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Fifteen Years of Recommender Systems Research in Higher Education: Current Trends and Future Direction

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ABSTRACT

Artificial intelligence applications have revolutionized business, industry, and education. Applications developed for other sectors are being adapted for education. The amount of data being generated by educational institutions is used to make recommendations for a wide range of areas. The study uses bibliometric analysis to evaluate the development and growth of recommender systems in higher education. Two hundred seventy-two (272) articles published between 2007 and 2021 in the Scopus database were utilized to collect data. The study examines the different patterns such as publication trends, the relative growth rate (RGR) and doubling time (DT) for publications. Results show a steady increase in publications, with 2017 recording the highest number of publications. China, Spain and the United States have the highest publications. The mean RGR decreased, and the mean doubling time increased in the three-five-year periods. The study identified sixteen themes covered by the research articles analyzed. Most articles focused on e-learning, followed by classroom activities and, thirdly, those focusing on course selection. The study provides essential insights into current and future research on recommender systems in higher education. This analysis helps researchers, policymakers, and practitioners better understand the development of recommender systems in higher education and possible practice implications.

ARTICLE HISTORY

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Introduction

The 21st-century technological boom has witnessed tremendous improvement in the rapid access to large amounts of information, offering opportunities for new online services. Advancements in pervasive computing result in significant data repositories, making searching, finding and choosing what one wants a complicated and time-consuming process. This is known as data overload. Billions of text and multimedia documents are uploaded to the World Wide Web daily, increasing information search overloads for

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consumers (Alhijawi and Kilani 2020). Buyers face difficulties selecting a product from many options and rely on the ratings of other consumers to decide quickly. Users are spoiled for choice through masses of online data and sometimes fail to figure out what they want; therefore, recommendation systems are ideal. The outbreak of COVID-19 accelerated the adoption of remote-based teaching technologies by higher education institutions (HEIs) (Maphosa 2022). The opportunities that technologies bring to higher education (HE) are enormous, allowing institutions to realign their pedagogies and meet the needs of learners. Technologies extend human capabilities and offer new pedagogical models that enhance teaching, learning and research. As students adopt online learning systems, these systems should guide and direct students to relevant content that support individual and personalized learning.

Predicting student enrollment and success is vital to timetabling and allocating lecturers to students to ensure student learning is adequately supported. Students require assistance in choosing career paths through selecting elective courses, and sometimes students lack information regarding the objectives of the courses. As the volume of data and information on available courses increases, students face challenges in making the right decisions. When students mismatch their current and preferred pathways, this results in academic disruptions such as low performance, high dropouts and longer course completion times, and graduates who quickly change their profession (Elfaki et al. 2014). As HEIs innovate, students are presented with various programmes and courses, and there is a need to support students in decision-making from the available information to ensure their academic success (Chang, Lin, and Chen 2016). HEIs traditionally employ guidance counselors to help students make their academic decisions on courses and programmes of study and address these challenges (Iatrellis, Kameas, and Fitsilis 2017).

Artificial intelligence (AI) assists hundreds of thousands of HE students in choosing the most appropriate course or programme (Maphosa and Maphosa 2022) (Lynn and Emanuel 2021). Teacherbots are slowly replacing teaching assistants for tutorials in online classes as well as performing some administrative parts of the teaching (Popenici and Kerr 2017), thus freeing the teacher from repetitive and mundane tasks to focus on higher-order tasks. AI predict learners' scores, thus impacting their academic performances, as remedial action can be taken earlier to reduce course failure. Many HEIs are adopting IBM's Watson supercomputer to provide students with academic and social advice 24/7, thus reducing the need for employing administrative staff (Popenici and Kerr 2017). The student's academic success depends on the good advice they get, while bad advice can negatively impact their ability to complete their chosen course or programme.

A recommender system (RS) is a technique that assists users in quickly locating exciting items from a large pool of related items. RS are intelligent programs that prescribe a user's next option based on several factors, such as preference or user's history. The abundance of choices in online systems has necessitated the deployment of RS to assist individuals in narrowing their searches and selection. Recommendation systems apply mathematical and artificial intelligence techniques to find the most optimal and suitable recommendation for the user. Users interact with RS daily as they traverse the Internet; for example, Facebook recommends prospective friends, YouTube recommends videos, Goodreads recommends books, and TripAdvisor recommends holiday destinations. RS have become popular as they address basic user tendencies, where humans mainly rely on the experiences of others to adopt a service or product, such as getting admitted into an institution, choosing a holiday destination or watching a movie (Sohail, Siddiqui, and Ali 2017).

RS emerged in the 1990s to address the challenge of information overload, and since then, scholars have refined them to solve problems that educational institutions face (Lu et al. 2015). define RS as software tools that provide recommendations for the most appropriate service or product to individual users. RS is being implemented in a wide range of application domains, such as e-commerce, education, and entertainment, to assist users in decision-making, using standard techniques such as content-based filtering, collaborative filtering and hybrid approaches (Verbert et al. 2012; Kotkov, Wang, and Veijalainen 2016).

