Journal of Global Information Management
Volume 30 • Issue 1

User Modeling and Profiling in Information Systems:

A Bibliometric Study and Future Research Directions

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ABSTRACT

User modeling or user profiling is fundamental to manage information overload issues in many adaptive and personalized systems (e.g., recommender systems, personalized search engines, adaptive user interfaces). Although there are some literature review papers that provide an overview of existing studies in user modeling and their usage, there is currently a lack of bibliometric studies that can provide a systematic and quantitative overview of this research area. Therefore, this paper aims to complete the existing literature in this research area through a bibliometric study based on 52,027 relevant publications extracted from Scopus, a world-leading publisher-independent global citation database. The analyses enabled the authors to identify the most relevant publications, sources of publications, authors, institutions, countries, and their collaboration. They also identify and classify the 12 most important associated topics, along with their subtopics and their trends. Some identified weak signals in topic trend analysis also provide good ideas of potential future research directions.

KEYWORDS

Adaptive Systems, Bibliometric, Personalized Systems, Recommender Systems, User Behavior, User Interest, User Modeling, User Profiling

1. INTRODUCTION

Adapting information to specific user needs is increasingly fundamental with the explosion of available data in information systems brought on by the advent of new technologies or services such as social network platforms, social media, the Internet of Things, big data, or cloud computing environments. If there is increasing information available in these systems, accessing these contents is increasingly difficult for users because of the high quantity and diversity of information that may interest them. This leads to information overload (Guo et al. 2020; Li et al. 2012) and a high increase in the user's cognitive load. Therefore, it is more difficult for the user to quickly find the information corresponding to his specific expectations. To avoid this problem, personalized or adaptive systems have been proposed with the aim of presenting the information corresponding to the user's specific needs (e.g., recommender systems, adaptive hypermedia, personalized information retrieval, adaptive

DOI: 10.4018/JGIM.307116 *Corresponding Author

user interfaces). A wide range of application domains are concerned (both on the Internet and in enterprise information systems), such as e-commerce (e.g., Amazon) (Smith and Linden 2017; Linden et al. 2003), video content (e.g., Youtube, Netflix) (Gomez-Uribe and Hunt 2015, Davidson et al. 2010), search engines (e.g., Google)(Speretta and Gauch 2005), e-learning (Wang and Wang 2021; Fink and Kobsa 2002), virtual reality (Griol et al. 2019), health (Mao et al. 2020; Glykas and Chytas 2004), and tourism (Al Fararni et al. 2021; Fink and Kobsa 2002). User modeling or user profiling is very important and fundamental for all these systems and applications because they all require a good inference of the user's needs. A user profile (or user model) can be defined as a summary of the user's interests, characteristics, behaviors, or preferences. In contrast, user profiling (or user modeling) collects, organizes, and infers user profile information. Information in the user profile can be explicitly provided by the user (explicit user profile), or more frequently, analyzed implicitly by using interaction data between the users and the system (implicit user profile) (Gauch et al. 2007). Beyond personalized or adaptive systems, user profiling can also be at the base of behavioral analysis systems for improving decision-making, such as anomaly detection systems (Kwon et al. 2021; Wang et al. 2018), fraud detection systems (Lausen et al. 2020; Zhao et al. 2016), customer scoring systems (Esmeli et al. 2020; Ramkumar et al. 2010), influencer or leader detection systems (Girgin 2021; Primo et al. 2021), and terrorist networks (Tundis and Mühlhäuser 2017; Yadav et al. 2019).

There is a wide array of interactive computer systems relying on user modeling that make it possible to access a greater number of related studies providing a survey or literature review on this field. These literature reviews can be separated into three groups. The first group includes studies that mainly focus on user modeling as a generic entity (or process) that can be studied separately from associated mechanisms (personalized or adaptive systems)(Carmagnola et al. 2011; Chen et al. 2019; Eke et al. 2019; Gauch et al. 2007; Piao and Breslin 2018; Webb et al. 2001). These studies usually review user modeling strategies including data collection, methods for building and updating profiles, profile representation, evaluation of constructed profiles, privacy issues or interoperability. The second group deals with some studies that rather focus directly on associated mechanisms and do not necessarily consider user modeling as an independent entity (or process) such as recommender systems (Shao et al. 2020; Adomavicius and Tuzhilin 2005; Batmaz et al. 2019; Bobadilla et al. 2013; Burke 2002; Gao et al. 2010), information retrieval (Ghorab et al. 2013) or online personalization (Zanker et al. 2019). This category of studies usually focuses on associated mechanism, issues and evaluations when integrating profile data to improve their outcomes. The last group encompasses some studies that specifically focus on associated mechanisms in one specific application domain such as intrusion detection (Peng et al. 2016), social commerce (Busalim 2016), or education (Feldman et al. 2015). However, to the best of our knowledge, except for these previous types of literature reviews, there is currently no bibliometric study that provides a way to systematically and quantitatively analyze the wide field of user profiling and their usages in information systems. Bibliometric analysis is a popular and rigorous method for exploring and analyzing large volumes of scientific data. The use of bibliometrics can complement systematic literature or meta-analysis reviews by providing quantitative measures and qualitative interpretations of a field when the scope is broad and the dataset is very large (Donthu et al. 2021). This study is a case in point, as we extracted up to 52,027 publications related to user modeling or user profiling from a world-leading publisher-independent global citation database (Scopus). The bibliometric approach is being used with a view to providing to all stakeholders interested in user profiling and their use (e.g., novices, scholars, experts, industrials), an analytical study allowing for a better understanding of this wide field. In this regard, we sook to answer the following three research questions: With regard to publications on user modeling and user profiling, what are the most relevant authors, sources of publications, institutions, countries, and their collaboration? What are the main related research topics and their trends? What are the potential future research directions? Bibliometric analysis can particularly help answering these questions using analytical performances analysis and science mapping techniques (Aria and Cuccurullo 2017; Donthu et al. 2021).

