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REVIEW

Recommender systems in education: A literature review and bibliometric analysis

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Abstract: This study aims to provide an overview regarding the use of recommender systems in education through a systematic review and a bibliometric analysis. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement was followed and a total of 1,622 related documents from Scopus and WoS are examined from 2001 to 2022. The study goes over the literature and describes personalized learning, artificial intelligence (AI) in education as well as recommender systems and educational recommender systems. Besides descriptive statistics about the document collection, the result analysis involves the citation, sources, authors, affiliations, countries, and document information and categories of the related articles. The thematic evolution of the topic throughout the years is also examined. Based on the results, the recency and significance of recommender systems and their potentials in the educational domain were evident. Their ability to take into account learners' unique traits, experiences, skills, and preferences was highlighted. Recommender systems emerged as a learning tool that can empower learners, improve education quality and learning outcomes, increase learners' motivation, engagement, achievements, and satisfaction, and enable learners to be in charge of their own learning. Finally, recommender systems arose as an effective educational tool that can promote and improve adaptive learning and personalized learning.

Keywords: recommender systems, recommendation systems, artificial intelligence, adaptive learning, pedagogical agents, intelligent tutoring systems, technology enhanced learning, bibliometric analysis, mapping study

1 Introduction

The technological advances have resulted in an exponential increase of digital content and information to which users have access in real time (Athanassopoulos et al., 2023; Ko et al., 2022). This drastic increase in the amount of dynamically generated information that users consume daily has brought about a need to effectively filter and suggest relevant and accurate information to avoid information overload (Isinkaye et al., 2015; Roetzel, 2019). This applies for many domains including education as finding meaningful and accurate learning material and content has become a more complex and difficult task (Dascalu et al., 2016; Ipek et al., 2023).

The current educational system and infrastructure does not effectively integrate technological applications or Internet services and, thus, it does not offer adequate personalized learning experiences (Wilson et al., 2007). Learning is an activity which entails users to engage in learning related activities and tasks which can lead to behavioral changes and can improve their knowledge, skills, understanding, and perspectives (De Houwer et al., 2013; Shemshack & Spector, 2020). Moreover, learning must meet individuals' needs, requirements, interests, and expectations (Brusilovsky & Peylo, 2003) which is a difficult task due to the diversified student body and individual's characteristics (Zhang et al., 2020). Hence and given the advances in technology, providing students with the same learning material when they have different needs, learning styles, skills, qualifications, experiences, and personality traits cannot be regarded as adequate which highlights the need for more personalized and adaptive learning experiences (Shemshack & Spector, 2020; Truong, 2016). Nonetheless, there are security, privacy, and ethical concerns that must be taken into consideration (Jurayev, 2023; Kanakaris et al., 2019).

Providing tailored to each individual learning experiences to meet their maximum potentials, promoting, adopting, and integrating personalized learning solutions is a must (Lee et al., 2018; Lin et al., 2013). By applying such solutions in education, it is possible to provide individualized instructions regarding what, how, and when something is taught based on individuals' unique and diversified characteristics (Brusilovsky & Peylo, 2003). Recommender systems are tools that search within large volumes of dynamic and heterogeneous data to provide users with relevant, meaningful, and customized information, content, and services. Thus, more personalized teaching and learning experiences can be created when using educational recommender systems (Isinkaye et al., 2015; Resnick & Varian, 1997).

Moreover, these tools can be used within the context of smart education which aims at providing learners with more advanced learning activities, processes, and tasks which allow for deep and meaningful learning to occur (Karakose et al., 2023; Lin et al., 2018). Smart education adopts intelligent technologies to create intelligent environments that empower learners through personalized learning activities and smart pedagogical approaches (Zhu & He, 2012; Zhu et al., 2016). Furthermore, learner engagement, achievements, and motivation, which are interrelated and correlated and constitute key components of successful learning (Hung et al., 2019; Xiong et al., 2015), can be improved through personalized learning experiences (Karakose et al., 2022; Lampropoulos, 2023b).

As the topic of recommender systems in education becomes more popular and the related technologies more advanced, it is important to analyze the state-of-the-art (Karakose et al., 2023). Consequently, this study aims to present an overview about the use of recommender systems in education through a literature review and a bibliometric analysis. Emphasis is put on the role of recommender systems in providing personalized learning experiences. Therefore, in Section 2, the concept of personalized learning, the use of artificial intelligence in education, and recommender systems and their integration in education are presented. In Section 3, the method adopted, the document processing, and the research process are showcased in detail. In Section 4, the results which are categorized into seven groups are presented and analyzed. Finally, in Section 5, the application of recommender systems in education and the findings of this study are discussed and in Section 6, conclusive remarks and directions for future research are provided.

2 Theoretical background

2.1 Personalized learning

In modern society, in which, information and knowledge is more accessible, learning can occur on demand and involve different activities, environments, and contexts (Kundu et al., 2021; Lampropoulos et al., 2023; McLoughlin & Lee, 2007). Technological advancements have allowed users and learners to search for, create, and share information in real time which, in turn, has transformed learners into active co-producers of knowledge and contents instead of passive consumers (Dabbagh & Kitsantas, 2012). Thus, self-regulated learning has seen a drastic increase in applicability. Self-regulated learning can be characterized as an individual's ability to proactively and independently engage in self-motivating learning activities and procedures which aim at increasing one's knowledge and skills (Zimmerman, 2000). Self-regulated learning can be realized and promoted within personalized learning environments.

Personalized learning is an interdisciplinary field of study which is becoming an aspirational standard in 21st century education across all educational levels and within formal as well as informal learning environments (Brown et al., 2020; Dabbagh & Kitsantas, 2012). Due to its diverse and complex nature, several definitions have been given that present and define personalized learning from different perspectives (Bernacki et al., 2021). Personalized learning environments take into account the targeted learning outcomes and learners' unique traits, personality, skills, knowledge, preferences, interest, motivations, culture, and experience to provide them with individualized, responsive, and customized learning experiences and methods that are paced and tailored to their demands, requirements, and capabilities (Bernacki et al., 2021; Education, 2010, 2016; Lampropoulos, 2023c; Raj & Renumol, 2022; Watters, 2023). Hence, the aim of such environments is to support learners, motivate and engage them, and meet their individual needs (Raj & Renumol, 2022) by continuously being modified and adapted according to the learners' knowledge, skills, and learning goals (Sampson et al., 2002).

Although most studies that explore the role and impact of personalized learning mostly focus on desktops, the interest in using mobile and wearable devices as well as virtual learning environments to create personalized learning experiences is increasing (Lampropoulos et al., 2022c; Xie et al., 2019). The drastic advancements in the fields of artificial intelligence, intelligent learning systems, intelligent tutoring systems, and learning analytics have created new opportunities and capabilities for effective personalized learning environments to be developed (Karakose et al., 2023; Lampropoulos, 2023d; Shemshack & Spector, 2020; Xie et al., 2019). Adopting and integrating artificial intelligence-driven recommender systems within personalized learning environments can yield further educational benefits (Kundu et al., 2021; Raj & Renumol, 2022).

2.2 Artificial intelligence in education

As a scientific field and a technology in itself, artificial intelligence has rapidly advanced in recent years due to its applicability in various domains and the research that is being conducted (Hinojo-Lucena et al., 2019). The aim of artificial intelligence is to create sophisticated, adaptable, and rational systems that can act autonomously and without requiring any external interventions by simulating the way human think and learn and by mimicking their actions (Brynjolfsson & Mcafee, 2017; Duan et al., 2019; Lampropoulos, 2023a; Li & Du, 2017; Stone et al., 2016). Hence, artificial intelligence is inspired by how human use their nervous system, how they interact with their surrounding environment, how they think, feel, and learn (Stone et al., 2016). Particularly, artificial intelligence is closely related to computational technologies and system capabilities of identifying, analyzing, processing, interpreting, and learning from heterogeneous and diversified data that derives from different sources in an autonomous, adaptable, and versatile manner (Haenlein & Kaplan, 2019; Lampropoulos, 2023b). Artificial intelligence can be grouped into human-inspired, humanized, and analytical when regarding the different intelligence types while when taking into account the evolution of artificial intelligence, it can be considered as narrow, general or super artificial intelligence (Katsaris & Vidakis, 2021; Russell, 2010).