RS can be used in HE to support individual learning by arranging learning content and activities for individual students based on their profiles. RS uses web usage data with artificial intelligence and statistical computations to provide superior results, such as personalized reading suggestions (Karimi, Jannach, and Jugovac 2018). RS assists workers who face difficulties choosing the right job by matching workers to jobs (Al-Badarenah and Alsakran 2016). RS assist students and their lecturers quickly finding learning materials based on individual learning pathways (Khribi, Jemni, and Nasraoui 2015). RS offer institutions a competitive advantage as they support students in planning and achieving their educational goals (Mostafa et al. 2014).

One significant application of RS in HE is the prediction of student grades in future courses to be enrolled (Sweeney et al. 2016). This has resulted in increased student retention and completion of courses (Sweeney et al. 2016). note that institutions are adopting RS to provide students with information that helps them select majors, choose paths when a semester's schedule is complex and alert advisors when the student requires assistance (Garanayak et al. 2020). developed an RS that assists students in choosing the institution of their choice.

Bibliometric analysis of a research area can find much valuable information, and this study is of great significance. This research aims to establish the evolution and expose the trends in RS research in HE in the past fifteen years (2007–2021). The study examines the publication trends, the geographic distribution of authors, the relative growth rate (RGR) and the doubling time (DT) of articles and keyword analysis. In this study, the contributions lie in the following aspects:

- The characteristics of publications are provided to describe the development of the research area from these aspects: article types, publication trends, top-cited articles and the most cited publications.
- Identifying the most influential countries and the degree of collaboration among the nations. •The RGR and DT will analyze the increase in articles and the doubling time of published articles.
- Summarizing the themes covered in the research articles.
- Identifying the research hotspots in the field using VOSViewer.

Classification of Recommender Systems

There are three main RS categories: content, collaborative, and hybrid-based approaches (Verbert et al. 2012). The scholarship indicates that some emerging variations are based on demographics and utility.

Collaborative Filtering Methods

Collaborative filtering (CF) recommends items to targeted users by finding other users with similar interests. This approach uses user behavior or user ratings to make recommendations on products liked by similar users. CF's foundation is that people with similar tastes will likely make similar choices in the future (Dakhel and Mahdavi 2013). The motivation is that users consider recommendations from family and friends whenever they decide on a career, investment or education. Thus, CF techniques begin by finding a group of users whose preferences are similar to the targeted user. All the items the group likes are recommended to the targeted user. The efficiency of CF is determined by the algorithm's accuracy in finding the group of users with similar preferences and dislikes to the targeted user. A study to examine RS that assists students in choosing elective courses showed that the CF was the most widely used RS technique (Maphosa, Doorsamy, and Paul 2020). In terms of performance, CF-based approaches suffer the cold start problem, where the system fails to make recommendations for new users as there is no historical information to predict their interests and preferences (Mu 2018).

Content-Based Methods

Content-based (CB) methods recommend items to the user based on historical data by learning the services or products the user acquired and then suggesting new items. This approach is widely used in e-commerce, social networks, and education, where product rating is a dominant attribute of this technique. Things that a user previously rated are used to build a user profile. Profiles include the user's user's demographic characteristics, including education and place of residence. The attributes of the items include full descriptions such as actor, genre, category, and type of movie (Lops, de Gemmis, and Semeraro 2011). The item attributes are obtained from tables and forms and through content analysis from unstructured sources such as articles and news.

The learning CB can also include additional data about the learner, such as background and current qualifications sought (Zhang, Lu, and Zhang 2021). The CB technique relies on similarity and matching user profiles and items to make recommendations. One advantage of the CB approach is that recommendation is independent of the user but based on content attributes. Additionally, CB does not experience the cold start problem associated with CF as new items can be recommended to users and explain the recommendation outcome (Lops, de Gemmis, and Semeraro 2011; Shambour and Lu 2012). CB's approach requires in-depth knowledge of item features to make accurate recommendations, and this information may be limited. The inability of this technique to extend the user's current preferences or interests is another limitation.

Hybrid

(Li, Lu, and Li 2005) concluded that hybrid-based systems aim to get the best results by combining collaborative filtering and content-based recommendation methods. A hybrid approach is used to overcome the inherent limitations of the two major recommendation techniques, and it aggregates the two techniques to develop other variations. Several variations are used by hybrid systems, such as one technique at a time, combining the methods, using the results of one technique as input of the other technique, or incorporating content-based affordances to a collaborative-based technique and vice versa. Thus, improving the recommendation process's performance and accuracy and overcoming each method's limitations. The hybrid RS includes monolithic, parallel and pipeline recommendation systems (Hussein et al. 2014; Mu 2018).