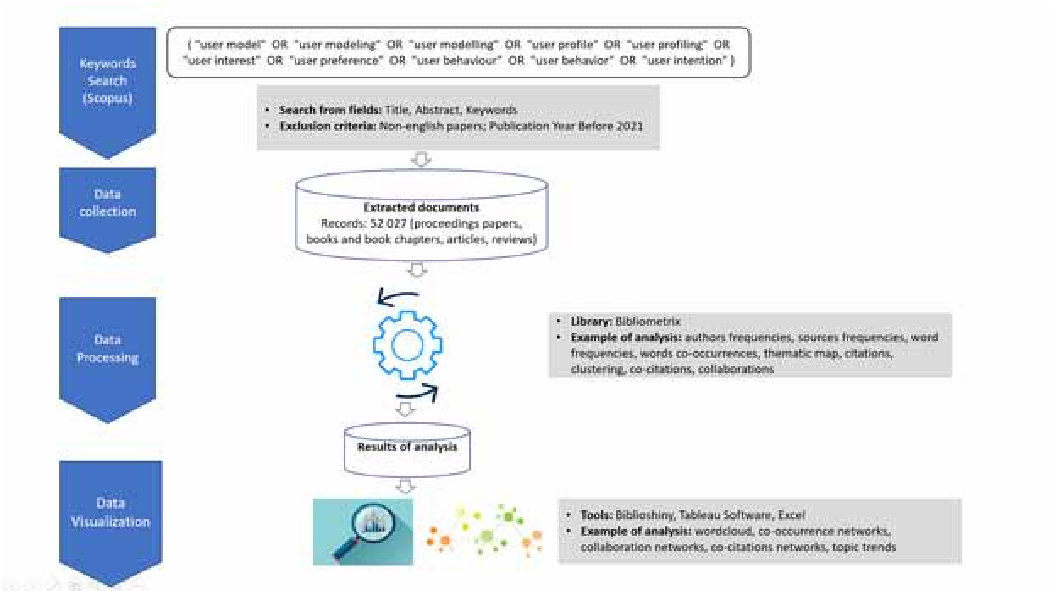
The rest of this paper is structured as follows: section 2 presents the research methodology. Section 3 presents our results. Sections 4, 5 and 6 deal with the discussion of findings, the future research avenues, various implications, limitations and conclusions.

2. METHODOLOGY

A bibliometric study enables the mapping and expansion of knowledge in a research area, evidencing connections between the main publications, authors, institutions, themes, and other characteristics of the field under study (Donthu et al. 2021; López-Robles et al. 2019; Srivastava et al. 2021; Fosso-Wamba et al. 2021). For instance, a bibliometric analysis can be used to analyze trends in an area of research, provide evidence about the impact of the research area, find new and emerging areas of research, identify potential research collaborators or identify suitable sources of publications. In this regard, we followed the best practices to lead a reliable bibliometric analysis (Donthu et al. 2021) of user modeling or user profiling and their usage in information systems. First, we found one of the trustworthy and leading databases, namely Scopus. Second, we performed a research protocol following four steps (Figure 1).

In the first step, we defined the keywords to use for the search in Scopus ("user model", "user modeling", "user modelling", "user profile", "user profiling", "user interest", "user preference", "user behaviour", "user behavior" "user intention"). We chose these keywords because they are the most common terms used in many literature reviews in user modeling or user profiling (Gao et al. 2010; Gauch et al. 2007). In the second step, we collected the results of the search (52,027 publications). Our search was interested only in papers in English and before 2021. As the data collection was done early in 2021, we made sure the number of papers in 2021 is fairly proportionate with those published previously. In the third step, the Bibliometrix library was used to perform data analysis (Aria and Cuccurullo 2017). Bibliometrix is an R-tool that provides comprehensive science mapping analysis (Aria and Cuccurullo 2017). It is increasingly used with good feedback for many bibliometric studies in many areas of research (e.g., Bretas and Alon 2021; Forliano et al. 2021; Shi et al. 2020; Srivastava et al. 2021). In the last step, we aimed to provide suitable and fast interpretable results, and thus used

Figure 1. Research protocol for the bibliometric study



some visualization tools such as Biblioshiny, which is an interface plugged on Bibliometrix (Aria and Cuccurullo 2017) complemented with Tableau Software or Excel for some specific views.

3. RESULTS

Table 1 shows the main information about the extracted documents. A total of 52,027 documents published between 1961 and 2020 were extracted from 12,182 different sources (e.g., journals, conferences, books, books chapter). The number of documents per source is shown in Table 1 below. The two most important sources are conferences papers (31,791 documents) and journal articles

Table 1. Information about the data set analyzed

Main Information About Data	
Timespan	1961:2020
Number of sources (journals, books, etc.)	12,182
Number of documents	52,027
Average citations per documents	12.76
Number of references	1,163,300
Document Types	
Number of articles	17,221
Number of articles in press	19
Number of books	69
Number of book chapters	1,021
Number of conference papers	31,791
Number of conference reviews	1,136
Number of data papers	3
Number of editorials	51
Number of erratums	23
Number of letters	10
Number of notes	24
Number of reports	3
Number of retracted	3
Number of reviews	630
Number of short surveys	23
Document Contents	
Number of authors' Keywords (DE)	67,096
Authors	
Number of authors	77,573
Authors Collaboration	
Number of single-authored documents	5,675
Number of authors per Document	1.49
Number of co-Authors per Documents	3.28

(17,221 documents). The large number of conference papers can be explained by the predominance of conferences as primary source of publications for researchers in Computer Science (the subject area with the highest number of papers related to user modeling from all extracted documents). The other sources are relatively marginal. The data analysis process used all the documents from the various sources. A total of 67,096 keywords (provided by authors) was extracted, while 77,573 authors were recorded (thus an average rate of 3.28 authors per document).

3.1 Publication Trend

Figure 2 shows that publications on this topic start in 1961 with a slight growth until the 2000s. However, since the 2000s, we can observe an exponential growth in the number of publications per year, thus the importance of the topics for researchers in recent years (e.g., 419 publications in 2000, 1,275 in 2005, 2,372 in 2010, 3,244 in 2015 and 4,240 in 2020). The slight drop in 2020 can be due to the Covid-19 pandemic.