Artificial intelligence can be adopted and integrated into various domains as it has the potential to transform them while yielding several benefits (Bughin et al., 2017; Cath et al., 2017; Makridakis, 2017). Hence, the educational sector is no exception since artificial intelligence can reshape the education landscape, transform and enrich the existing educational process, and offer new solutions to address both the current and future educational needs, demands, and requirements (Chassignol et al., 2018; Holmes et al., 2020; McArthur et al., 2005; Roll & Wylie, 2016). Specifically, adopting artificial intelligence in teaching and learning activities can help develop new learning and teaching strategies, approaches, and methods (Holmes et al., 2023; Pedro et al., 2019) and reevaluate and modify cognition, culture, and knowledge (Hwang et al., 2020).

Furthermore, by integration artificial intelligence within education, not only students can be helped but also teachers who play an even more significant role in educating and assisting students develop in a data-driven and digitalized learning environment (Cope et al., 2021; Papadakis et al., 2023). In order for artificial intelligence to improve the overall education sustainability and efficiency, provide them with personalized learning activities, material, experiences, feedback, and empower their agency and role in education, it must be integrated using student-centered approaches (Chiu & Chai, 2020; Ouyang & Jiao, 2021). The role of artificial intelligence in education, the potential impact it can have, the solutions it can offer, and the benefits it can provide have been examined and presented in several recent studies (Chen et al., 2020; Chen et al., 2022; Tang et al., 2021; Zhai et al., 2021). Despite this fact, there are various challenges, open issues, concerns, and theoretical gaps that should be further explored and addressed before artificial intelligence can be more widely accepted, adopted, and integrated (Chen et al., 2020; Pedro et al., 2019).

2.3 Recommender systems

Recommender systems aim to assist and augment users' ability to choose or select when they are lacking in personal experience in the matter or in the alternatives (Burke, 2000; Resnick & Varian, 1997). Several studies have provided thorough surveys, overviews, and reviews regarding recommender systems, their classification, their use in various sectors, and the different algorithms and filtering methods used (Adomavicius & Tuzhilin, 2005; Bobadilla et al., 2013; Ko et al., 2022; Koren et al., 2009; Lu et al., 2015; Lü et al., 2012; Su et al., 2008).

Recommender systems are the intelligent systems that use various filtering methods, machine learning algorithms, artificial intelligence and data mining techniques, and data sources to provide users with personalized guidance and individualized recommendations based on their needs and preferences which is the significant factor that differentiates them from information retrieval systems which retrieve generally useful and interesting information (Maphosa & Maphosa, 2023; Mu, 2018; Park et al., 2012; Papadakis et al., 2023; Ricci et al., 2011; Tarus et al., 2018). Hence, the core of recommender systems is their ability to successfully predict users' preferences and needs and recommend meaningful and suitable items (Bobadilla et al., 2013; Lu et al., 2015; Resnick & Varian, 1997). Although there are various approaches to filter data in recommender systems, these approaches can be broadly categorized into collaborative filtering (Schafer et al., 2007), which uses ratings and users' prior interaction, content-based filtering (Pazzani & Billsus, 2007), which uses attribute information, and hybrid filtering, which uses a combination of different techniques (Aggarwal et al., 2016; Burke, 2002; Herlocker et al., 2004; Jannach et al., 2010; Melville & Sindhwani, 2011; Park et al., 2012; Verbert et al., 2012).

Therefore, recommender systems are software applications that perform computational tasks to gather users' characteristics and preferences and through advanced decision-making processes offer users suggestions on items that are most likely interesting and suitable for them for the specific use case (Karakaya & Aytekin, 2018; Ricci et al., 2011, 2015). These systems depend on the characteristics of the data and information that they have acquired both explicitly and implicitly (Bobadilla et al., 2013; Melville & Sindhwani, 2011; Pan & Li, 2010; Park et al., 2012). Their goal is to reduce information overload (Konstan & Riedl, 2012), to improve user experience (Lu et al., 2015) and to create, identify, and provide meaningful and diversified recommendations on things and information (Zourmpakis et al., 2023), most often referred to as items, that interest users and meet their specific requirements and preferences (Aggarwal et al., 2016; Melville & Sindhwani, 2011; Pavlidis, 2019).

Due to the diverse nature of recommender systems and their applicability into several domains, it is important to assess and evaluate recommender systems based on a set of general and specific criteria and properties to ensure accurate, proper, and valid outcomes (Zourmpakis et al., 2023; Shani & Gunawardana, 2011). Additionally, there are several limitations and challenges that must be taken into account to develop and deploy effective recommender systems, such as cold start, responsiveness, accuracy, data sparsity and diversity, scalability, fraud detection, security and privacy concerns, and cyber-attack vulnerabilities (Lü et al., 2012; Melville & Sindhwani, 2011).

2.4 Educational recommender systems

Education is one of the domains in which recommender systems can be implemented to offer learners personalized and adaptive learning experiences, services, and content based on their profiles and characteristics by searching and processing through an exponentially increasing volume of dynamically generated data (Isinkaye et al., 2015; Lampropoulos et al., 2022a; Maphosa & Maphosa, 2023). Hence, their use in educational settings is becoming more popular (Zhong et al., 2019). The academic interest in their adoption and integration in education is also increasing with several systematic review and bibliometric studies having been conducted in recent years which examine the use of educational recommender systems from different dimensions, such as education in general (Rivera et al., 2018; Urdaneta-Ponte et al., 2021; Zhong et al., 2019), higher education (Maphosa & Maphosa, 2023), teaching and learning activities (Silva et al., 2023), learning objectives (Nascimento et al., 2017), technology-enhanced learning (Drachsler et al., 2015), course recommendations (Ashraf et al., 2021; Lynn & Emanuel, 2021), and e-learning environments (George & Lal, 2019; Khanal et al., 2020; Klašnja-Milićević et al., 2015).

By using user-item interactions and trademark data (Kundu et al., 2021) to identify what users prefer and seek (Lynn & Emanuel, 2021), recommender systems can assist both teachers and learners (Garcia-Martinez & Hamou-Lhadj, 2013) by facilitating and supporting teaching and learning activities in multiple ways, such as information and material identification, course and activity selection, academic choices, information management, etc. (Lin et al., 2018; Lynn & Emanuel, 2021; Maphosa & Maphosa, 2023; Rivera et al., 2018). Hence, recommender systems make suggestions based on learners' data, their learning preferences and styles, behavior, progress, knowledge, and competencies as well as on information from other learners having similar data (Pan & Li, 2010; Urdaneta-Ponte et al., 2021).

Due to their nature, recommender systems can be implemented in all educational levels and domains as they can ensure and facilitate the acquisition of relevant and useful knowledge and information by reducing information overload and the time users have to spend searching and retrieving information from the ever-increasing amount of digital content (Amato et al., 2019; Ko et al., 2022; Urdaneta-Ponte et al., 2021; Wakil et al., 2015). Although there are issues that need to be considered when deploying recommender systems, such as learners' individual factors, unique traits, skills, and needs as well as meeting learners' expectations, providing accurate recommendations, etc., there are several educational benefits that can be yielded (Silva et al., 2023). Some educational benefits of using recommender systems in education while following student-centered design approaches and adopting hybrid techniques (Silva et al., 2023; Zourmpakis et al., 2022) involve personalized and adaptive experience provision, learners' decision-making and critical thinking skill improvement (Pathak et al., 2010), learners' motivation and academic performance increase (Garcia-Martinez & Hamou-Lhadj, 2013), learning outcomes improvement (Huang et al., 2023), and lifelong learning support (Dascalu et al., 2016).