Application of Recommender Systems in Higher Education

Assisting Teachers

RS has been applied in HE to assist teachers (Miranda et al. 2012). developed a hybrid system for recommending contextual information to peers by synthesizing online comments about the teacher's educational experience. Another RS assists teachers by analyzing the learner's opinions regarding online material to determine whether it is difficult to understand (Tewari, Saroj, and Barman 2016). (Karga and Satratzemi 2019) developed an RS called Mentor to help teachers by recommending good practices and learning designs to improve the quality of teaching. An RS for mapping students to supervisors was developed by Zhang et al. (2016) which uses quality, relevance and connectivity for mapping.

Course and Content Selection by Students

Today's learners face many difficulties, despite the importance of choosing the right career path. Universities now offer online admissions, and students must choose from a large pool of courses with little guidance (Chen, Song, and Liu 2017). Another challenge students face when selecting study materials from multiple sources of information. Adopting digital learning platforms results in the production and accessibility of large information repositories, which overwhelms the learner, resulting in information overload. Finding relevant information is difficult for learners, especially when the course requirements are sometimes not fully known and the content's technical format is unclear.

(Upendran et al. 2016) developed an RS course to assist students entering college by using the student's legacy data and data from students who have completed the course to address some of the challenges. The model is premised on the fact that when a student with a specific demographic and set of skills passes a particular course, then a student with the same abilities and demographic information is likely to pass that course. As students enter college, they have inadequate information about their courses and are often confused; RS can assist students in choosing courses through data mining techniques to uncover relationships with other students who graduated (Bendakir and Aïmeur 2006). (Maphosa, Doorsamy, and Paul 2020) recommended the creation of accurate user profiles by employing deep learning techniques such as convolutional networks, restricted Boltzmann machines, deep belief networks and stacked auto-encoders. More precise user profiles lead to more accurate recommendations.

Methodology

This study analyses RS in HE in the past fifteen years, using bibliometric indicators such as RGR and DT of the corpus, leading scholars, and countries and unveiling collaborative work. At the time of research and data collection, no bibliometric analysis had been performed to synthesize the corpus on RS, as most reviews were systematic literature reviews. The Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) guidelines provide a comprehensive contextual understanding of previous studies published as a transparent and critically assessed report. PRISMA consists of three phases:

identification, screening, and inclusion (Page et al. 2021). In July and August 2022, we searched and collected data from the Scopus database, a comprehensive and widely used repository for bibliometric analysis. We conclude by providing promising application trajectories for future research.

The initial search string involved selecting articles focused on recommender/recommendation systems by searching "recommend* system" in the titles, abstracts and keyword fields. A preliminary literature review identified search keywords related to RS and HE. This search yielded 39,337 articles covering all articles focusing on recommender/recommendation systems. In the next step, we filtered the search results by the "education" keyword, leaving 443 articles. Thereafter, we screened the results to include articles published between 2007 and 2021, leaving 413 articles. The 413 papers were checked to ensure they covered both RS and HE. One hundred and forty-one articles were excluded as they covered one aspect, not both. Figure 1 shows the article selection process. The final 272 articles were downloaded from the Scopus database in Excel. We then exported the complete records for these articles to VOSviewer, a free bibliometric tool that offers visualization and text-mining abilities.

Results

Characteristics of Publications

Table 1 shows the document types of the articles retrieved. Conference proceeding papers account for three-quarters of all articles, and more than a fifth of the publications are journal articles. There were seven book chapters (2.6%), an indication of the growth and maturity of the field. Reviews and data papers combined account for less than 1% of all articles.

Figure 2 plots the publication trends. Less than ten articles were published annually in 2007, 2010, 2011 and 2020. 2008, 2009, 2012, 2014, 2018 and 2021 had more than ten articles, but less than 20 manuscripts were published annually. 2017 had the highest number of articles published, with 77, followed by 2016, with 49 articles. The decrease in publications in 2020 could be due to the impact of COVID-19 on research and publications in general.

Table 2 shows the top 10 cited research articles. The citation data was obtained from the Scopus database. The research paper "Collaborative filtering adapted to RS of e-learning," published in 2009, is the most cited, with 209 citations. The next top-cited article is "Recommender system for predicting student performance," published in 2010 with 178 citations. The article "An architecture for making recommendations to courseware authors using association rule mining and collaborative filtering" was published in 2009 with 119 citations. "Predicting student performance using personalized analytics," published in 2016, is the fourth most cited article with 110 citations. The rest of the articles have less than 100 citations each.

