of prevalent trends and explored subjects within the field. This study aims to gather statistical information on educational recommender systems by conducting a bibliometric analysis of related papers published in the Web of Science (WoS) database from 2002 to 2022. The analysis includes examining the annual publication trend, the leading authors, journals, and countries, the most impactful articles, and the collaborative networks among countries. Then, the most common keywords, keyword clusters, and relationships between keywords were analysed with a word cloud and keyword co-occurrence network. This study also uncovers the important themes in education recommender systems research over time. The findings indicate that the main technique used in educational recommender systems is the collaborative filtering technique. However, in recent years, content-based filtering has also been applied with an inclination for natural language processing techniques. Overall, this paper presents broad insights into studies on educational recommender systems to allow the discovery of potential future topics in the domain.

Keywords: bibliometric; collaboration network; co-occurrence network; education recommender system

ABSTRAK

Sistem pengesyoran telah digunakan merentasi pelbagai domain untuk menangani cabaran lebihan maklumat dengan memberikan pengguna pengesyoran yang peribadi dan berkaitan. Lonjakan dalam sumber pendidikan, terutamanya dalam alam kandungan e-pembelajaran, telah mendorong kemunculan sistem pengesyoran pendidikan. Banyak kajian telah mengkaji sistem-sistem ini dengan menggunapakai pelbagai pendekatan dan teknik untuk meningkatkan ketepatan pengesyoran. Oleh itu, menganalisis kerja ilmiah berkenaan sistem pengesyoran pendidikan menjadi penting dalam memberikan gambaran keseluruhan tentang trend lazim dan isu yang diterokai dalam bidang ini. Kajian ini bertujuan untuk mengumpulkan maklumat statistik berkenaan sistem pengesyoran pendidikan dengan menjalankan analisis bibliometrik terhadap makalah berkaitan yang diterbitkan dalam pangkalan data *Web of Science* (WoS) dari tahun 2002 hingga 2022. Analisis termasuk mengkaji trend penerbitan tahunan, mengenalpasti pengarang, jurnal, dan negara yang menerajui bidang ini, mengenalpasti makalah yang paling memberikan impak, dan rangkaian kerjasama antara negara. Kemudian, kata kunci yang paling biasa, kelompok kata kunci dan hubungan antara kata kunci telah dianalisis dengan awan perkataan dan rangkaian kejadian bersama kata kunci. Kajian ini juga meninjau tema penting dalam penyelidikan sistem pengesyoran pendidikan dari semasa ke semasa. Dapatan menunjukkan bahawa teknik utama yang digunakan dalam sistem pengesyoran pendidikan ialah teknik penapisan kolaboratif. Walau bagaimanapun, dalam beberapa tahun kebelakangan ini, penapisan berasaskan kandungan juga telah digunakan dengan kecenderungan terhadap teknik pemprosesan bahasa semula jadi. Secara keseluruhannya, kertas kerja ini membentangkan pandangan yang luas tentang kajian yang berkaitan dengan sistem pengesyoran pendidikan untuk membolehkan penemuan potensi topik dalam domain ini pada masa hadapan.

Kata kunci: bibliometric; rangkaian kerjasama; rangkaian kejadian Bersama; sistem pengesyor pendidikan

1. Introduction

The explosive growth of digital technology has escalated the amount of available information, leading to information overload. Information overload occurs when decision-makers are presented with information that exceeds their information processing capacity (Roetzel 2019). A solution to alleviate the burden of information overload among users in different domains is introducing recommender systems. Recommender systems are information filtration systems that offer users content or information based on their preferences, interests, and behaviours, also known as users' profiles (Isinkaye *et al.* 2015; Konstan & Riedl 2012; Roy & Dutta 2022).

Today, owing to an increased usage of recommender systems for various applications such as e-learning, movies, music, and e-commerce, multiple approaches for building recommender systems have been developed based on the data availability and the objectives of recommendations. Referencing previous research (Adomavicius & Tuzhilin 2005; Li & Kim 2021; Mettouris & Papadopoulos 2014), the well-known categories of recommendation approaches are collaborative filtering (CF), content-based filtering (CBF), and hybrid recommendation, which combines CF and CBF approaches. CBF techniques provide recommendations based on the previous choices of a target user. CF techniques calculate users' similarities to offer recommendations tailored to individuals with comparable profiles (Garcia-Martinez & Hamou-Lhadj 2013; Urdaneta-Ponte *et al.* 2021). CF approaches can be divided into two categories: memory-based and model-based approaches. The memory-based approaches can be subdivided into user-based CF and item-based CF. User-based CF recommends items preferred by similar users, while item-based CF recommends items similar to those users have liked in the past (Maphosa *et al.* 2020; Li & Kim 2021; Lu *et al.* 2015; Zhang *et al.* 2021). Model-based CF uses machine learning (ML) algorithms or data mining methods to predict a user's rating for an unrated item (Roy & Dutta 2022).

There is a necessity in education to develop educational recommender systems that provide personalised teaching and learning recommendations due to the surge in educational resources. According to Chen *et al.* (2022), learning recommendation is one of the research areas with increasing interest in educational technology. Recommender systems can be beneficial for educators to enhance their pedagogical and curriculum approaches via suggestions that aid them in planning and refining educational resources. Meanwhile, recommender systems can improve students' academic performances by suggesting personalised learning content based on their interests and constraints (Garcia-Martinez & Hamou-Lhadj 2013; da Silva *et al.* 2022). Based on a systematic review of recommender systems for education (Urdaneta-Ponte *et al.* 2021), most works were oriented to recommend courses and learning resources for students. This is due to the vast number of online courses on the web, called Massive Open Online Courses (MOOCs), which causes students to be overwhelmed with too many options and confused about the most suitable courses for them (Garcia-Martinez & Hamou-Lhadj 2013).