3 Methods

Bibliometric analysis and scientific mapping are widely used methods to explore broad topics and to examine their evolution throughout the years (Ellegaard & Wallin, 2015). In the context of this study, the bibliometric analysis approach of Aria & Cuccurullo (2017) and the guidelines of Donthu et al. (2021) were followed and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement was adopted (Page et al., 2021). To meet the requirements of a thorough and cohesive bibliometric and mapping study (Donthu et al., 2021; Gusenbauer & Haddaway, 2020), Scopus and Web of Science (WoS) databases were used as they are widely used and highly assessed as accurate and impactful (Mongeon & Paul-Hus, 2015; Zhu & Liu, 2020).

For this study, the open-source R package "Bibliometrix" (Aria & Cuccurullo, 2017) was used due to its capabilities and accuracy. As the goal was to examine and present the overall use of recommender systems in education, the search query set was: ("recommender system*" AND "recommendation system*") OR ("education") and no further limitations were set. In both databases the query was applied on a topic level that is within the title, abstract, and keyword fields of each document. A total of 2,387 documents (1,179 from Scopus and 668 from WoS) were retrieved from 2001 to 2022. Particularly, 2001 was the year in which the first related document from the collection was published and 2022 was the end point to provide results that describe the whole year and not a part of it and that is the reason why data from 2023 was not included. A total of 555 duplicate documents were identified and removed. Hence, the screening process involved the assessment of 1,832 documents. Additionally, 210 documents were excluded as they involved documents that were retracted (5), entries that referred to proceedings and not to documents (140), and documents that were not in English (65). Therefore, the total number of documents included and examined in this study was 1,622. The detailed flowchart of the document processing is presented in Figure 1.

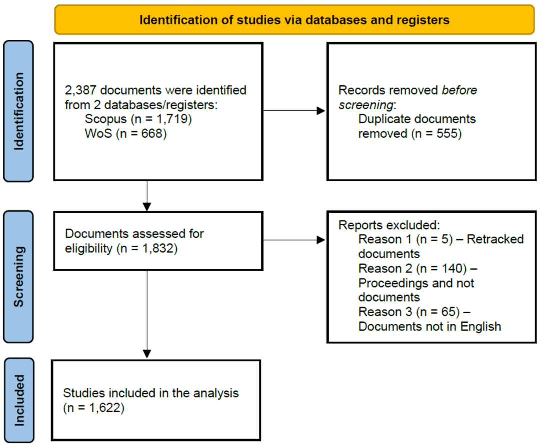

Figure 1 Document processing flowchart

The analysis of the results is grouped into seven categories. Based on the information presented the results are separated into 1) Collection information, 2) Citations, 3) Sources, 4) Authors, 5) Affiliations, 6) Countries, and 7) Documents categories. Tables, diagrams, and figures are used to display the results. The complete research process and steps followed are showcased in Figure 2.

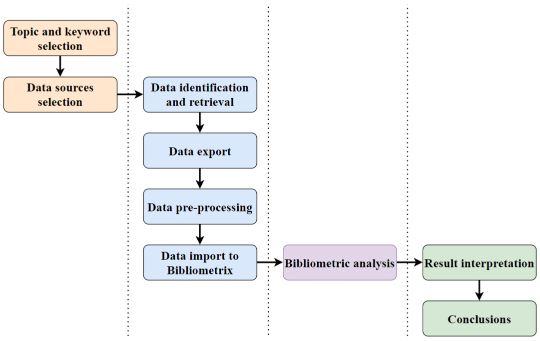

Figure 2 Research process

4 Result analysis

In this section, the results of this study are presented and analyzed. To present them more clearly, the results are separated into seven categories.

4.1 Collection information

In total, 1,622 documents from 879 different sources are included within the collection examined. The documents, which were published from 2001 to 2022, have an average document age of 5.55 and present an annual growth rate of 31.1%. On average, each of the documents received 12.58 citations. These facts highlight the recency and significance of the topic. In total, 3,976 authors have contributed to the creation of these scientific documents. The average number of co-authors for each document is 3.45 and 167 were singled-authored articles. The international co-authorship is 2.281% which highlights the need for more international collaboration. Most of the 1,622 documents examined were published in conferences and proceedings (66.09%), followed by journal articles (28.91%), and book chapters (2.71%). In Table 1, the detailed descriptive statistics of the documents included and analyzed are presented.

Table 1 Collection information

Description	Results	Description	Results
Timespan	2001:2022	Authors Collaboration	
Sources (Journals, Books, etc)	879	Single-authored docs	167
Documents	1,622	Co-Authors per Doc	3.45
Annual Growth Rate %	31.1	International co-authorships %	2.281
Document Average Age	5.55	Document Types	
Average citations per doc	12.58	article	469
Document Contents		book	3
Keywords Plus (ID)	6,662	book chapter	44
Author's Keywords (DE)	3,462	conference and proceedings paper	1,072
Authors		data paper	1
Authors	3,976	editorial	3
Authors of single-authored docs	145	review	30

4.2 Citations

As the technologies that enable the development and implementation of recommender systems in education become more advanced, the interest surrounding this topic increases. This can be justified by the positive annual growth rate (31.1%) that is present within the collection analyzed. The annual scientific production is presented in Figure 3 using a polynomial trendline. Although most documents (295) were published in 2022, an increase in the number of related documents published is observed starting in 2008 (30 documents) and followed by 2012 (57 documents) and 2017 (166 documents). The average number of citations per year is presented in Figure 4 in which the documents published in 2015 (6.58) and 2005 (4.24) appear to be the most impactful. This information is presented in more details in Table 2 along with the number of citable years. Hence, it can be inferred that 2022 was the year in which most documents were published and 2015 was the year with the most impactful documents thus far.

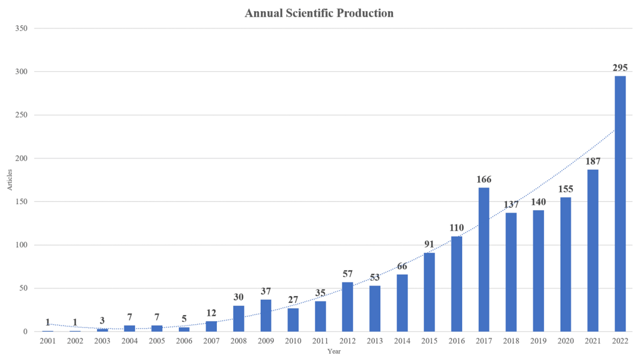

Figure 3 Annual scientific production

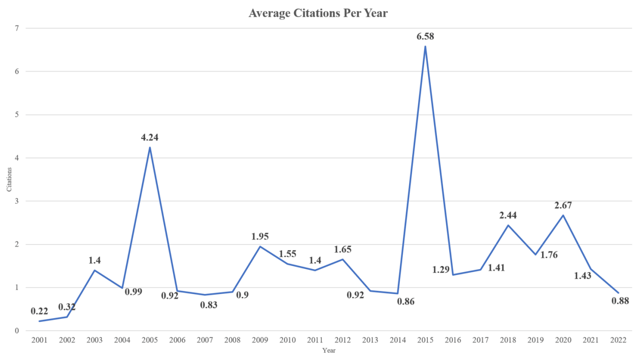

Figure 4 Average citation per year

Table 2 Annual scientific production and citations per year

Year	Mean TC per Art	N	Mean TC per Year	Citable Years
2001	5.00	1	0.22	23
2002	7.00	1	0.32	22
2003	29.33	3	1.40	21
2004	19.86	7	0.99	20
2005	80.57	7	4.24	19
2006	16.60	5	0.92	18
2007	14.17	12	0.83	17
2008	14.33	30	0.90	16
2009	29.19	37	1.95	15
2010	21.67	27	1.55	14
2011	18.20	35	1.40	13
2012	19.81	57	1.65	12
2013	10.09	53	0.92	11
2014	8.64	66	0.86	10
2015	59.18	91	6.58	9
2016	10.32	110	1.29	8
2017	9.87	166	1.41	7
2018	14.64	137	2.44	6
2019	8.79	140	1.76	5
2020	10.69	155	2.67	4
2021	4.29	187	1.43	3
2022	1.77	295	0.88	2