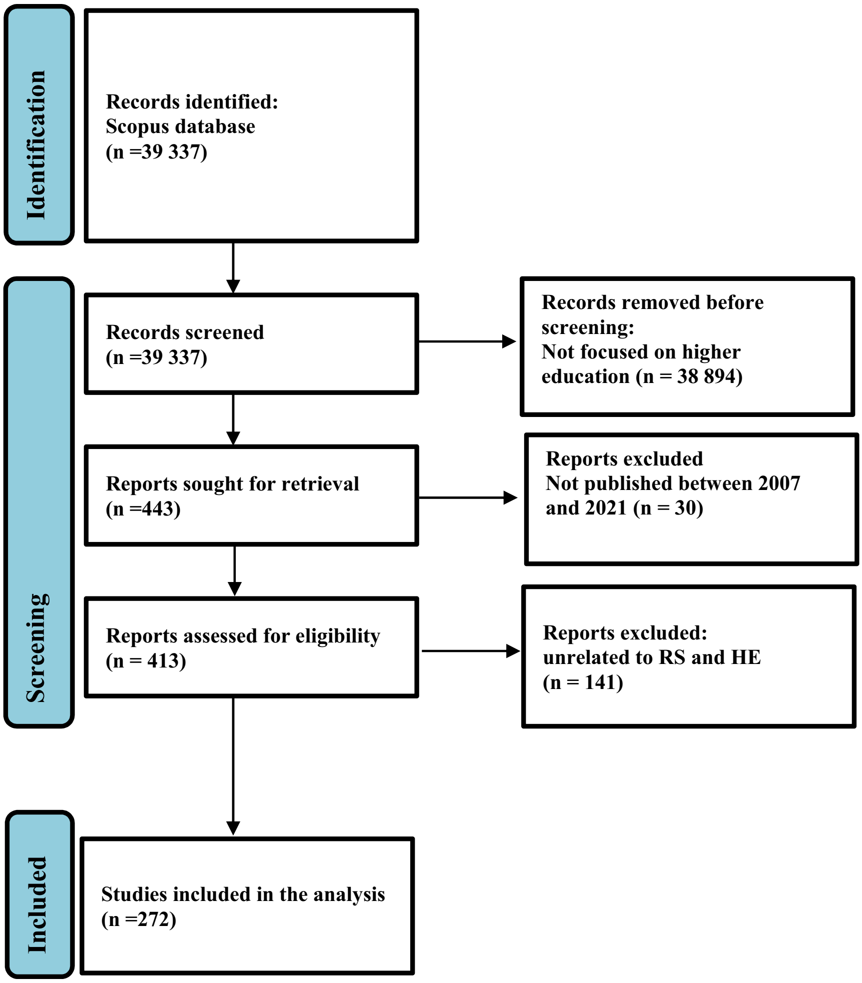

Figure 1. PRISMA flowchart (adapted from (Page et al. 2021).

Table 1. Document types of articles analyzed.

Document Types	Count	% of 272
Conference Paper	204	75
Article	59	21.7
Book Chapter	7	2.5
Review	1	0.4
Data Paper	1	0.4

Geographical Distribution of Authors

Researchers from 62 countries authored the 272 articles analyzed. China, Spain and the United States dominate research in RS Authors from China have written the most articles, with 36 accounting for over 13% of all publications. Spain had 30 articles published, and the United States with 29. Table 3 shows the top 10 countries with the most research writing. The geographical

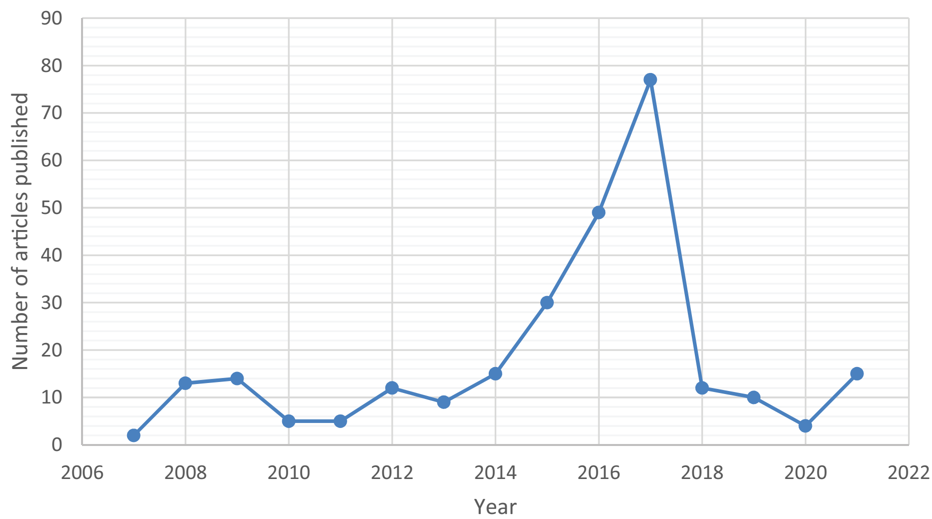

Figure 2. Publication trends of the 272 articles.

Table 2. Top 10 most cited articles.