Several issues must be addressed when designing a recommender system in education. First, the recommender system needs to account for extensive academic interest among students to capture their expectations (da Silva *et al.* 2022; Verbert *et al.* 2012). Second, when recommending a complete learning path, the recommender system should consider different personal factors that can affect one's learning path (Buder & Schwind 2012; da Silva *et al.* 2022). Furthermore, a course recommender system in a university environment differs from the typical recommender systems, such as movies or music, as it is more prone to severe suffering from a cold start problem due to limited past course-enrolment data. As a result, commonly used approaches such as collaborative filtering (CF) will only generate mediocre recommendations (Jing & Tang 2017; Ma *et al.* 2021). Besides, a single recommendation strategy might not be appropriate for all students because while some students already have a clear career goal, others may have a general picture (Ma *et al.* 2021).

Given the diversity and benefits of recommender systems in education, various approaches and techniques have been explored to improve recommendation performance. Therefore, getting an overview of the scientific efforts on educational recommender systems is crucial to understanding and summarizing the trends and themes in the research area. Some papers provide a systematic review of recommender systems for various applications and applications specific to the field of education (Roy & Dutta 2022; Urdaneta-Ponte *et al.* 2021). Although a systematic review reveals the current state and gaps in a research topic, integrating methodological approaches like bibliometric analysis can give a quantitative perspective on the development of the topic (Cao & Alon 2020; Zheng *et al.* 2023). A bibliometric analysis applies statistical methods to quantify, synthesise and analyse written communication such as books and articles (Donthu *et al.* 2022; Han *et al.* 2020). It is conducted on a research topic at a particular time to obtain an insightful perspective of the topic in that period and to apprehend its progress over time (Aria & Cuccurullo 2017).

Anandhan *et al.* (2022) conducted a bibliometric study to determine the growth rate of publications and identify current trends based on analysis of author co-citations and keyword co-occurrences on social media recommender systems. Moreover, Rashid *et al.* (2021) analysed keyword co-occurrences to discover clusters of keywords in social support in education. Bibliometric analysis is also helpful for visualizing the thematic evaluation of a research area (Rojas-Galeano *et al.* 2022) and investigating collaboration among countries in a domain (Chen *et al.* 2022). Recently, Lampropoulos (2023) performed bibliometric analysis for educational recommender system in general by setting search query to ("recommender system*"AND "recommendation system*") OR ("education"). This paper aims to conduct a bibliometric analysis of educational or, more specifically, course recommender systems, by looking at scholarly publications, including proceedings, related to both educational and course recommender systems. This is because course recommender system is one of the most prominent types of recommender systems in the education field (Urdaneta-Ponte *et al.* 2021). Course recommender systems are still being developed to this day and knowledge in this field is still being explored in various studies. For example, Valtolina *et al.* (2024) design a recommender system to help teachers to create digital courses while Frej *et al.* (2024) build a course recommender system to propose Massive Open Online Courses (MOOCs) to users. Hence, the bibliometric analysis was done to achieve the following objectives:

(1) Identify the annual publication trend in educational recommender system research from 2002 to 2022.
(2) Identify the most productive authors, most relevant sources, most impactful papers, and most productive countries in educational recommender system research.
(3) Investigate collaborative networks among countries in educational recommender system research.

(4) Determine the most common keywords, keyword clusters, and the relationship between keywords in educational recommender system research.
(5) Examine the thematic structure and thematic evolution in educational recommender system research.

The remainder of this paper is organised as follows: Section 2 details the data collection and methodology of the bibliometric study. Section 3 presents the results of applying various bibliometric methods, while Section 4 provides the related discussion. Section 5 concludes the study, identifies its limitations, and suggests future work.

2. Methodology

This section describes the bibliographic data collected and the analysis conducted using different methods to achieve the objectives. The open-source R programming software-based bibliometrix package was used to analyse the collected bibliographic records (Aria & Cuccurullo 2017) and construct relevant graphical visualizations.

2.1. *Bibliographic data collection and processing*

The bibliographic records were retrieved from the Web of Science (WoS) database. WoS is a reliable database offering extensive coverage of scientific papers in various fields and is considered one of the titans of bibliographic information (Pranckutė 2021). It has been widely used to collect research papers for bibliometric analysis (Anandhan *et al.* 2022; Aria & Cuccurullo 2017; Cao & Alon 2020; Munim *et al.* 2020). The first step in bibliographic data collection is to define the search scope. The following WoS compatible search query was used: Title ((“recommend* system”) AND (course$ or education*)) or Author Keywords ((“recommend* system”) AND (course$ or education*)) or Keyword Plus ((“recommend* system”) AND (course$ or education*)) or Abstract ((“recommend* system”) AND (course$ or education*)). The search scope was limited to only English language articles, proceeding papers, and book chapters for the document type and timespan from January 2002 to December 2022. This is to ensure that more than two decades worth of studies is being considered and the results describe the whole year and not part of any year. A total of 797 records were obtained from the initial search results.

The title and abstract of each record were then manually screened to exclude documents deemed irrelevant, such as studies not centred on the application of recommender systems in education, resulting in a collection of 679 bibliographic records. This collection was imported into R software to check for duplicates and missing values in essential columns. Four duplicated records were eliminated. Nine records with missing publication years were detected and handled by manually filling in the correct years, identified using Google Search. There is one missing value for abstract and cited references and 89 records with missing author keywords. These records were not eliminated as they amount to less than 15% of the total records and have important information in other columns. The remaining 675 records were finalised for bibliometric analysis, comprising 265 articles, 395 proceeding papers, nine book chapters, and six records classified as articles and proceedings papers. The data collection and processing are depicted in Figure 1 in the form of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) flow diagram as recommended by Page *et al.* (2021).