3.2 Most Relevant Journals

Among the available statistics about bibliometric performance analysis, the h-index is considered, in our case, the main reference used to evaluate productivity and influence. The h-index is defined as “the number of papers with citation number ^{3}h”, where h is the number of papers published. For example, an h-index of 20 indicates that an individual has published twenty papers with at least 20 citations. The advantage of the h-index is that it measures both productivity and influence and can be calculated for different bibliometric units of analysis: authors, countries, journals, and institutions. Table 2 shows the top 20 journals ranked according to their h-index (local h-index computed only from extracted documents), respectively. The most influential journal in the area of user modeling is User Modeling and User-Adapted Interaction (h-index of 50). The top 10 includes other renowned journals such as Expert Systems With Applications (45), Computers in Human Behavior (45), Knowledge-Based Systems (35), Information Sciences (35),

Figure 2. Publications trend

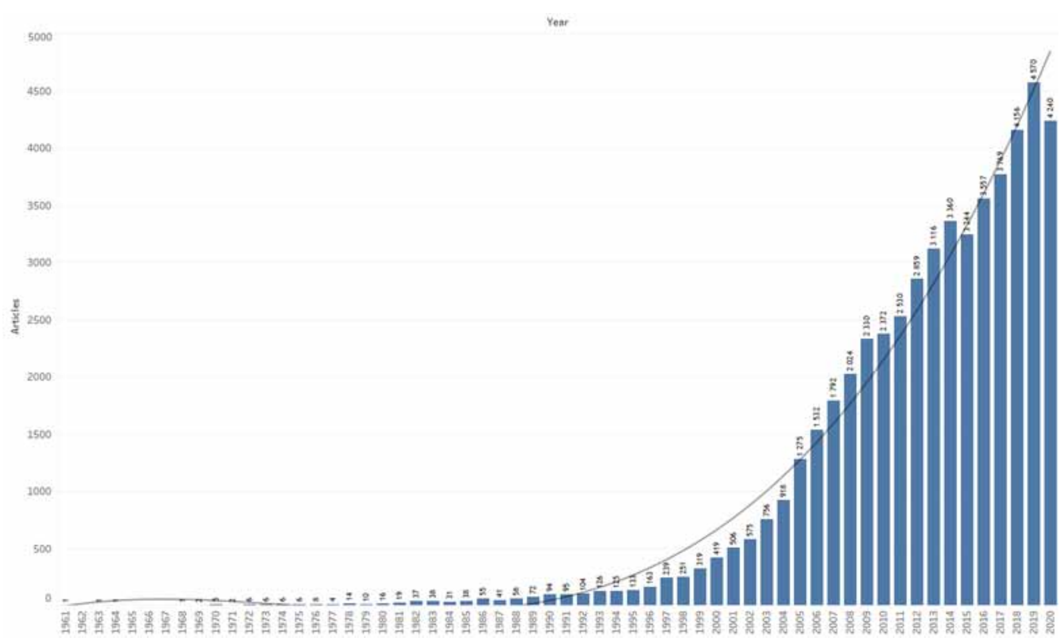


Table 2. Top 10 journals by h-index

Rank	Journal Title	h-index	# of publications	Total Citations	Start Year
1	User Modeling and User-Adapted Interaction	50	217	15,327	1991
2	Expert Systems With Applications	45	224	7,436	1990
2	Computers in Human Behavior	45	145	7,180	1993
4	Knowledge-Based Systems	35	141	4,029	1990
4	Information Sciences	35	121	3,496	1995
6	IEEE Transactions on Knowledge and Data Engineering	34	120	7,057	1991
7	IEEE Transactions on Multimedia	30	78	2,741	2000
8	Information Processing and Management	28	102	2,540	1983
9	International Journal of Human Computer Studies	27	122	3,927	1978
9	Decision Support Systems	27	70	2,175	1986

IEEE Transaction on Knowledge and Data Engineering (34), IEEE Transactions on Multimedia (30), Information Processing and Management (28), International Journal of Human Computer Studies (27), and Decision Support Systems (27).

3.3 Most Relevant Authors

Table 3 shows the top 10 authors (with their last known affiliation from Scopus) ranked according to their h-index (local h-index computed only from extracted documents). The most influential author is BRUSILOVSKY Peter (h-index of 24). The other authors in this top 10 are WHITE Ryen W. (22), RICCI Francesco (22), MOBASHER Bamshad (21), CANTADOR Iván (20), SHIN Donghee (20), BURKE Robin D. (19), SEMERARO Giovanni (19), HORVITZ Eric J. (18), CHUA Tat Seng (18), and LOPS Pasquale (18).

Table 3. Top 10 authors by h-index

Rank	Author	h-index	# Nb. pub	Total Citations	Start Year	Last known affiliation (from Scopus)
1	BRUSILOVSKY Peter	24	69	8,985	1995	University of Pittsburgh, United States
2	WHITE Ryen W.	22	33	7,187	2005	Microsoft Research, Redmond, United States
2	RICCI Francesco	22	78	5,328	2005	Free University of Bozen-Bolzano, Italy
4	MOBASHER Bamshad	21	50	7,923	1999	DePaul University, Chicago, United States
5	CANTADOR Iván	20	50	2,587	2006	Universidad Autónoma de Madrid, Spain
5	SHIN Donghee	20	33	5,971	2004	Zayed Universitydisabled, Dubai, United Arab Emirates
7	BURKE Robin D.	19	35	7,104	2002	University of Colorado Boulder, United States
7	SEMERARO Giovanni	19	108	3,289	1998	Università degli Studi di Bari, Bari, Italy
9	HORVITZ Eric J.	18	26	13,963	1999	Microsoft Research, Redmond, United States
9	CHUA Tat Seng	18	39	19,690	2007	National University of Singapore, Singapore
9	LOPS Pasquale	18	91	1,945	2001	Università degli Studi di Bari, Bari, Italy

3.4 Most Relevant Affiliations

Table 4 shows the top 10 of affiliations according to the number of publications. We can see that the most prolific affiliations are from China, the USA, and Singapore. All these affiliations are universities, except Microsoft Research (ranked 8). Tsinghua University in China is the top university with a total of 784 publications. The other affiliations featuring in the top ten are Beijing University of Posts and Telecommunications, University of California, Carnegie Mellon University, Zhejiang University, Wuhan University, Peking University, Microsoft Research, National University of Singapore, and Nanyang Technological University.