No	Article title	Year	Authors	Citations
1	Collaborative filtering adapted to recommender systems of e-learning	2009	Bobadilla J., Serradilla F., Hernando A.	209
2	Recommender system for predicting student performance	2010	Thai-Nghe N., Drumond L., Krohn-Grimberghe A., Schmidt-Thieme L.	178
3	An architecture for making recommendations to courseware authors using association rule mining and collaborative filtering	2009	García E., Romero C., Ventura S., Castro C.D.	119
4	Predicting student performance using personalized analytics	2016	Elbadrawy A., Polyzou A., Ren Z., Sweeney M., Karypis G., Rangwala H.	110
5	A recommender agent based on learning styles for better virtual collaborative learning experiences	2015	Dascalu M.-I., Bodea C.-N., Moldoveanu A., Mohora A., Lytras M., De Pablos P.O.	79
6	PCRS: Personalized course recommender system based on a hybrid approach	2018	Gulzar Z., Leema A.A., Deepak G.	68
7	Recommender system and Web 2.0 tools to enhance a blended learning model	2016	Hoic-Bozic N., Holenko Dlab M., Mornar V.	60
8	Domain-aware grade prediction and top-n course recommendation	2016	Elbadrawy A., Karypis G.	59
9	Next-term student grade prediction	2015	Sweeney M., Lester J., Rangwala H.	59
10	Collaborative filtering adapted to recommender systems of e-learning	2009	Zhang H., Huang T., Lv Z., Liu S.Y., Zhou Z.	52

distribution of researchers who wrote the articles shows that developed nations dominate interest in research in this field. Worryingly, no African countries are in the top 10 most productive countries.

Visualization of collaboration among countries with minimum productivity of 5 publications is indicated in Figure 3. VOSviewer version 1.6.18, a tool for creating networks, was used to generate the collaboration map. The map shows three prominent clusters, each with a different color. Countries with

Table 3. Top 10 most productive countries.

	Country	Count	% of 272
1	China	36	13.24
2	Spain	30	11.03
3	United States	29	10.66
4	Taiwan	18	6.62
5	India	18	6.62
6	Brazil	12	4.41
7	Colombia	11	4.04
8	Germany	10	3.68
9	Greece	10	3.68
10	Japan	10	3.68

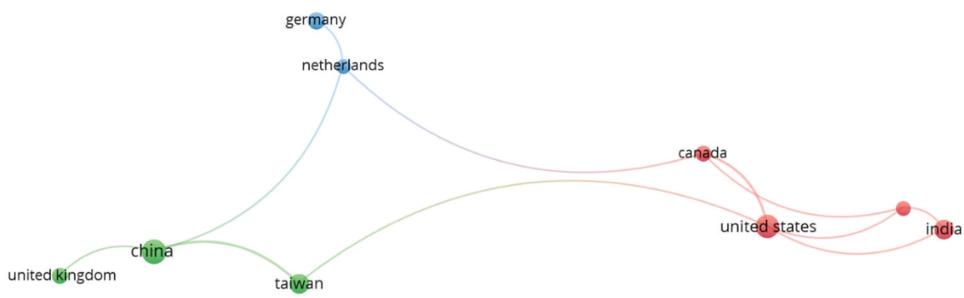

Figure 3. Collaboration among countries.

similar color form one group. For example, countries marked red, such as the United States, Canada, India and South Korea, existed in one cluster and had the highest percentage of collaboration. Germany and Netherlands are in the blue cluster. The green cluster comprises China, Taiwan, and the United Kingdom.

Relative Growth Rate and Doubling Time

The research outcome, comprising the total number of publications, was measured using two scientometric techniques: RGR and DT (Mahapatra 1985). RGR refers to the increase in the number of articles per unit of time. These metrics are employed to compute the growth rate of research productivity from 2007–2021. The RGR over the specific period of the interval can be calculated from the following equation:

$$\mathrm{RGR} : 1{-}2^{\mathrm{R}} = \log_e W_2 - \log_e W_1 / T_2 - T_1 \quad (1)$$

where $1–2^R$: is the mean relative growth rate over the specific period of the interval.

$\mathrm{Log}_e\ W_1$: log of the initial number of articles.

$\mathrm{Log}_e\ W_2$: log of the final number of articles after a specific interval period.

T_2-T_1: the unit difference between the initial time and the final time.

Table 4. Relative growth rate and doubling time of publications.