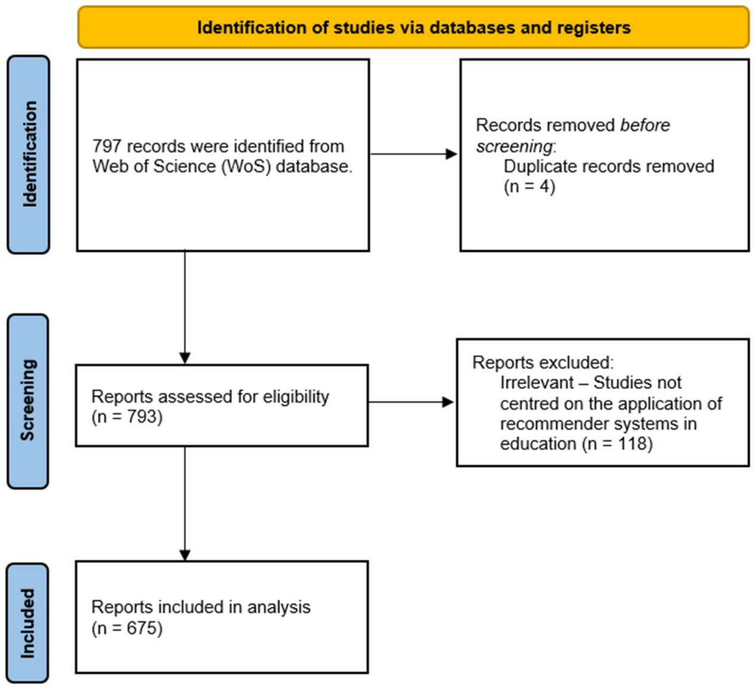

Figure 1: PRISMA 2020 flow diagram for data collection and processing

2.2. *Bibliographic data analysis*

Descriptive analysis was done to ascertain fundamental bibliometric indicators including the annual publication trends, influential papers, and prominent authors, sources, and countries. For this purpose, biblioAnalysis function within the bibliometrix package were employed.

2.3. *Analysis of country collaboration*

For investigating collaboration among countries, a country collaboration network was plotted. A country collaboration network displays the association between countries to produce a research paper in a domain (Aljohani *et al.* 2022). This study considered countries with at least ten publications and one co-authored publication to construct the network. The walktrap clustering algorithm was selected for community detection since it often has the best performance, reliability, and flexibility in choosing community structures (Gates *et al.* 2016; Lancichinetti & Fortunato 2009; Smith *et al.* 2021). The size of the vertices in a collaboration network shows the publication count of a country. The larger the vertex, the higher the number of published papers. Colours differentiate clusters or communities in the network, while the thickness of edges represents the strength of collaboration between countries (Xiao *et al.* 2022).

2.4. *Analysis of keywords*

Word cloud and keyword co-occurrence networks were employed as tools to identify the prevalent and pivotal keywords or topics within the domain of educational recommender system, as well as to decipher the relationship among these keywords (Anandhan *et al.* 2022;

Xiao *et al.* 2022). Both the word cloud and co-occurrence network were constructed utilising author keywords.

A word cloud visually depicts author keywords found within the bibliographic records. Notably, keywords that exhibit a higher frequency or occurrence manifest in a larger size compared to their less frequent counterparts. In constructing the word cloud, exclusively those author keywords boasting a minimum frequency of four were incorporated. To ensure data accuracy, all keywords satisfying this frequency criterion were cleaned. This involved transforming them into lowercase and eliminating any trailing white spaces. Additionally, plural forms of keywords were substituted with their respective singular form. Subsequently, the frequency of each keyword was computed to facilitate the creation of the word cloud.

A keyword co-occurrence network graphically represents keywords' occurrences and co-occurrences, making it helpful in determining high-occurrence keywords and keyword clusters and investigating relationships among keywords. Only keywords with a minimum frequency of 35 were considered to ensure that there are at least two keywords in each cluster. Association strength was used to normalise the co-occurrences as co-occurrences data are best normalised using association strength, while the walktrap clustering algorithm was applied for keyword clustering (van Eck & Waltman 2009). A unique keyword denotes each vertex in the network; its size is proportional to the keyword occurrence. The strength of the relationship between two keywords is visualised as the thickness of the edge between them. Clusters, as differentiated by colours, can be considered subfields in the research area (Chaparro & Rojas-Galeano 2021).

2.5. *Analysis of thematic structure and evolution*

Author keywords were used to visualise educational recommender systems' thematic structure and evolution due to their sufficiency in extracting topical aspects (Agbo *et al.* 2021; Song *et al.* 2019). A thematic map was plotted to derive the thematic structure of publications on educational recommender systems. Thematic map characterises themes by two measures, namely density, and centrality. Centrality quantifies topic importance or relevance, while density quantifies topic development. These two measures are obtained based on Callon's centrality, c, and Callon's density, d, measure (Callon *et al.* 1991). Callon's centrality can be written as

$$c = 10 \times \sum e_{kh} \tag{1}$$

with k and h refer to a keyword belonging to the theme and a keyword belonging to other themes respectively (Cobo *et al.* 2011). On the other hand, Callon's density is defined as

$$d = 100 \times \left(e_{ij}/w\right) \tag{2}$$

with i and j representing keywords belonging to the theme while w is the number of keywords in the theme (Cobo *et al.* 2011). In both Eq. (1) and Eq. (2), e refers to the equivalence index which is defined as

$$e_{ij} = c_{ij}^2/c_i c_j \tag{3}$$

where c_i and c_j are the number of documents in which two keywords, i and j, appear respectively while c_{ij} is the number of documents in which the two keywords appear together (Cobo *et al.* 2011).

A thematic map can be divided into four quadrants, each defining a unique typology of themes. Themes in the upper-right quadrant are called the motor themes, developed and essential for the field of study. The lower-right quadrant represents fundamental themes that are vital and general topics. Themes in the lower-left quadrants are emerging or declining themes of minor significance and low development, while the upper-left quadrant comprises highly specialised but isolated or niche themes (Agbo *et al.* 2021; Aria *et al.* 2020).

The thematic structure was mapped using the top 200 most frequent author keywords. Each cluster was restricted to encompass a minimum of five keywords to be considered. For the clustering process, the walktrap algorithm was selected. Each cluster denotes a distinct theme and is identified by its most prevalent keyword. The size of each cluster is directly proportional to the cumulative occurrence of the keywords constituting it (Aria *et al.* 2020).

Simultaneously, the evolution of these themes over time was depicted through a Sankey diagram. The essential purpose of a Sankey diagram is to represent flows or changes of resources from one state or time to another state or time (Lee *et al.* 2022). In this study, this visual representation illustrates the interrelation and progression of themes from 2002 to 2022. In this depiction of thematic evolution, the top 200 keywords with the highest occurrences were utilised. The evolution was demonstrated across four distinct periods: 2002-2007, 2008-2014, 2015-2019, and 2020-2022. Each box symbolises a theme within the thematic evolution map, and its size corresponds to the frequency of that theme's occurrence (Xiao *et al.* 2022).