4.3 Sources

Since 2001, the related documents have been published in 879 different sources. The most relevant sources are displayed in Figure 5, based on the number of related documents published. Particularly, "Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)" (115 documents), "ACM International Conference Proceedings Series" (58 documents), and "CEUR Workshop Proceedings" (43 documents) have been the sources with most documents published. When taking into account the h-index of the sources as it can be seen in Table 3, "Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)" (h-index: 15), "IEEE Access" (h-index: 13), "Procedia Computer Science" (h-index: 10), and "ACM International Conference Proceedings Series" (h-index: 9) are the sources with the highest h-index.

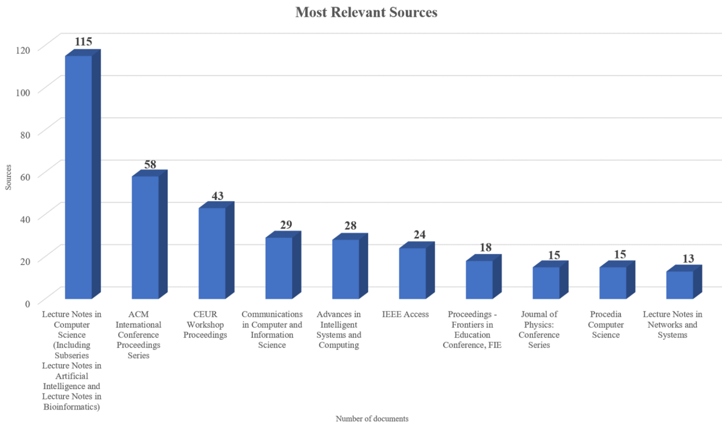

Figure 5 Sources with most documents published

Using Bradford's law, the sources were clustered into 3 clusters. Cluster 1 consisted of 34 sources in which 538 documents were published, cluster 2 involved 310 sources and 549 published documents, and cluster 3 was composed of 538 sources and 538 published documents. The top 10 most impactful sources according to Bradford's law are presented in Table 4. The top-5 most highly ranked sources were "Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)", "ACM International Conference Proceedings Series", "CEUR Workshop Proceedings", "Communications in Computer and Information Science", and "Advances in Intelligent Systems and Computing". Based on the production over time of the top-10 sources following Bradford's law that is presented in Figure 6, most documents were published in 2022 (47), 2021 (45), 2017 (43),

Table 3 Most impactful sources based on h-index

Sources	h_index	g_index	m_index	TC	NP	PY_start
Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	15	21	0.75	745	115	2004
IEEE Access	13	22	1.857	489	24	2017
Procedia Computer Science	10	15	0.714	584	15	2010
ACM International Conference Proceedings Series	9	14	0.563	296	58	2008
CEUR Workshop Proceedings	7	11	0.412	160	43	2007
Expert Systems with Applications	7	11	0.467	409	11	2009
IEEE Transactions on Learning Technologies	7	11	0.778	390	11	2015
Advances in Intelligent Systems and Computing	6	10	0.5	135	28	2012
Education and Information Technologies	6	7	1.2	111	7	2019
IEEE Global Engineering Education Conference, EDUCON	6	9	0.5	96	11	2012
International Journal of Emerging Technologies in Learning	6	8	0.545	76	12	2013

and 2020 (41). When taking into account the fact that sources of various types (e.g., book series, conferences, journals, etc.) are among the top sources, the scale, applicability, and importance of the topic becomes evident.

Table 4 Most impactful sources based on Bradford's law

Source	Rank	Freq	cumFreq	Cluster
Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	1	115	115	Cluster 1
ACM International Conference Proceedings Series	2	58	173	Cluster 1
CEUR Workshop Proceedings	3	43	216	Cluster 1
Communications in Computer and Information Science	4	29	245	Cluster 1
Advances in Intelligent Systems and Computing	5	28	273	Cluster 1
IEEE Access	6	24	297	Cluster 1
Proceedings - Frontiers in Education Conference, FIE	7	18	315	Cluster 1
Journal of Physics: Conference Series	8	15	330	Cluster 1
Procedia Computer Science	9	15	345	Cluster 1
Lecture Notes in Networks and Systems	10	13	358	Cluster 1

Year	Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	ACM International Conference Proceedings Series	CEUR Workshop Proceedings	Communications in Computer and Information Science	Advances in Intelligent Systems and Computing	IEEE Access	Proceedings - Frontiers in Education Conference, FIE	Journal of Physics: Conference Series	Procedia Computer Science	Lecture Notes in Networks and Systems
2001	0	0	0	0	0	0	0	0	0	0
2002	0	0	0	0	0	0	0	0	0	0
2003	0	0	0	0	0	0	0	0	0	0
2004	3	0	0	0	0	0	0	0	0	0
2005	0	0	0	0	0	0	0	0	0	0
2006	4	0	0	0	0	0	0	0	0	0
2007	0	0	1	0	0	0	0	0	0	0
2008	2	1	0	0	0	0	1	0	0	0
2009	5	0	2	0	0	0	1	0	0	0
2010	1	0	0	0	0	0	1	0	2	0
2011	0	0	1	7	0	0	0	0	0	0
2012	3	2	7	1	1	0	0	0	0	0
2013	5	0	2	1	2	0	1	0	0	0
2014	5	2	2	0	2	0	0	0	1	0
2015	12	0	1	0	1	0	4	0	2	0
2016	15	2	3	6	1	0	0	0	2	0
2017	15	14	2	5	5	1	1	0	0	0
2018	9	6	2	1	5	3	0	2	3	1
2019	9	3	5	1	2	5	3	3	1	0
2020	5	8	5	2	4	8	1	6	2	0
2021	7	10	5	4	5	2	4	4	0	4
2022	15	10	5	1	0	5	1	0	2	8
Total	**115**	**58**	**43**	**29**	**28**	**24**	**18**	**15**	**15**	**13**

Figure 6 Top-10 sources production over time based on Bradford's law

4.4 Authors

In total 3,976 authors contributed to these documents. Figure 7 and Table 5 present the most productive authors of the collection based on their number of published documents. According to the results, the top-5 most productive authors are Wang Y, Li X, Santos O, Li J, and Boticario J. The authors' production over time is displayed in detail in Figure 8. Furthermore, the most impactful authors based on their h-index within the collection are presented in Table 6. Santos O, Drachsler H, and Li X were the most impactful authors out of the 3,976 authors within the collection.