Year	Articles	Cumulative Articles	$\log_e W_1$	$\log_e W_2$	RGR	Mean RGR	DT	Mean DT
2007	2	2	0	0.69	0	0.59	0	2.21
2008	13	15	0.69	2.71	2.02		0.34	
2009	14	29	2.71	3.37	0.66		1.05	
2010	5	34	3.37	3.53	0.16		4.33	
2011	5	39	3.53	3.66	0.13		5.33	
2012	12	51	3.66	3.93	0.27	0.28	2.57	2.76
2013	9	60	3.93	4.09	0.16		4.33	
2014	15	75	4.09	4.32	0.23		3.01	
2015	30	105	4.32	4.65	0.33		2.10	
2016	49	154	4.65	5.04	0.39		1.78	
2017	77	231	5.04	5.44	0.40	0.11	1.73	15.82
2018	12	243	5.44	5.49	0.05		13.86	
2019	10	253	5.49	5.53	0.04		17.33	
2020	4	257	5.53	5.55	0.02		34.65	
2021	15	272	5.55	5.61	0.06		11.55	

The DT over the specific period of the interval can be calculated from the following equation:

$$DT = 0.693/R \tag{2}$$

where R = relative growth rate. Table 4 presents the RGR and DT of RS in HE research from the Scopus database between 2007 and 2021. The observation from Table 4 is that the RGR increased from 0 in 2007 to 0.06 in 2021. The lowest RGR was observed in 2007 (0.02), while the highest RGR occurred in 2008 (2.02). The fluctuation in the RGR is revealed from the analysis, but the mean RGR show a steady decrease. To better understand RGR, averages for every five years are recorded. There is a steady decrease in the mean RGR from 0.59 (2007–2011) to 0.28 (2012–2016) and then to 0.11 (2017–2021). DT of research output fluctuated during the study period. The highest value of the DT was 34.65 in 2020, while the lowest DT was observed in 2008 as 0.34. The mean DT for the five years increased from 2.21 (2007–2011) to 2.76 (2012–2016). The impact of the 77 articles published in 2017 can be seen with an increase to 15.82 in the next five years. DT fluctuated during this period, but the mean DT gradually increased. These figures suggest a rapid and progressive increase in the research on RS in HE. It is also interesting to observe that in 2020 DT is at its highest point while RGR is at its lowest, which reveals the fast growth of publications in the year. A higher value of RGR and a lower value of DT in a unit of time indicates the rapid growth of literature and vice-versa.

Themes Covered in the Analyzed Articles

Each author read the titles, keywords and abstracts of the 272 articles to determine the central theme covered by the article. The authors then discussed where there were different classifications until they reached a consensus. The

Table 5. Summary of the themes covered in the articles.

Theme	Articles covering the theme	Percentage of 272
Academic advising	2	0.74
Assessments	15	5.51
Career choice	11	4.04
Classroom activities	42	15.44
Course selection	26	9.56
Curriculum development	5	1.84
Distance education	2	0.74
E-learning/online learning	70	25.74
Library	6	2.21
MOOCs	16	5.88
Performance prediction	19	6.99
Personal learning	21	7.72
Reinforcement learning	6	2.21
Research	12	4.41
Tutoring	12	4.41
University choice	7	2.57

authors identified sixteen themes discussed in the articles. The e-learning/online learning theme is contained in over a quarter of all articles, followed by the theme of classroom activities which appears in about 15% of the articles. Course selection is the third most common theme covered in almost 10% of the articles. Table 5 shows the summary of the themes covered. As can be seen, the themes covered in the articles indicate the use of RSs to address some of the main challenges faced in HE.

Keyword Analysis

Using VOSviewer, we created a co-occurrence map using the keywords based on bibliographic data downloaded from the Scopus database. A total of 694 keywords were extracted from the 272 articles. The minimum occurrence of each keyword was set to five, resulting in 24 keywords. We removed keywords appearing with plurals, leaving 21 keywords. These keywords were grouped into two clusters, representing different areas that research has focused on. The top five most frequently co-occurring keywords were *recommender system* (48), *education* (32), *recommendation system* (27), *e-learning* (26) and *collaborative filtering* (24). Their occurrences indicate that these keywords are central to research and help to reinforce the influence.

Figure 4 shows the keyword co-occurrence network map. A shorter distance generally reveals a more substantial and stronger relationship. The prominent clusters that emerged in this network map, which presents an RS research subfield, are differentiated by the red, green and blue clusters. The line between the two keywords shows that they have appeared together. Nodes with a similar color belong to the same group. The red cluster has thirteen keywords. It focuses on applying RS in HE, such as personalization, adaptive learning, and reinforcement learning. The red cluster also depicts the