3.5 Most Relevant Countries

Table 5 presents the top 10 of countries according to the number of publications. The table also indicates the total number of citations, the average citation per publication, the total number of single (intra)country publications (SCP), the total number of multiple (inter)countries publications

Table 4. Top 10 affiliations by number of publications

Rank	Affiliations	Country	# of publications
1	Tsinghua University	China	784
2	Beijing University of Posts and Telecommunications	China	534
3	University of California	USA	521
4	Carnegie Mellon University	USA	368
5	Zhejiang University	China	305
6	Wuhan University	China	297
7	Peking University	China	255
8	Microsoft Research	USA	254
9	National University of Singapore	Singapore	254
10	Nanyang Technological University	Singapore	253

Table 5. Top 10 countries by number of publications

Rank	Country	# of publications	Citations	Avg. Citation per paper	SCP	MCP	MCP Ratio
1	China	6,448	60,668	9	5,252	1,196	19%
2	Usa	4,833	185,338	38	4,232	601	12%
3	South Korea	1,816	24,436	13	1,599	217	12%
4	United Kingdom	1,681	31,273	19	1,316	365	22%
5	Germany	1,560	21,372	14	1,278	282	18%
6	Japan	1,404	9,979	7	1,306	98	7%
7	Italy	1,378	18,297	13	1,159	219	16%
8	Spain	1,225	17,264	14	967	258	21%
9	India	1,165	6,725	6	1,082	83	7%
10	France	953	10,196	11	769	184	19%

(MCP), and the multiple countries publications ratio (MCP ratio) are also provided. According to the number of publications, China is the most productive country, followed in the top 10 by the USA, South Korea, United Kingdom, Germany, Japan, Italy, Spain, India and France. However, according to the number of citations per publication, the USA is by far the most influential country. In terms of the inter-country collaboration ratio (MCP), the United Kingdom have the highest inter-country collaboration ratio (22%), while Japan and India have the lowest (7%).

3.6 Collaboration Between Countries

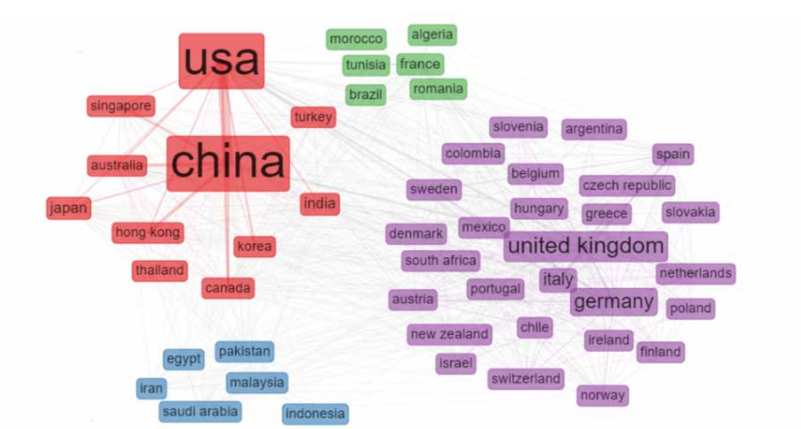
Table 6 shows the top 10 of countries' collaborations according to the number of common publications (at least one author of each country). The highest number of collaborations is by far recorded between China and the USA (1,058). The top ten of countries' collaborations always involves at least China and the USA. The other countries in this top ten are Australia, Hong Kong, Canada, the United Kingdom, Singapore, and Germany.

Figure 3 shows the collaboration network along with clusters of the top 50 countries. There is a link between two countries if they have at least one collaboration (one coauthor from each country for a paper). The clusters are built using the Louvain method for community detection in large

Table 6. Top 10 collaborations between countries

Rank	From	To	# of collaboration
1	China	Usa	1,058
2	China	Australia	352
3	China	Hong Kong	323
4	Usa	Canada	275
5	Usa	United Kingdom	266
6	China	United Kingdom	254
7	China	Singapore	215
8	Usa	Germany	198
9	China	Canada	191
10	Usa	Korea	187

Figure 3. Collaboration network of countries



networks (Blondel et al. 2008). We can identify four clusters in this network. The first one (in red) is led by the USA and China with other countries in Asia (Singapore, India, Turkey, Japan, Hong Kong, Korea, Thailand), Australia, and Canada. The second cluster (in purple) is led by the United Kingdom, Germany, Italy, and the Netherlands, with other countries in Europe (e.g. Greece, Belgium, Portugal, Czech Republic, Spain, Austria), South America (Argentina, Colombia, Mexico, Chile), Africa (South Africa), and New Zealand. The third one (in green) contains France, Romania, and some North African countries (Algeria, Morocco, Tunisia). The fourth one (in blue) is more isolated from the others and contains Egypt and several Middle East countries (Pakistan, Iran, Malaysia, Saudi Arabia, Indonesia).

3.7 Cocitation Network

Figure 4 presents the cocitation network (with the top 50 documents). There is a link between two documents if they are cited in a third document. The more cocitations two documents receive, the higher their co-citation strength, and the more likely they are semantically related. Cocitations networks can also reflect the state of intellectual production in a given field and the evolution of the school of thought (Batistič and Van Der Laken 2019). The clusters are built using the Louvain method for community detection in large networks (Blondel et al. 2008). We can clearly identify three clusters in green, red, and blue. The cluster in green points out the influence of (Adomavicius and Tuzhilin 2005) and other related documents discussing mostly recommender systems topics. The cluster in red points out the influence of (Koren et al. 2009) and other related documents mostly related to matrix factorization techniques in recommender systems. The cluster in blue is more isolated and indicates the influence of (Davis 1989) and other related documents mostly related to the technology acceptance models.