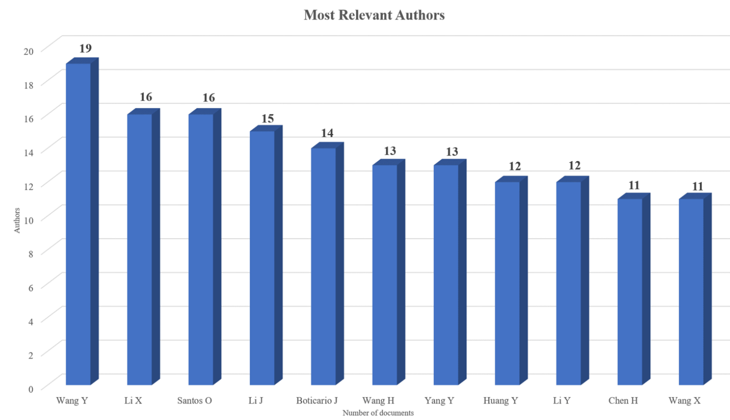

Figure 7 Most productive authors based on the number of published documents

Table 5 Most productive authors based on the number of published documents

Authors	Articles	Articles Fractionalized
Wang Y	19	5.50
Li X	16	5.78
Santos O	16	6.31
Li J	15	7.03
Boticario J	14	3.99
Wang H	13	4.09
Yang Y	13	3.71
Huang Y	12	2.89
Li Y	12	4.28
Chen H	11	5.08
Wang X	11	4.90

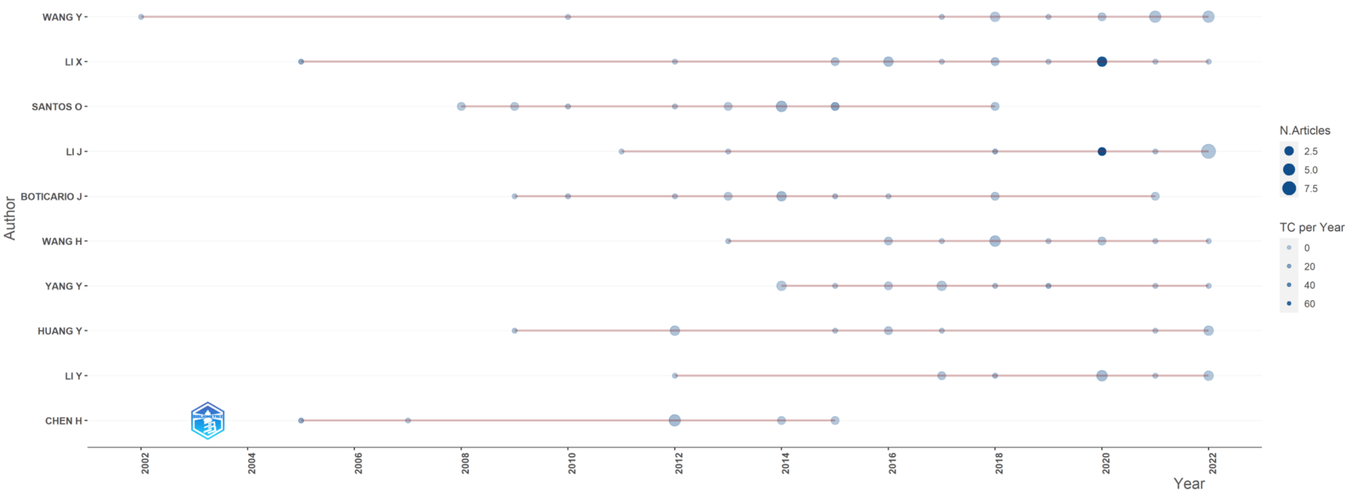

Figure 8 Author production over time

Table 6 Most impactful authors based on their h-index on this topic

Element	h_index	g_index	m_index	TC	NP	PY_start
Santos O	10	16	0.625	401	16	2008
Drachsler H	9	10	0.529	279	10	2007
Li X	8	16	0.421	744	16	2005
Boticario J	7	14	0.467	234	14	2009
Wang J	7	9	0.583	152	9	2012
Li Y	6	10	0.5	115	12	2012
Liu X	6	9	0.375	84	9	2008
Wang H	6	10	0.545	110	13	2013

Although there was an average of 3.45 co-authors in each document, the international co-authorship was low (2.281%). Additionally, 167 documents were single-authored (10.30%) out of the 1,622 documents. The authors' collaboration network is depicted in Figure 9. The need to further expand the international collaboration is observed.

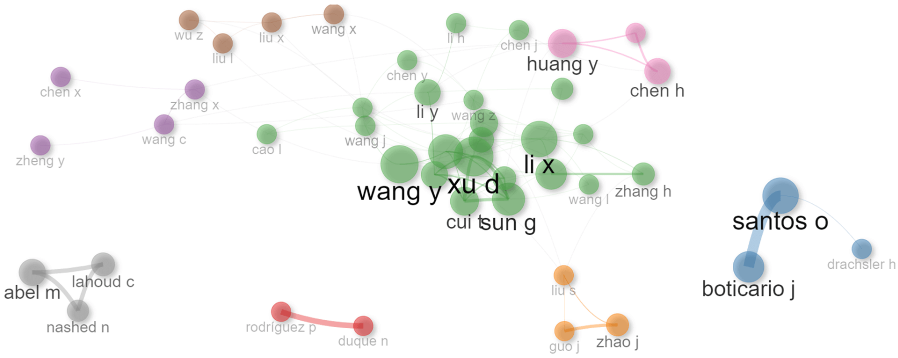

Figure 9 Author collaboration network

Using Lotka's law, the authors' overall productivity is presented in Figure 10 and further explained in Table 7. It can be observed that the vast majority of authors have contributed toward the creation of only one document (79.80%), followed by authors that have contributed to two documents (12.10%).

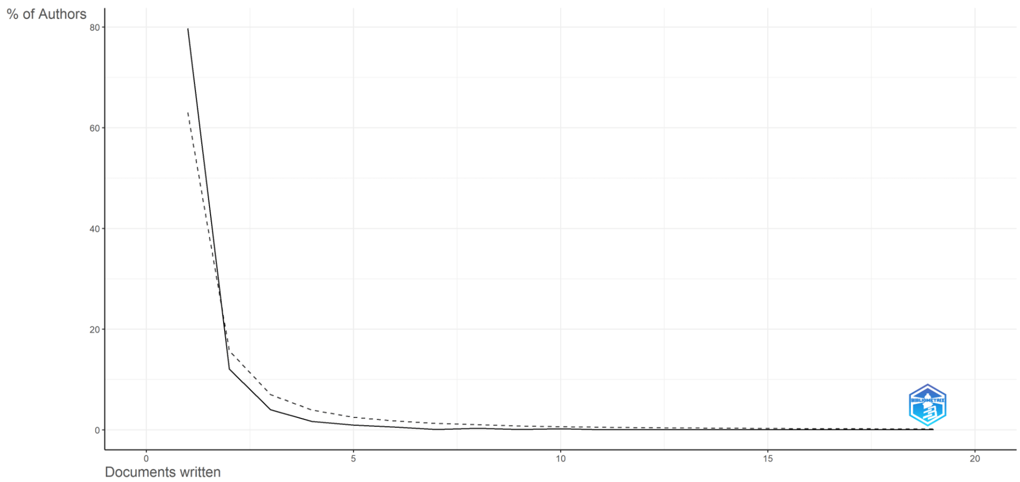

Figure 10 Author overall productivity through Lotka's law

Table 7 Lotka's law analysis

Documents written	N. of Authors	Proportion of Authors
1	3171	79.80%
2	480	12.10%
3	158	4.00%
4	67	1.70%
5	38	1.00%
6	22	0.60%
7	4	0.10%
8	12	0.30%
9	4	0.10%
10	9	0.20%
11	2	0.10%
12	2	0.10%
13	2	0.10%
14	1	0.00%
15	1	0.00%
16	2	0.10%
19	1	0.00%

4.5 Affiliations

Authors from 1,871 affiliations have contributed to the documents of this collection. In Figure 11 the affiliations with most documents are presented. Bina Nusantara University, University of Rijeka, Xiamen University, University of California, and University of Minnesota are the top-5 affiliations with most documents published on the topic. The affiliation collaboration network is depicted in Figure 12.