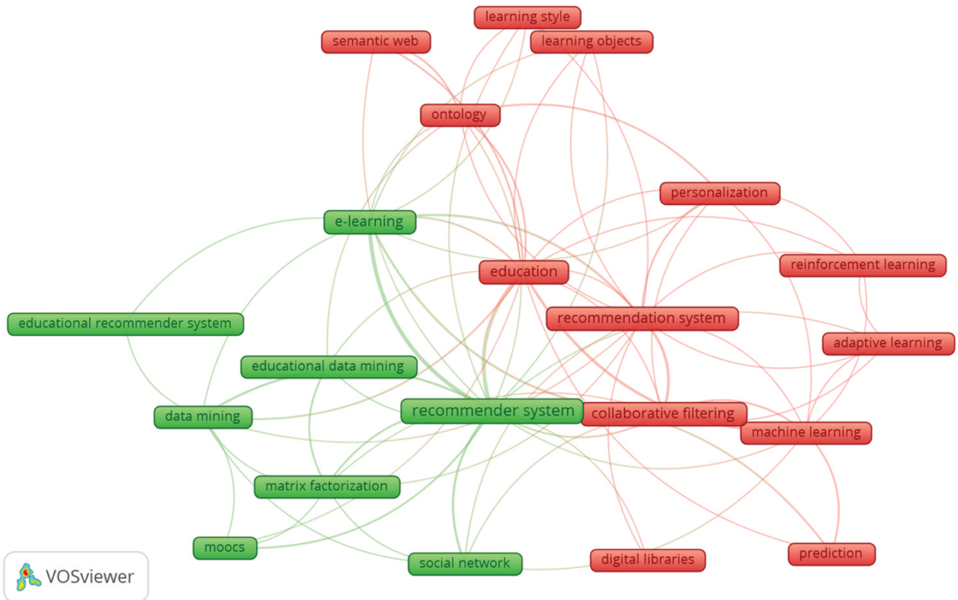

Figure 4. Network visualization co-occurrence map of high-frequency terms.

incorporation of ontology and the semantic web in RS The green cluster has eight keywords and highlights the core methods used in educational RS.

We used VOSviewer to generate the density map of the keyword co-occurrence network. Each node in the co-occurrence network is color-coded and relative to the items' density at that point. From blue to red, the redder the node represents, the greater importance of a keyword (topic). At the same time, related keywords may grow close and form a cluster to describe one topic in the keyword co-occurrence network. The node density is determined by the number of neighboring nodes, which results in more weight for the nodes.

Additionally, the smaller the distance between these nodes and the target node, the higher the node density (van Eck and Waltman 2017). Figure 5 shows the broad topics' research hotspots in the study field. The map (Figure 5) highlights that the research hotspots are centered around recommender/recommendation systems, education and collaborative filtering. Another important topic is built around the keyword – *e-learning. Adaptive learning* and *reinforcement learning* are prominent. These three topics represent the matured research subfields. Emerging topics such as MOOCs, prediction, and the semantic web are green.

Discussion

Research covering RS has been steadily increasing during the period under review. 2017 has the highest number of publications. China, Spain and the

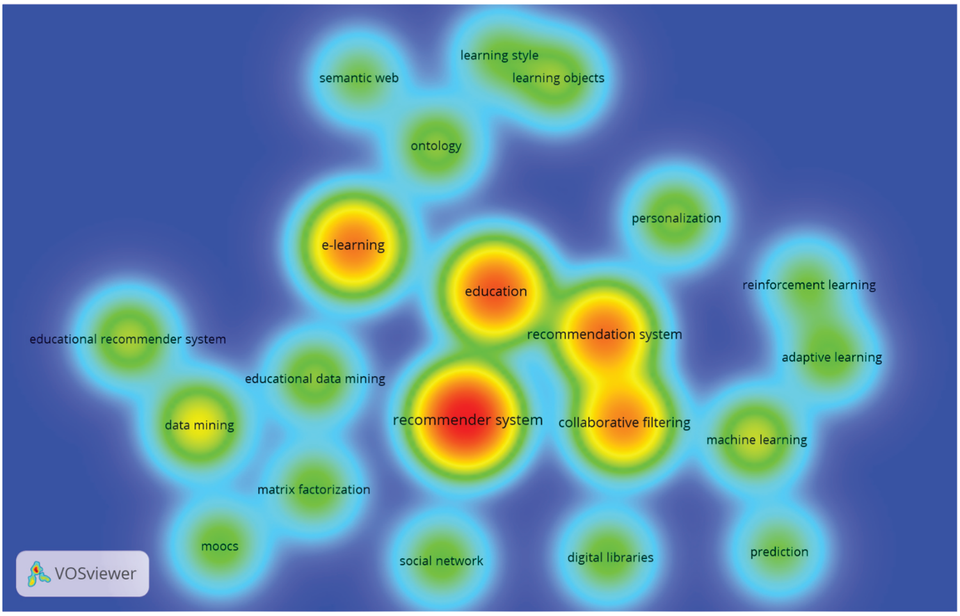

Figure 5. Keyword density map of high-frequency terms in titles and abstracts.

United States are the top three most productive countries. The study reveals that the RGR decreased from 2.02 in 2008 to 0.06 in 2021. The DT increased steadily until 2010, and the surge in articles in 2017 saw a remarkable increase. The mean DT for the five years increased from 2.21 (2007–2011) to 2.76 (2012–2016) and then to 15.82 (2017–2021). The five leading RS publications focus on e-learning/online learning, classroom activities, course selection, personal learning and performance prediction.