3. Results

3.1. *Main statistics and annual publication trend*

The main statistics about the collected bibliographic data are summarised in Table 1. A total of 675 documents comprising articles, proceedings papers, and book chapters from 510 unique sources, contributed by 1826 unique authors, were analysed. Sources refer to journals or books in which the documents were published. 90% of the research on educational recommender systems were multi-authored, and on average, each document in the collection was co-authored by three individuals. A collaboration index of 2.90 suggests that each leading author is associated with more than one author to produce a paper in this domain. The annual research production grew at 25.89% from 2002 through 2022.

Table 1: Main statistics about the bibliographic collection

Description	Results
Period	2002-2022
Number of documents	675
Number of sources	510
Average citation per document	6.44
Number of authors	1826
Number of authors of single-authored documents	65
Number of authors of co-authored documents	1761
Number of single-authored documents	67
Number of co-authored documents	608
Number of documents per author	0.37
Number of authors per document	3.03
Collaboration index	2.90
Annual percentage growth rate	25.89%

Figure 2 shows the annual publications related to the educational recommender system from 2002 to 2022. Publications gradually increased between 2002 and 2009, from 2010 to 2018, and from 2019 to 2021. The productivity reduced in 2010, 2018, and 2019 compared to previous years. A major increase in the publication is observed from 2021 to 2022, with 2022 having the maximum number of publications. Thus, the influential increase observed from 2021 to 2022 is also reflected in the annual growth rate of publications shown in Table 1.

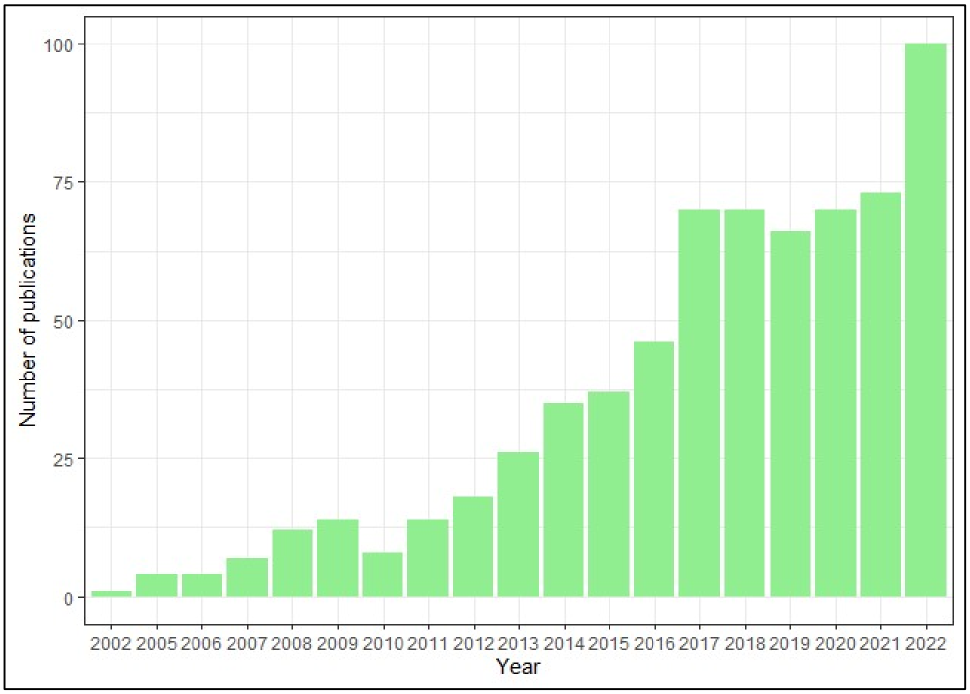

Figure 2: Number of publications by year

3.2. *Top authors, sources, papers and countries*

Table 2 lists the ten authors with the highest scientific productions related to educational recommender systems from 2002 to 2022. Dlab, M. H., affiliated with the University of Rijeka in Croatia, has published eight papers, higher than any other authors. Brusilovsky, P., Hoic-Bozic, P., and Romero, C. are the second most productive authors, each with seven publications.

The ten most relevant sources in the educational recommender system and their respective Journal Impact Factor (JIF) quartile as of 2021 are presented in Table 3. The sources with the highest publication frequency are all journals. IEEE Access has published the maximum amount of research work per source, followed closely by the International Journal of Emerging Technologies in Learning. Eight top ten sources belonged to the first or second JIF quartile. This shows good chances for research on educational recommender systems to be published in prestigious artificial intelligence and education journals.

Table 2: Ten most productive authors from 2002 to 2022

Authors	Number of documents
Dlab, M. H.	8
Brusilovsky, P.	7
Hoic-Bozic, N.	7
Romero, C.	7
Duque, N.	6
Rodriguez P.	6
Abel, M. H.	5
Julian, V.	5
Lahoud C.	5
Zhang H.	5

Table 3: Ten most relevant sources from 2002 to 2022

Sources	Number of documents	JIF Quartile
IEEE Access	13	2
International Journal of Emerging Technologies in Learning	12	2
Education and Information Technologies	9	1
Computational Intelligence and Neuroscience	7	2
Frontiers in Psychology	6	1
Mobile Information Systems	6	4
Applied Sciences-Basel	5	2
Journal of Intelligent & Fuzzy Systems	5	4
Security and Communication Networks	5	3
Computers & Education	4	1

Table 4 presents the ten most impactful or cited papers on recommender systems in the education sector from 2002 to 2022. The most cited paper is the oldest in the collection. It is a proceedings paper authored by Zaiane O. R. in 2002 with 172 total global citations and 8.19 global citations per year. The second most impactful paper is an article from Hsu C. K., Hwang G. J., and Chang C. K. in 2013, with 158 total global citations and 15.80 global citations per year. Conversely, an article by Xiao, J., Wang, M., Jiang, B., and Li, J in 2018 showcases 60 total global citations, substantiated by an average of 12 global citations per year. The lower total citations gained by Xiao et al. can be attributed to its recent publication date. Meanwhile, the latter two articles exhibit higher global citations per year than the proceedings paper, possibly due to their relatively recent publication date and heightened citation activity in recent years.