3.8 Most Relevant Words and Topics Trend

Figure 5 shows the top 50 most frequent keywords provided by authors. The more frequent a keyword, the bigger and closer to the red color it is.

Through a visual inspection of this word cloud, we can divide the most important keywords around user profiling and user modeling (e.g. user profiling, user modeling, user behavior, user interest) into 12 topics (ranked based on total frequencies of associated keywords in the legend of Figure 6): recommender systems (e.g. recommender systems, collaborative filtering, matrix factorization); learning methods (e.g. machine learning, web mining, deep learning); personalization and information retrieval (IR) (e.g. personalization, information retrieval); applications fields (e.g. e-commerce,

Figure 4. Co-citation network with top 50 documents

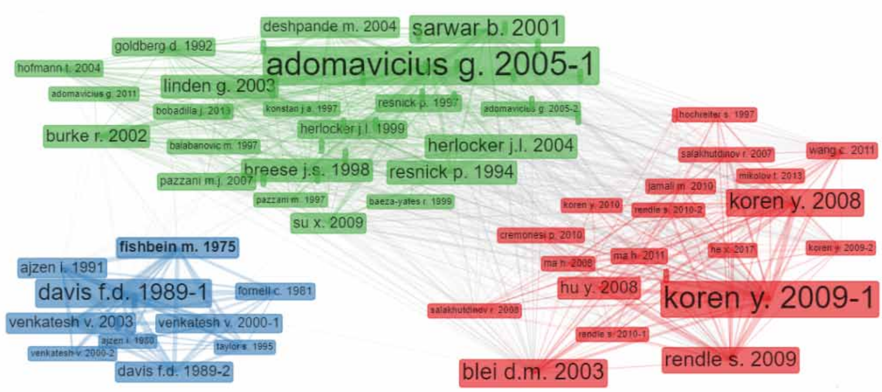
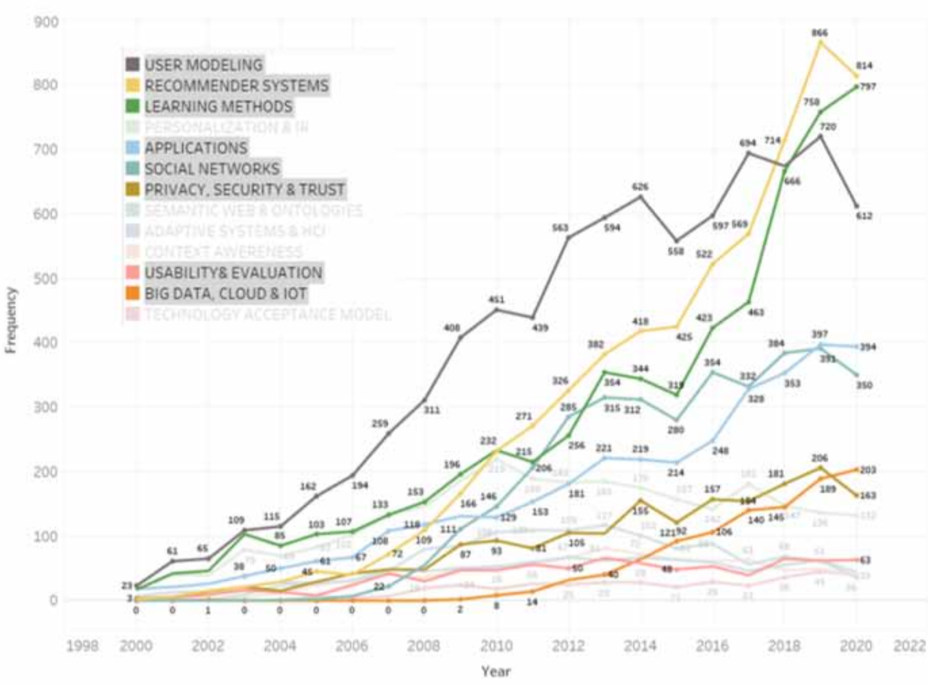


Figure 5. Word cloud with top 50 frequent keywords

e-learning, virtual reality); social networks (e.g. social networks, online social networks, social media); privacy, security and trust; semantic web and ontologies; adaptive systems and human-computer interaction (HCI); context awareness; usability and evaluation; big data, cloud computing, and internet of things; technology acceptance model. Figure 6 presents the trend for the last 20 years for each of

Figure 6. Global trends of topics



these topics that helps identify the fastest growing and hot topics (also highlighted in the legend). By order of importance, that the following topics are considered to have the fastest pace in literature: recommender systems, learning methods, social networks, applications fields, privacy, security and trust, big data, cloud computing and internet of things, usability and evaluation. The other topics (not highlighted in the legend) have a stable or decreasing trend. For a better understanding of each topic, the next section displays the most important associated keywords or subtopics, and their trends.

3.9 Subtopics Trends

For each of the twelve topics identified in the previous section, Figure 7 to Figure 18 present the trend of frequent associated keywords of subtopics.

The keywords or subtopics associated with each topic are identified from the top 500 most frequent keywords in all extracted documents. From these figures we can easily identify for each category the most important subtopics (ordered based on the total number of frequencies in the legends), trending subtopics (when the overall trend is increasing, they are highlighted in the legends), and emerging subtopics (they started very recently and have been showing an upward trend). Such trends of topics and subtopics trends are categorized and synthesized in Table 7. They will be discussed in the next section.