Research shows that 75% of students enter college before finally deciding on their career paths, and between 50–75% of the students change their majors more than once during their studies (Gordon and Steele 2015). Techniques such as using the nearest neighbor algorithm are applied to develop RS that assist students in selecting their majors after comparing historical data about the student (Mostafa et al. 2014). Educational RS uses collaborative filtering and the nearest neighbor algorithm techniques to calculate and rank the ratings of the targeted user in line with the neighbor ratings (Zhang, Lu, and Jin 2021). Some publications used techniques such as content-based recommendations that use the user and item profiles previously preferred to make new recommendations to the learners or users (Adomavicius and Tuzhilin 2005). Content-based filtering uses data mining and machine learning techniques to circumvent the challenge of finding sufficient user preferences and profiles (Lops, de Gemmis, and Semeraro 2011). RS assist users in rating the items, and the ratings are collected implicitly or explicitly (Roy and Dutta 2022).

Over a quarter of the publications focused on RS in e-learning systems. The rise in the adoption of e-learning has led to the development and broader use of RS for modeling individual and adaptive learning (Aguilar, Valdiviezo-Díaz, and Riofrio 2017; Khribi, Jemni, and Nasraoui 2008; Zaina, Rodrigues, and Bressan 2010). E-learning rule-based RS assists teachers by classifying students and recommending learning objects based on their competencies (García et al. 2009). Mobile phones enable RS to detect other learners nearby working on a similar topic of discussion and recommend the learner to collaborate with them for effective learning (Verbert et al. 2012).

The green cluster highlights data mining, educational data mining and matrix factorization, which are used in RS. The blue cluster shows that RS use machine learning and predictive learning techniques to support adaptive and personalized learning. Past behavioral and preference data is mined to generate recommendation information for the target users (Bobadilla et al. 2013; Sharma, Gopalani, and Meena 2017). The red cluster shows how ontologies, semantic webs and digital libraries filter learning objects to recommend learning styles (Yang and Liu 1999). note that CF uses recommendations from other users with similar choices to recommend to the targeted user called a neighbor. Students can be asked to rank their choices (1–5) explicitly, and this feedback can be used to recommend courses and learning materials to other students (Bobadilla et al. 2013). Early warning systems are used to predict future grades and assist through various student engagement programmes to increase retention rates and overall throughput to circumvent the challenge of students failing courses and dropping out (Sweeney et al. 2016).

Identifying students who risk not completing a course or programme is critical to improving throughput (Maphosa, Doorsamy, and Paul 2020). Incorrect path choices can derail a student's academic progress and often result in non-completion of the course and extended completion periods (Dalipi, Imran, and Kastrati 2018). RS evaluate the intelligence, comprehension, analytical skills and past academic records to determine the student's preferences and assist them in selecting suitable majors (Aslam and Khan 2011). RS provide teaching and pedagogical patterns to assist teachers in achieving their course goals (Cobos et al. 2013). RS are used in libraries to rank books collected and read before using text mining techniques to extract ranked keywords and recommend books to the readers. Content-based recommendation technique matches the attributes of the user and those of the subject's content to create a model reflecting user interests (Jamiy et al. 2015).

This study has several limitations: The results were obtained from the Scopus database and are far from exhaustive, thus restricting the research. Searching for articles using the title, abstract, and keywords could have excluded some papers that may not have summarized their content, which can only be picked through the full text.

Conclusion

This study evaluates the growth and development of RS in HE in the Scopus database. The initial search yielded 39,337 articles published between 2007 and 2021. Through iterative filtering using PRISMA, consisting of identification, screening, and inclusion resulted in 272 articles were selected for the final analysis. Research covering RS has been steadily rising during the period under review. The top keywords include RS, education, and e-learning. The study examined publication trends, RGR and DT for publications.

A steady increase in publications is shown, with the highest number of publications achieved in 2017— China, Spain and the United States as the countries which published the most in the 15 years. The mean RGR for the five-year periods was found to increase and decrease significantly, and the mean DT increased in the three five-year periods. The leading research areas on RS in education include e-learning learning (26%), classroom activities (15%), course selection (10%), personal learning (8%) and performance prediction (7%).

RS assist learners in selecting majors, courses and learning material by building learner profiles using their historical records and combining them with courses, prerequisites, learning activities and material chosen by the learner in the past. Popular techniques include collaborative filtering, content-based and hybrid filtering techniques. We provide one of the few comprehensive studies on RS research conducted in HE.

To our knowledge, no study has been conducted combining the bibliometric analysis and the PRISMA methodology to provide an overview of RS research in higher education. The study gives essential insights into current and future research on RS in HE. This analysis helps researchers, policymakers, and practitioners better understand the development and trajectory of RS in HE with possible practice implications. Most of the research on RS comes from developed countries. AI applications such as RS will be disruptive and critical to the success of educational institutions; therefore, this study recommends that developing countries adopt such systems to improve student learning outcomes.

Disclosure Statement

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