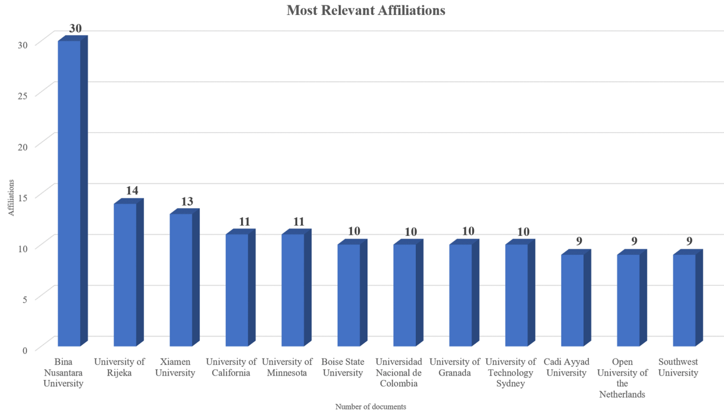

Figure 11 Top affiliations based on the number of documents published

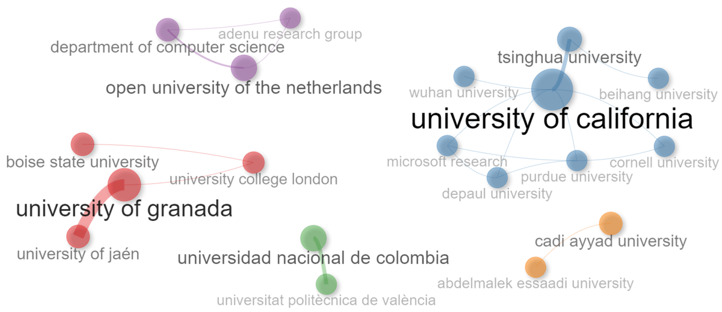

Figure 12 Collaboration network based on affiliations

4.6 Countries

Authors from 83 countries have contributed to the documents of this collection. In Figure 13, the countries with most documents published are presented while the countries that received most citations are depicted in Figure 14. China, the United States of America, India, and Spain were the countries with most documents published while China, the United States of America, Spain, Australia, and Germany were the countries that received most citations. The country collaboration network is presented in Figure 15 while the country collaboration map is showcased in Figure 16.

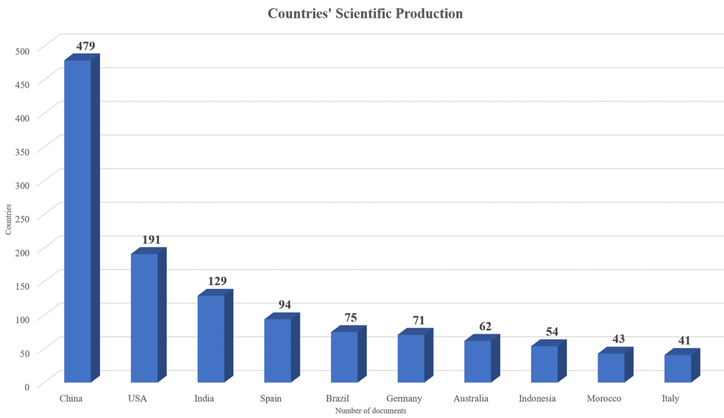

Figure 13 Top-10 countries that published the most over time

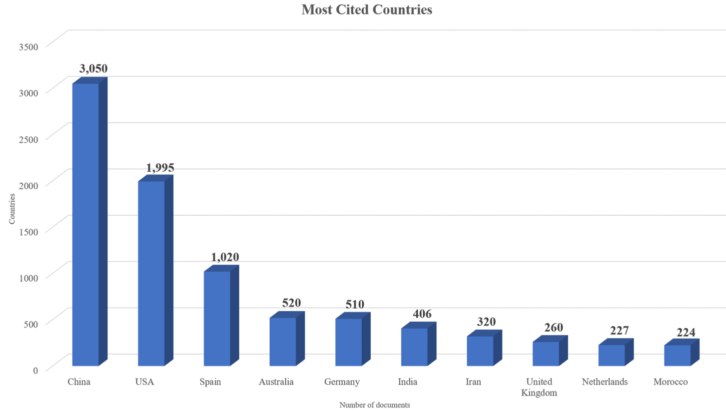

Figure 14 Top-10 countries that received most citations

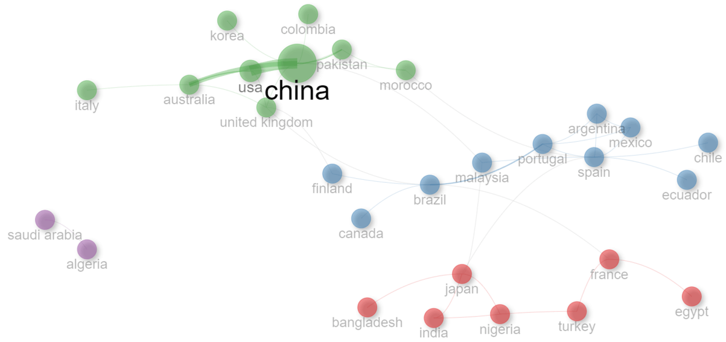

Figure 15 Country collaboration network

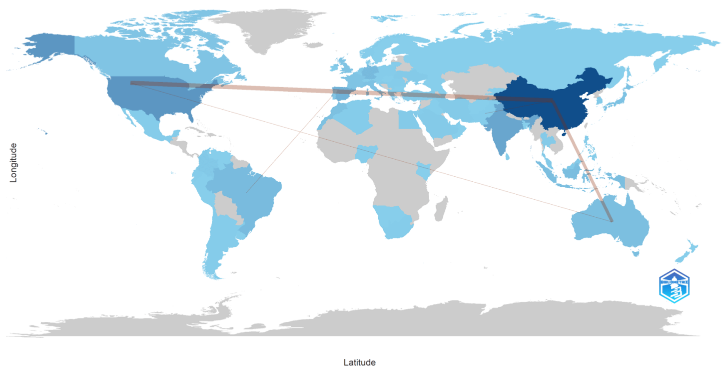

Figure 16 Country collaboration map

4.7 Documents

Most of the documents within the collection were published in conferences and proceedings (66.09%), followed by journal articles (28.91%), and book chapters (2.71%). The keywords within the keyword plus category can adequately present the document knowledge structure when using data from both Scopus and WoS (Zhang et al., 2016). Therefore, the keywords examined in this study belong to the category keyword plus. "Recommender systems", "students", "education", "e-learning", "learning systems", and "education computing" were the most common keywords used. The frequency of the most commonly used keywords is depicted in Figure 17. The keyword co-occurrence network is presented in Figure 18 and 19. In Figure 20, the relationship among the top-10 countries, keywords, and sources is presented.