4. DISCUSSION

In this study, we performed a bibliometric analysis of research publications related to user modeling or user profiling. To the best of our knowledge, this is the first bibliometric study in this research field. The bibliometric approach on this research field can complement existing systematic literature

Figure 7. Recommender systems keywords trend

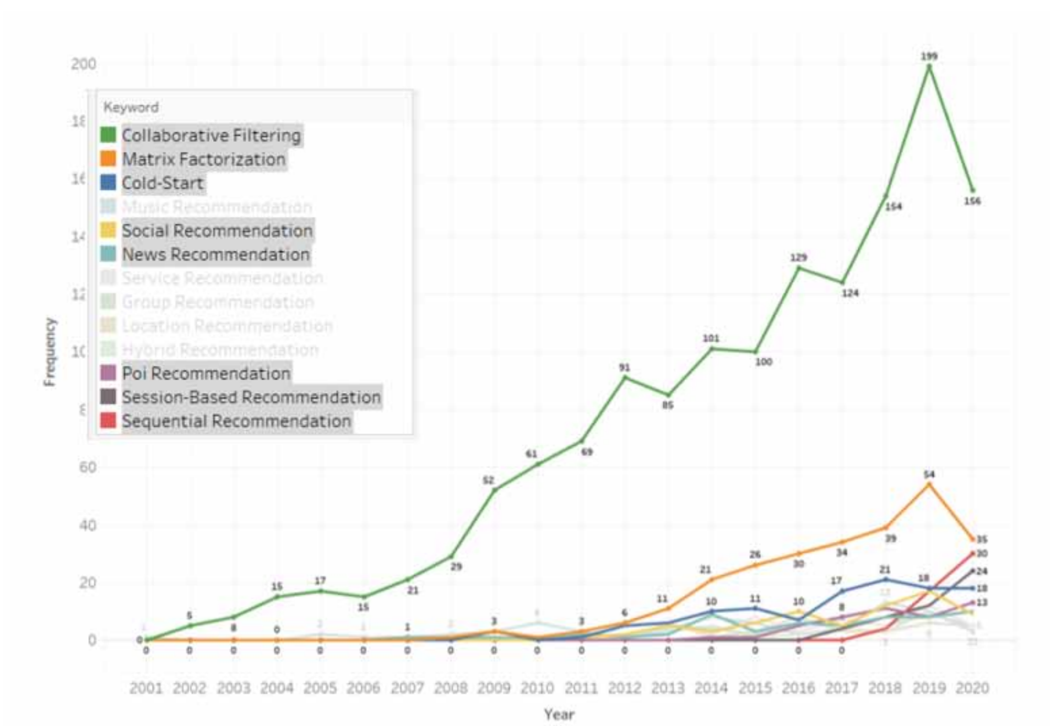


Figure 8. Personalization and information retrieval keywords trend

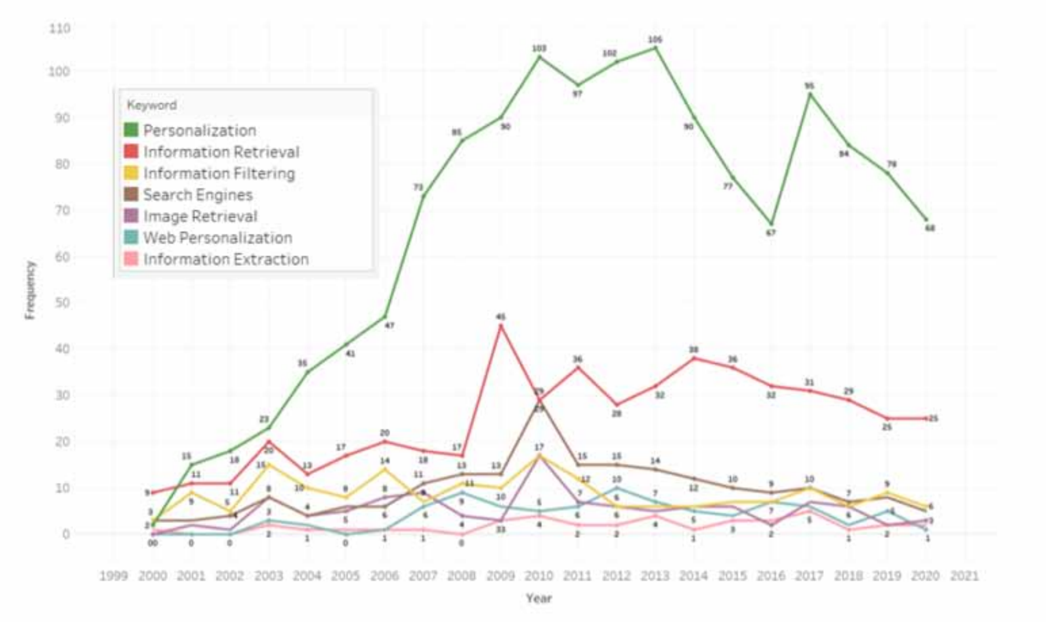


Figure 9. Social networks keywords trend

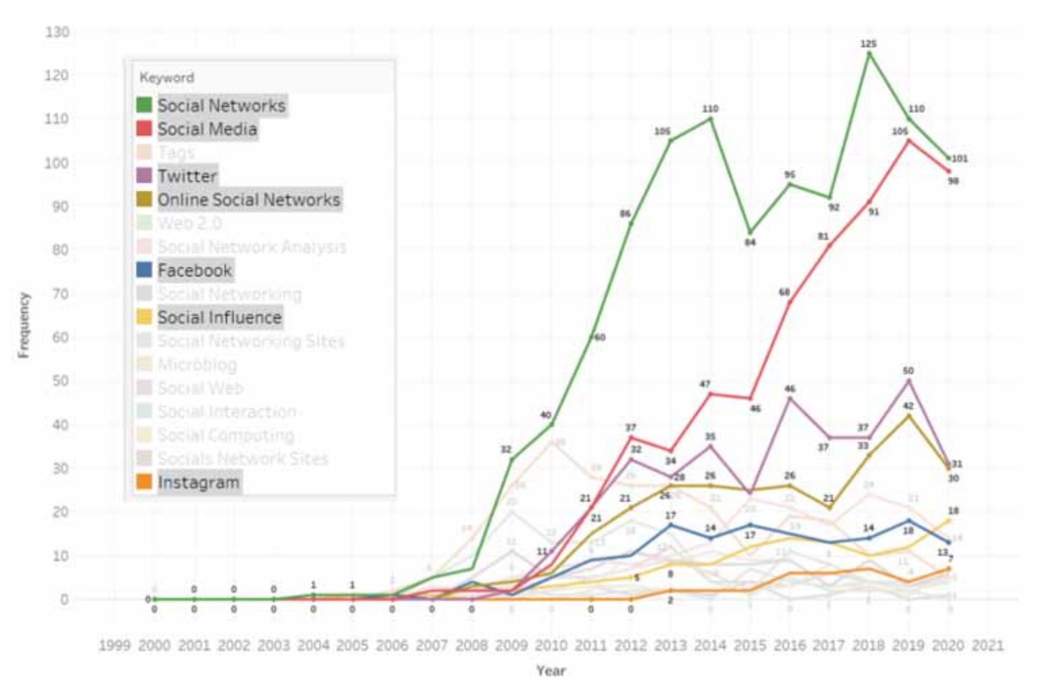


Figure 10. Privacy, security and trust keywords trend

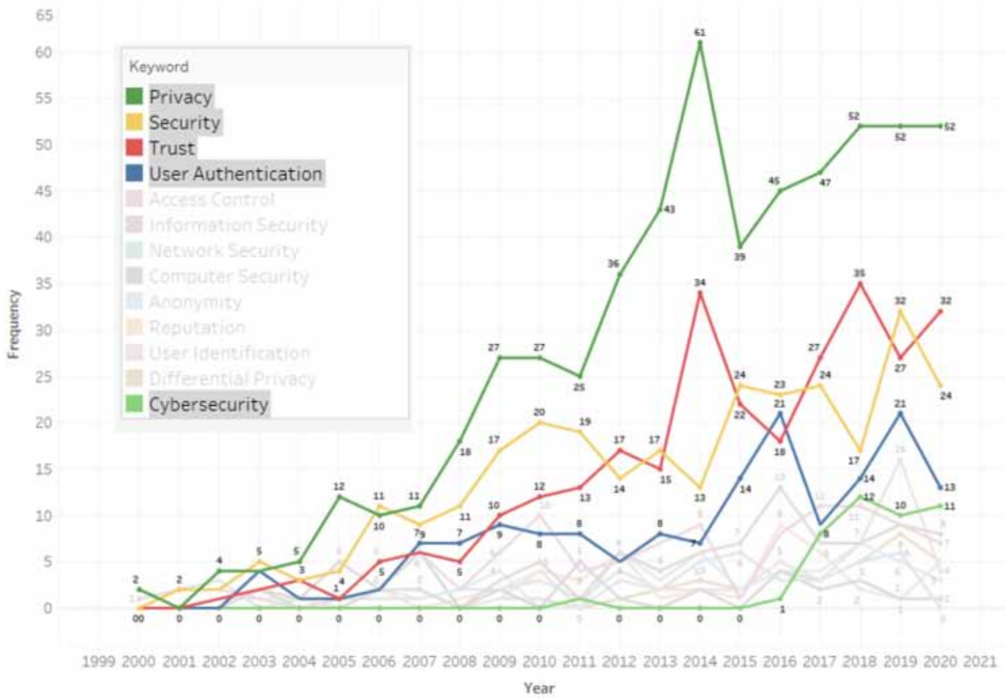