The top ten countries with the highest research publications related to educational recommender systems in the period evaluated based on the first author's affiliation are shown in Table 5. China emerges as the leader in this arena, accounting for a substantial 24.70% of the research output, overshadowing other nations by a considerable margin. The United States of America (USA), with 7.42% publications, occupies the second place, followed closely by India (6.52%) and Spain (5.30%). China, the USA, and Spain dominate Asia, North America, and Europe, respectively. The countries listed in Table 5 exhibit a trend of being developed or developing nations, aligning with expectations based on research productivity patterns.

Table 4: Ten most impactful papers from 2002 to 2022

(Authors Year)	Title	Total global citations	Total global citations per year
(Zaiane, 2002)	Building a recommender agent for e-learning systems	172	8.19
(Hsu et al., 2013)	A personalised recommendation-based mobile learning approach to improving the reading performance of EFL students	158	15.80
(Nguyen et al., 2010)	Recommender system for predicting student performance	110	8.46
(Romero et al., 2009)	Applying Web usage mining for personalizing hyperlinks in Web-based adaptive educational systems	110	7.86
(Aher & Lobo, 2013)	Combination of machine learning algorithms for recommendation of courses in E-learning System based on historical data	78	7.80
(Garcia et al., 2009)	An architecture for making recommendations to courseware authors using association rule mining and collaborative filtering	77	5.50
(Dascalu et al., 2015)	A recommender agent based on learning styles for better virtual collaborative learning experiences	65	8.12
(Garcia et al., 2011)	A collaborative educational association rule mining tool	64	5.33
(Farzan & Brusilovsky, 2006)	Social navigation support in a course recommendation system	61	3.59
(Xiao et al., 2018)	A personalised recommendation system with combinational algorithm for online learning	60	12.00

Table 5: Ten most productive countries from 2002 to 2022

Countries	Number of documents	Percentage of documents (%)
China	163	24.70
USA	49	7.42
India	43	6.52
Spain	35	5.30
Morocco	26	3.94
Brazil	24	3.64
Japan	17	2.58
Germany	13	1.97
Thailand	13	1.97
Canada	12	1.82

3.3. *Analysis of country collaboration*

Figure 3 illustrates the collaboration network among countries with a minimum of ten publications in the scope of the educational recommender system from 2002 to 2022. As indicated by their labels and vertices sizes, China, the USA, India, and Spain contributed the most work in the field. This observation is aligned with that observed in Table 5. Five clusters or communities of countries are formed. Countries within the same communities collaborated more frequently with each other than with countries in different communities. China forms a community with the USA, Canada, Saudi Arabia, Australia, and a few other countries. In this community, China and the USA demonstrate the strongest collaboration, followed by the USA and Canada, as indicated by the thickness of the edges between them. Another community that connects Spain, Ecuador, Greece, Columbia, Brazil, the United Kingdom (UK), and Mexico can be observed. Spain has closely cooperated with Columbia, Ecuador, and Mexico to produce research papers on the educational recommender system. Further collaborations are observed, such as between France and Egypt, India and Indonesia, the Netherlands and Germany, the UK and Spain, as well as Saudi Arabia and Pakistan. This insightful network portrayal highlights that collaborations transcend continental boundaries, encompassing nations from various parts of the world.

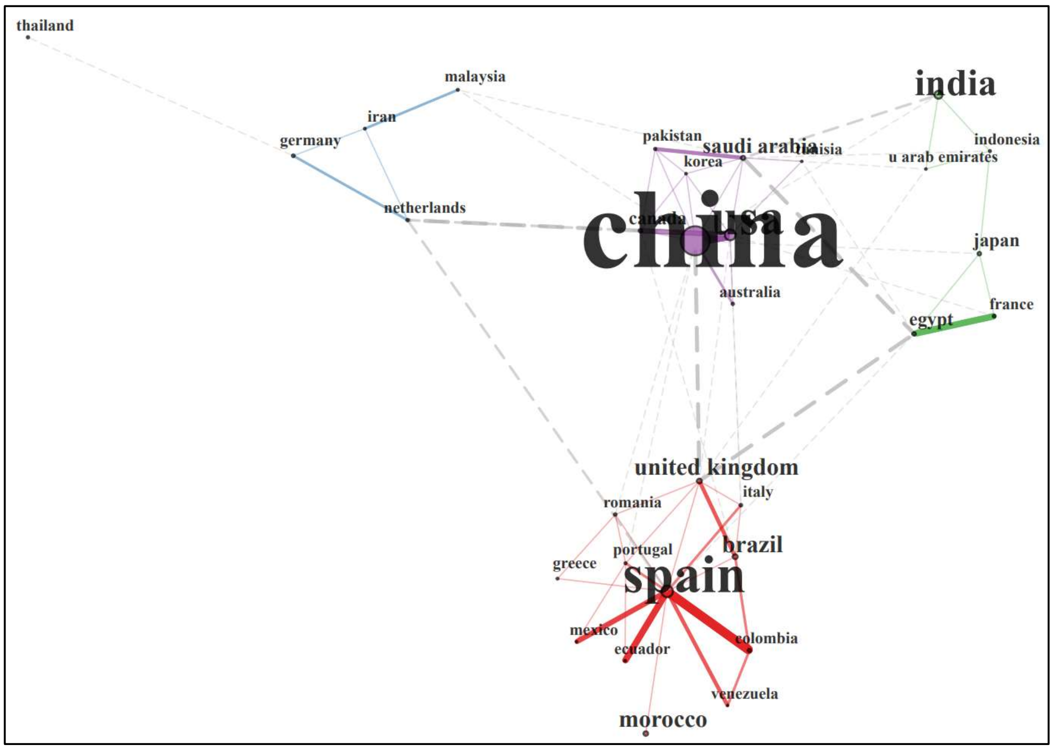

Figure 3: Country collaboration network

3.4. *Analysis of keywords*

Figure 4 displays the word cloud of author keywords that appeared in at least four publications. The keyword "recommender system" is the most common in educational recommender system. However, it is more useful to identify other common keywords that were not included in the search query. The second most common keywords are "e-learning" and "collaborative filtering", suggesting that a large percentage of the work done in this field are focused on recommending e-learning courses or other online educational resources and using collaborative filtering technique for recommendations. Furthermore, recurring keywords such as "machine learning" and "ontology" underscore the noteworthy prominence of employing machine learning algorithms and ontology applications within the educational recommender system. These recurrent themes within the keywords reflect the significant role that machine learning and ontology play in shaping the landscape of research within this field.