Figure 21 presents the trend topics over the period of 2001-2022. Based on the results, the initial focus on the Internet and web mining was followed by the one on technology-enhanced learning and computer-aided instructions. The advancement of the topic toward artificial intelligence, big data, machine learning, and deep learning is evident in the recent years. To cluster the documents, keywords were used as the coupling measure while global citation score was used as the impact measure. As it can be seen in Figure 22, five clusters arose. The clusters involve the use of recommender systems in education settings and the role of and emphasis on

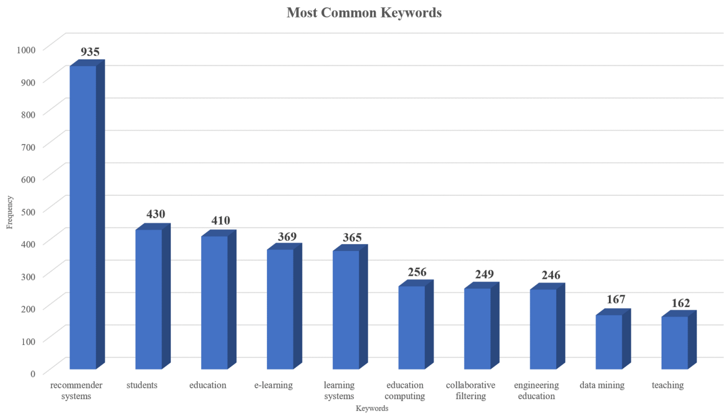

Figure 17 Most frequent keywords plus

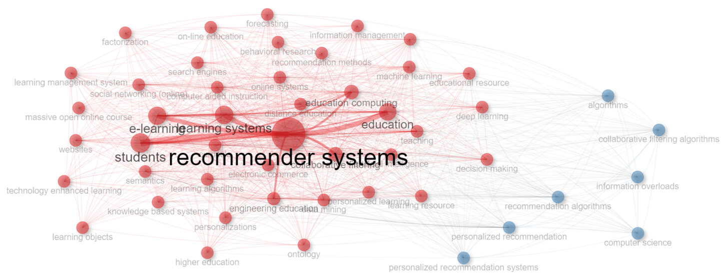

Figure 18 Keywords co-occurrence network

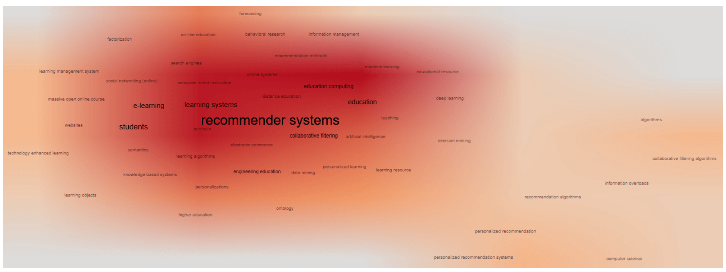

Figure 19 Keywords co-occurrence network heatmap

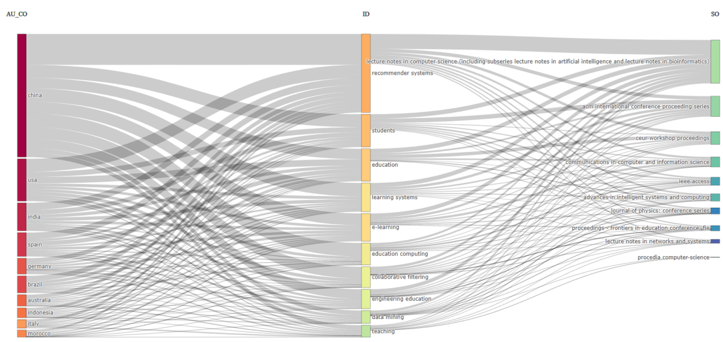

Figure 20 Top-10 countries, keywords, and sources relationship

students is evident. Additionally, the focus on e-learning, learning systems, teachers, education computing, and data mining is highlighted.

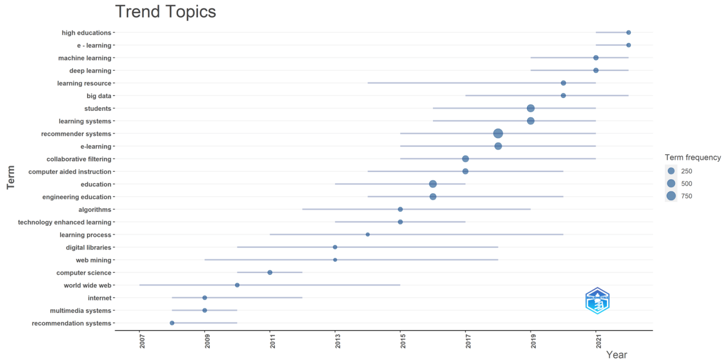

Figure 21 Trend topics based on keywords

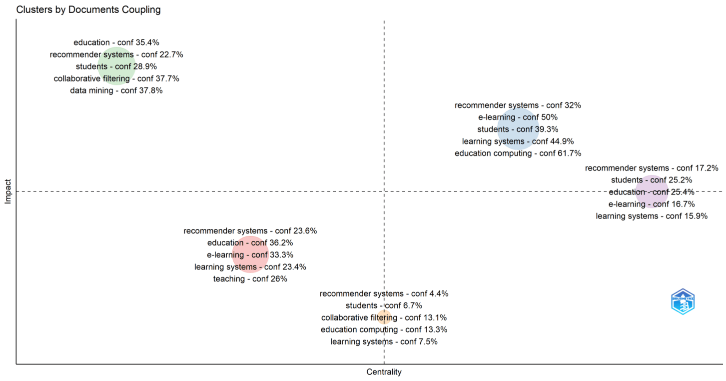

Figure 22 Documents clustered by coupling

Moreover, the thematic structure of the topic was examined and is presented in Figure 23. A total of six clusters arose. The first cluster involves recommender systems, e-learning, and learning systems and is one of the motor themes along with the second cluster which involves education, teaching, and knowledge based systems. The third cluster comprises collaborative filtering, personalized recommendation, and recommendation algorithms and is in the intersection of motor and niche themes. The fourth cluster consists of students, data mining, and artificial intelligence and is in the intersection of motor and basic themes. The fifth cluster involves decision-making, algorithms, and information management and the sixth cluster consists of algorithm and learning. Clusters five and six belong to the emerging or declining themes of this topic.

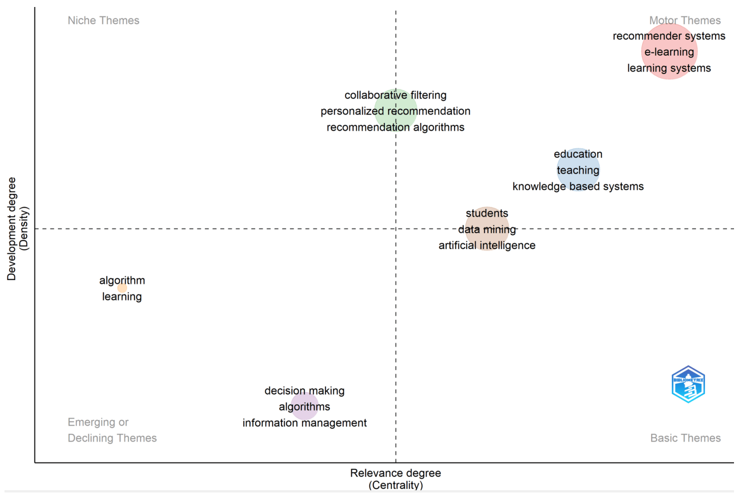

Figure 23 Thematic map of the topic

The documents examined were published from 2001 to 2022. Hence, to examine the evolution of the topic over the years, the time period was divided into four parts: i) 2001-2010, ii) 2011-2014, iii) 2015-2018, and iv) 2019-2022. The thematic evolution is presented in Figure 24. The focus on humans and learners is evident in each period as well as the applicability of recommender systems in various domains. The close relationship of recommender systems with intelligent systems, personalized systems, and computer aided instructions is highlighted.