Figure 4: Word cloud of keywords

The network of author keyword co-occurrences with a minimum of 35 occurrences per keyword in the domain of educational recommender system from 2002 to 2022 is shown in Figure 5. The frequently used keywords are “recommender system”, “collaborative filtering”, “e-learning”, “machine learning”, “course recommender system”, “education”, “ontology”, and “mooc”, as these words have larger labels and vertices sizes, similar to the findings from Figure 4. High occurrences of these keywords suggest they were central and important in the research domain. Keywords that are closely related to each other are grouped in a cluster. There are four main clusters in Figure 5 where each cluster indicates a subfield of research. The highest occurring keyword, “recommender system”, is situated in the largest cluster along with keywords such as “e-learning”, “collaborative filtering”, “education”, “ontology”, “data mining”, “clustering”, “course recommender system”, “mooc”, “content-based filtering”, and “personalization”. This cluster contains most of the frequently used keywords in research related to educational recommender systems. It is a general cluster representing various techniques to build a personalised recommender system, especially for online learning. The second largest cluster, which consists of keywords like “machine learning”, “big data”, “educational recommender system”, “natural language processing”, and “classification”, groups scientific works that utilise machine learning techniques on a large amount of data. The green cluster with unique keywords like “artificial intelligence” and “information retrieval” represents the research subfield focusing on data retrieval to build a recommender system. The fourth cluster, which is composed of “personalized learning”, “knowledge graph”, and “distance learning”, portrays a small collection of publications that use knowledge-based recommender systems in education.

The keyword “recommender system” has the highest co-occurrence or strongest relationship with "e-learning", as indicated by the thickest edge. Most recommender systems were built to suggest online educational resources or courses. It also has high co-occurrences with "collaborative filtering", "educational data mining", and "machine learning", indicating that these approaches have been frequently used for building educational recommender systems. There are some notable co-occurrences among "recommender system", "clustering", "content-based filtering", "matrix factorization", and "online learning". Besides specific model-based collaborative filtering techniques such as clustering and matrix factorization, content-based filtering has also been applied to recommend online learning resources, but not often.

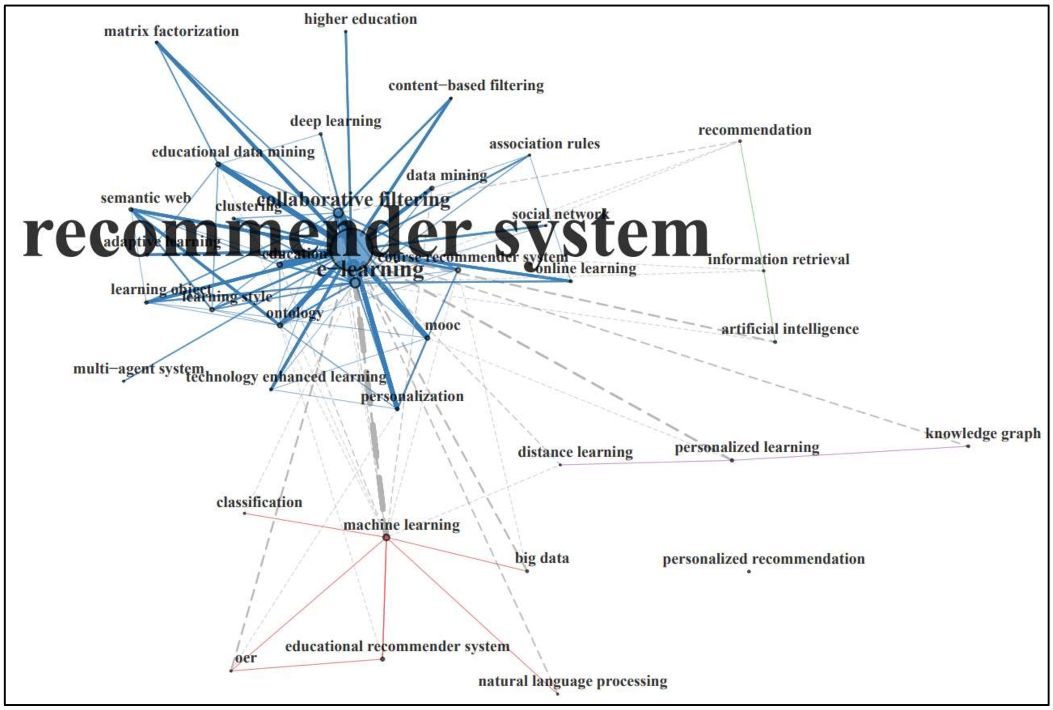

Figure 5: Keywords co-occurrence network

3.5. *Analysis of thematic structure and evolution*

Figure 6 shows the thematic map of the 200 most occurring author keywords in educational recommender system research from 2002 to 2022. Each cluster was restricted to at least five keywords corresponding to a theme. Each theme is labelled with its corresponding most frequent keyword. The cluster labelled with "recommender system" is the largest. This cluster has the highest total occurrence of keywords that compose it, probably due to each keyword in this cluster having relatively high occurrences. The upper-right quadrant consists of a motor theme, "personalised recommendation". The high centrality of this theme indicates that it is important and developed in the educational recommender system. However, there is still room for development as it is situated in the lower part of the upper-right quadrant. On the other hand, the lower-right quadrant comprises basic themes such as "machine learning" and "collaborative filtering", which require development and transversal to other themes in the domain.

The only emerging theme on the map in the lower-left quadrant is the "knowledge graph", suggesting that knowledge-based recommender systems are weakly developed and of minor importance. Some of the niche themes found in the upper-left quadrant are “natural language processing”, “multi agent system”, and “information retrieval”. These themes are well-developed but considered isolated and of limited importance for the domain. Peculiarly, natural language processing (NLP) is not the most important in building an educational recommender system. This might be due to the satisfactory results obtained by other approaches, such as collaborative filtering, which performed well without the complexity and resources needed for NLP techniques.

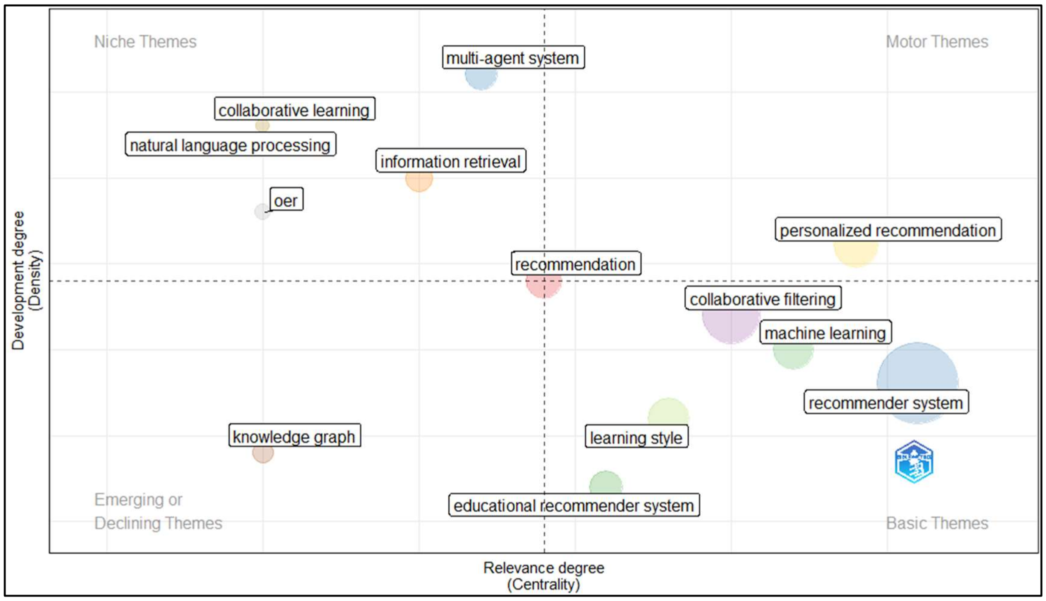

Figure 6: Thematic map of keywords from 2002 to 2022

Thematic evolution map of the 200 most occurring author keywords in four time periods (2002-2007, 2008-2014, 2015-2019, 2020-2022) is depicted in Figure 7. Overall, educational recommendation system research themes have become increasingly diverse over time. This reveals that the field has grown, and researchers have adopted various approaches to develop educational recommender systems. Themes or keywords such as “recommender system”, “educational recommender system”, “course recommender system”, and “personalization” have appeared in at least two periods as they are central to the bibliometric study.

Educational or course recommender systems were initially dominated by “content-based filtering”. In the second period, “content-based filtering” split into “course recommender system” and “personalization”, exhibiting the emergence of personalised recommender systems in education, most probably those that utilised user information. Moreover, “adaptive learning” and “interest model” have been explored in the second period, further indicating the emergence of user-specific recommender systems such as those based on a learner’s present status and interest.

In the third period, many new specialised themes began to flourish, such as “natural language processing”, “clustering”, “prediction”, and “information retrieval”. This shows that researchers have started to utilise text data to build an educational recommender system and the revival of content-based recommender systems. Clustering has also been one of the common studies in the domain during this period. “Natural language processing” remained a significant theme till the final period. The final period is composed of more varied themes, including "evaluation", "data mining", "score prediction", and "artificial intelligence".

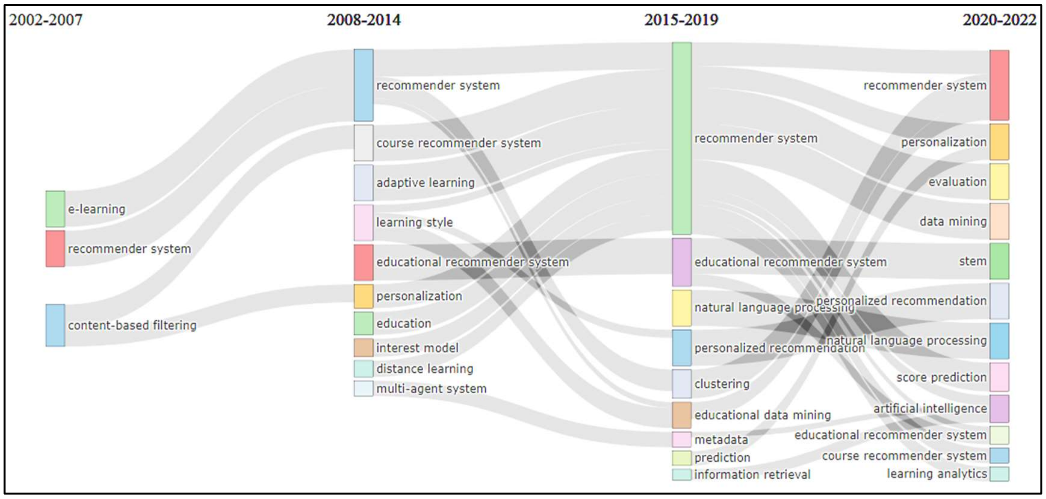

Figure 7: Thematic evolution of keywords from 2002 to 2022 through the sub-periods

4. Discussion

This study analysed 675 papers on educational recommender systems published in WoS from 2002 to 2022 using bibliometric methods. When observing the annual publications of educational recommender system scientific papers in Figure 2, there is an increase in publications from 2002 to 2022, but not monotonically. Additionally, the thematic evolution map in Figure 7 reveals the increasing topical diversity observed in research articles concerning educational recommender system over time. This trend indicates that educational recommender systems have been developed for diverse purposes and objectives in recent years. Therefore, the volume of publications on educational recommender systems has been growing, with researchers exploring different techniques to achieve their respective objectives and enhance the accuracy of recommendations. One of the primary reasons for this positive trend is the abundance of learning resources, such as online courses, which necessitates automation services to support students in making choices.