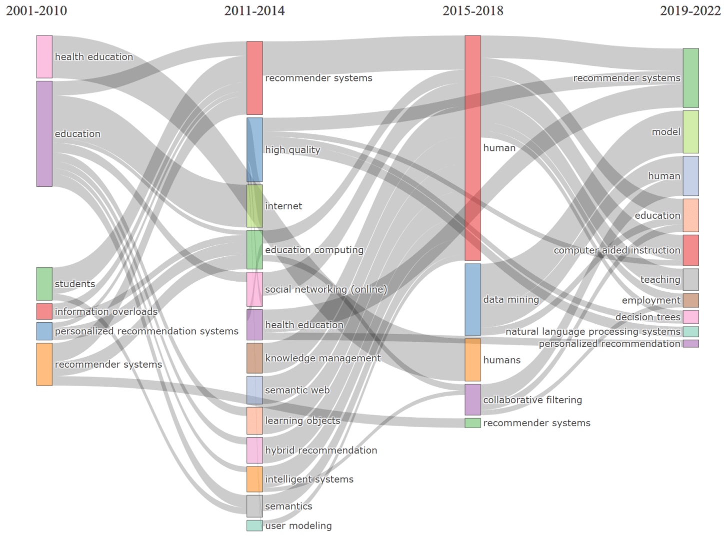

Figure 24 Thematic evolution of the topic

5 Discussion

The integration of recommender systems in education is becoming more popular as they can transform and enrich traditional learning environments and practices and satisfy the new educational needs. Recommender systems can be used in educational contexts to offer personalized and adaptive learning experiences. Particularly, recommender systems retrieve general data and gather particular for each learner data, such as existing knowledge and skills, preferences, traits, interests, learning goals and needs, etc. After collecting the required information, data is preprocessed and transferred to the recommender system to process using various machine learning algorithms, artificial intelligence and data mining techniques, and filtering methods. Finally, meaningful, interesting, and relevant items are recommended to learners (Figure 25). Systems that take into account users' unique characteristics and personality traits can result in better outcomes (Lampropoulos et al., 2022b).

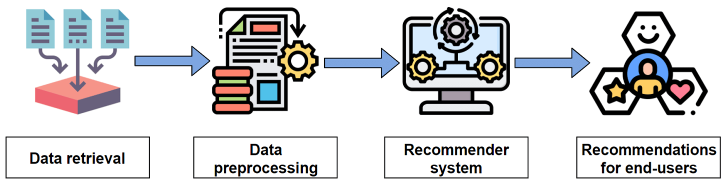

Figure 25 Recommender system application

Moreover, educational recommender systems can be regarded as effective educational tools to design student-centered learning activities that match an individual's preferences and requirements based on appropriate conceptual frameworks and theories (Becker et al., 2017; Dabbagh & Kitsantas, 2012). Through the personalized learning opportunities that educational recommender systems yield, learners are empowered and encouraged to assume ownership of their own learning which can increase their learning achievements, motivation, and engagement, improve their satisfaction and enhance the overall learning efficiency and effectiveness (McLoughlin & Lee, 2010; Rubin, 2010; Shemshack & Spector, 2020). Therefore, learners can improve their learning capabilities and discover their own preferences, potentials, and limits (Dascalu et al., 2016). Despite this fact, most studies solely focus on learners' cognitive aspects (Raj & Renumol, 2022). Hence, more emphasis should be put on all aspects of learners.

Due to their nature, educational recommender systems can be used in all educational levels and by both learners and teachers. Learners can use them to search for educational material that suits their needs, to find adaptive learning opportunities, to seek for tailored learning activities, to acquire feedback, to identify their knowledge and skills gap, to explore appropriate courses and academic paths. Using educational recommender systems, teachers can improve their ability to offer individualized instructions and personalized learning experiences, identify students' weaknesses more easily, find more appropriate learning material, and assess their students more effectively. Teachers can also use educational recommender systems to search and identify material, resources, and courses to further improve their own skills, practices, and approaches. Despite the applicability and benefits of educational recommender systems, there are several ethical concerns and challenges that must be addressed, such as security and privacy concerns, cyber-attack vulnerabilities, accuracy, fraud detection, etc. for them to be more broadly adopted and integrated. Additionally, there is a need for training programs to be created so that teachers can effectively integrate and use educational recommender systems in their classroom and for appropriate strategies and methodologies to be developed. Finally, there is a need to develop effective evaluation tools both for the performance of recommender systems in terms of educational gains but also on how learners use them and what their preferences, emotion, and habits are.

In the context of the bibliometric and scientific mapping analysis, several aspects were examined. These aspects involved descriptive statistics of the document collection as well as analysis of the citations, sources, authors, affiliations, countries, and documents. To create the collection of documents, Scopus and WoS databases were used. In total, 1,622 documents were examined from 2001 to 2022. A total of 3,976 authors contributed to the creation of these documents which were published in 879 sources. Most documents were published as conference or proceedings articles followed by journal articles.

Summing up the analysis results, the scientific interest in the use of recommender systems in education has been increasing annually with most related documents being published in 2022. Based on the average number of citations received, the articles published in 2005 and 2015 appear to be the most impactful. The annual growth rate of the documents in this collection was 31.1% while their average age was 5.55 and the average citations were 12.58. These facts highlight the significance and recency of this topic as well as the potential of recommender systems in the educational domain. The most impactful source when considering the total number of documents published, their h-index, and Bradford's law ranking is "Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)" followed by "ACM International Conference Proceedings Series". Despite this fact, different types of sources, such as journals, conferences, book series, etc., appear among the top which further highlights the scope of this topic. Although several authors contributed to this field, Wang Y, Li X, Santos O, Li J, and Boticario J emerged as the most productive authors based on the number of published documents while Santos O, Drachsler H, and Li X were the most impactful authors based on the h-index. The vast majority of authors contributed to a single document. The affiliations with most documents published were Bina Nusantara University, University of Rijeka, Xiamen University, University of California, and University of Minnesota. When taking into account both the number of published documents and the number of citations received, China, the United States of America, and Spain arose as the most impactful countries on this topic. The topic analysis revealed that the initial focus on the Internet, web technologies, and data mining was followed by a shift to technology-enhanced learning and computer-aided instructions and a transition to integrating more novel technologies, such as artificial intelligence, big data, machine learning, deep learning, etc. Throughout the evolution of the topic, its close relationship with intelligent systems and its focus on learners were evident. Finally, its role in providing personalized learning and empowering students was highlighted.

6 Conclusion

It is imperative to provide quality education which is also one of the 17 sustainable development goals. Due to the digitalization, the amount of digital data information has exponentially increased. Consequently, it is more difficult and complex to find meaningful and relevant information. This is particularly true in the educational domain in which learners must search for adequate learning material, activities, and information. Due to their nature, recommender systems can be used in educational settings to help meet the new educational needs and requirements.

This study aimed at providing an overview regarding the use of recommender systems in education. Hence, it went over the new educational needs and requirements, presented the significance of personalized learning, and described the use of artificial intelligence in education. Additionally, the study presented the concept of recommender systems and described in detail their use in education. It also discussed how they can be used in educational settings to assist both learners and teachers.

All in all, it can be inferred that recommender systems which are intelligent information systems that predict and suggest appropriate to each user items based on their characteristics and prior interactions can be used in educational settings to suggest and provide learners with appropriate learning material and activities based on their preferred learning style and strategies and their individual traits and preferences. Therefore, recommender systems can empower learners and can promote and improve personalized and adaptive learning while also increasing the quality of education, learners' motivation, engagement, achievements, and satisfaction and allow them to be in charge of their own learning. Despite the fact that recommender systems can enhance the overall learning efficiency and effectiveness, there still remain several open issues and challenges that must be further investigated and addressed. Future studies should look into exploring how recommender systems affect all aspects of learners, on how learners' different characteristics affect learning when using recommender systems, on developing appropriate teaching strategies and evaluation tools, as well as on conducting comparative studies to better assess the impact of recommender systems in education.

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