As seen in Table 2 and Table 3, Dlab, M. H., Brusilovsky, P., Hoic-Bozic, P., and Romero, C. are the most productive authors. At the same time, IEEE Access and the International Journal of Emerging Technologies in Learning are the most relevant sources. Among the most impactful papers, as listed in Table 4, are a proceedings paper by Zaiane O. R. in 2002, an article by Hsu, C., Hwang, C. and Chang, C. in 2013 and an article by Xiao, J., Wang, M., Jiang, B. and Li, J. in 2018. These papers can be references for future studies on educational recommender systems. It is important to note that bibliometrics assumes that the higher the total citations of a paper, the more distinguished it is. Nevertheless, recently published articles might be cited much later and have lower citations (Cao & Alon 2020). When inspecting the most productive countries and collaborations between countries, the findings from Table 5 and Figure 3 show that China is the most productive country, with a contribution of almost a quarter of publications in the domain, followed by the USA, India, and Spain. In contrast, countries collaborating frequently are China and the USA, Spain and Columbia, Spain and Ecuador, as well as France and Egypt.

When analysing the keywords of publications on educational recommender systems, Figure 4 and Figure 5 allow the identification of the most frequent keywords, keyword clusters, and relationships between keywords. Four clusters were discovered in which the largest cluster groups different types of methods used to provide personalised recommendations of learning resources. The most common keywords in educational recommender system research are “collaborative filtering”, “e-learning”, “machine learning”, and “ontology”, excluding the keywords containing the word “recommender” or “education”. These keywords also co-occurred frequently with “recommender system” in the publications. Other keywords like “clustering”, “personalization”, “educational data mining”, and “content-based filtering” have also co-occurred with “recommender system”. Ergo, most publications on educational recommender systems focused on recommending online learning resources or courses and applied model-based collaborative filtering techniques such as clustering and data mining. However, some papers used content-based filtering to build educational recommender systems.

When examining the themes in educational recommender system research, observations from the thematic structure map in Figure 6 further underpin the abovementioned findings. The “collaborative filtering” and “machine learning” themes are classified as basic themes and are highly relevant and crucial in this domain. Since these themes are located at an average position along the density axis, they are still evolving and not underdeveloped. Conversely, the “knowledge graph” theme is lagging and unimportant. This observation somewhat aligned with the keyword co-occurrence network because the keyword “knowledge graph” does not exhibit high frequency. “Natural language processing” is a niche theme with low importance but quite developed, consistent with its low occurrence in Figure 5.

The thematic evolution map in Figure 7 shows that the “content-based filtering” theme had only been dominant in the earliest period, corresponding to its low occurrences and co-occurrences and absence in the overall thematic structure map. Despite that, “content-based filtering” may have evolved into more specific and recent themes over the years, such as “natural language processing”, as observed in the final period in Figure 7. Figure 7 also depicts that “natural language processing” has only been explored between 2015 and 2022, contributing to its relatively low occurrences and importance when considering the entire timespan of records. The current boom of NLP suggests that research on content-based educational recommender system, especially one that utilises NLP, is still relevant and should be explored in future studies. Specific themes like “interest model”, “clustering”, “prediction”, and “artificial intelligence” that reasonably fall under the category of model-based collaborative filtering recommender system have emerged between 2008 and 2022. This indicates that collaborative filtering techniques, particularly model-based methods, have been dominant for an extended period. Thus, it can be deduced that most scholarly works on educational recommender systems use collaborative filtering techniques rather than content-based or knowledge-based methods.

In addition, there needs to be more job and skill-related themes or keywords within publications on educational recommender systems. This suggests that many educational recommender systems have been developed without adequately considering the job market requirements or the growing emphasis on skill-based hiring practices. Consequently, future research could be directed toward designing educational recommender systems that meticulously incorporate job market demands. This approach would better equip students with the necessary skills and knowledge to thrive in various industries and career paths.

This work offers a general understanding of the current research status and trends in educational recommender systems. Although bibliometric analysis can effectively integrate, summarise, and assess large volumes of research on educational recommender systems, it must provide thorough details on their contents (Donthu *et al.* 2022). It is important to take extra caution when evaluating assertions made from bibliometric analysis (Donthu *et al.* 2022).

5. Conclusions

This paper carried out a bibliometric analysis of publications on educational recommender systems. Generally, the annual production of research related to educational recommender systems reflects an increasing trend. The collaborative networks among countries were investigated using a country collaboration network. The word cloud and co-occurrence network of keywords were visualised to determine the most common keywords, keyword cluster, and relationships between keywords. Lastly, the relevance and development of themes in educational recommender system research were examined through the thematic structure and evolution map. Themes on educational recommender systems are becoming increasingly diverse over time.

In summary, the findings reveal that research on educational recommender systems is progressing with advancement in the types of educational recommender systems and the techniques used to build them. This study is useful to scholars, publishers, and others interested in educational recommender systems as it provides them with a comprehensive overview of related studies published over more than two decades. This study could also be used as a foundation to initiate further studies in the research area.

There are several limitations to this study. Firstly, the analysis is exclusively confined to English-language publications available in the WoS database. Future work should include publications from other databases, such as Scopus and Google Scholar, to provide a more comprehensive overview. Secondly, the search query for retrieving educational recommender systems publications might only encompass some relevant works, potentially leading to omitting pertinent materials. Future studies should consider a broader range of keywords to enhance inclusivity. Thirdly, a major fraction of the analysis primarily focused on authors' keywords, possibly neglecting information embedded in other attributes of the bibliographic records. Future research could also explore the content within titles and abstracts. Lastly, this study lacks co-citation analysis, indicating that future research should integrate co-citation analysis to achieve a more thorough bibliometric evaluation.

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