Figure 11. Semantic web and ontologies keywords trend

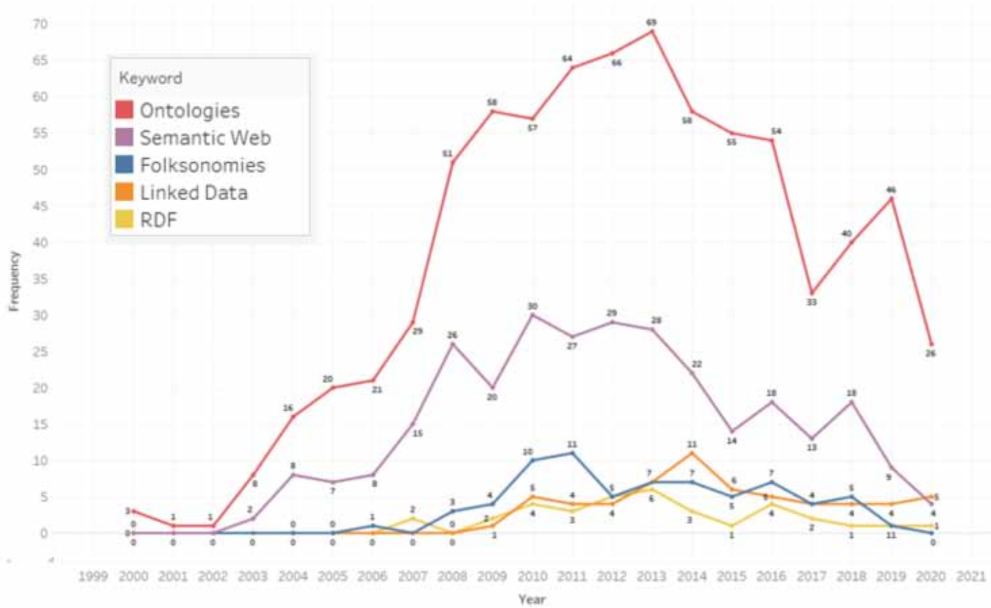


Figure 12. Adaptive systems and HCI keywords trend

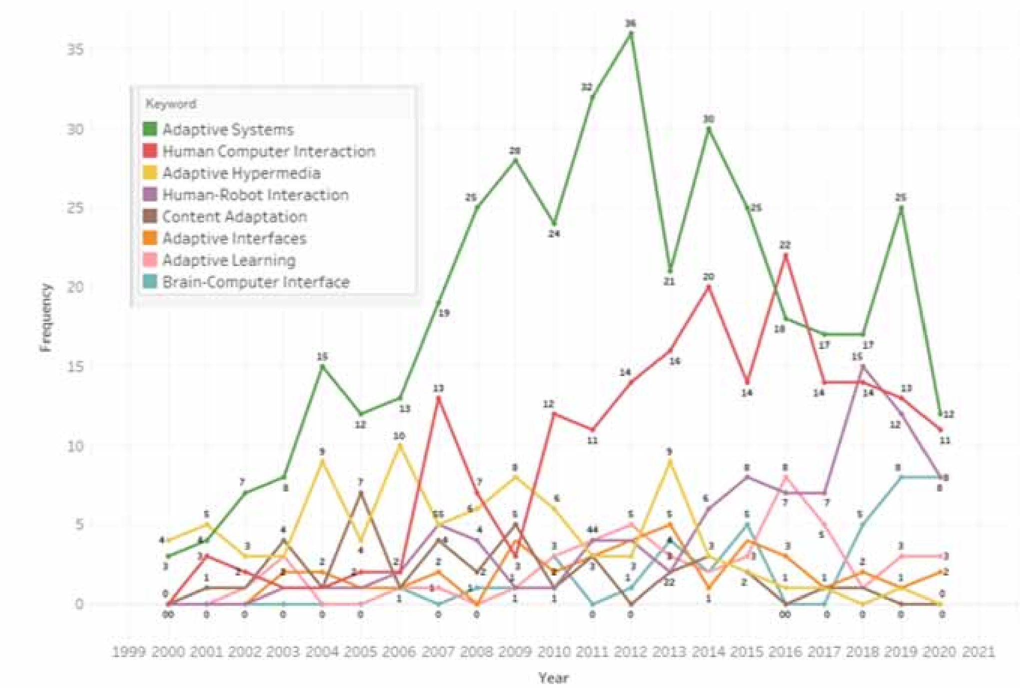


Figure 13. Learning methods keywords trend

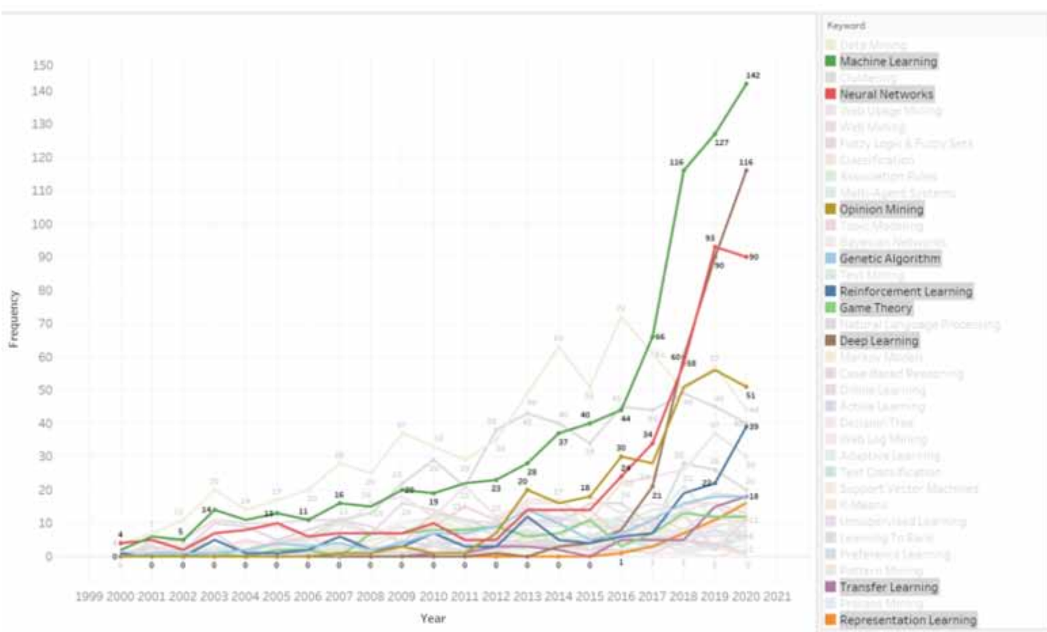


Figure 14. Applications fields keywords trend

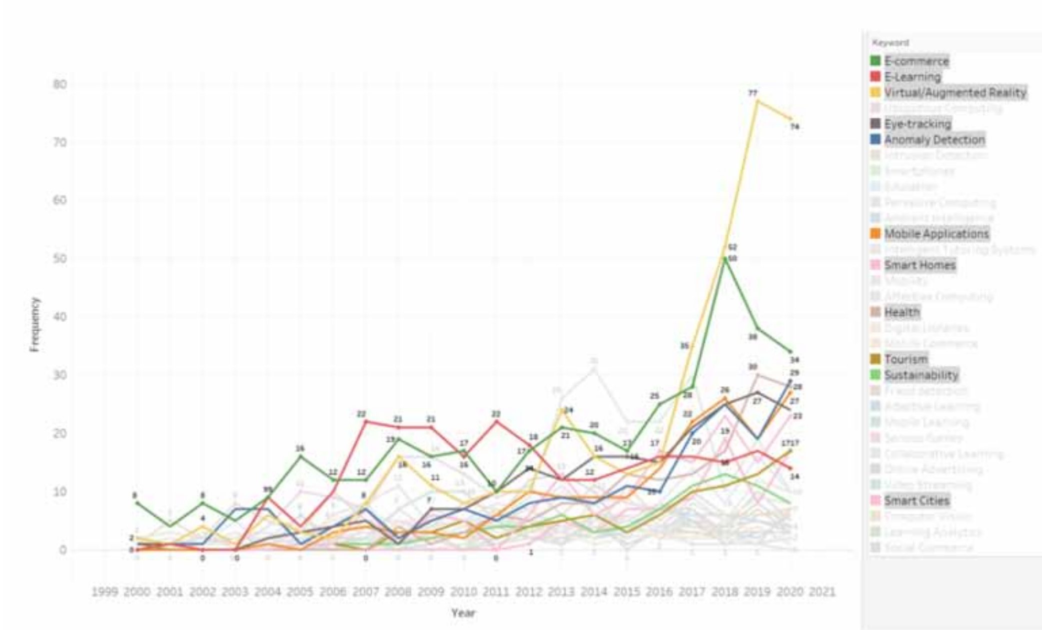
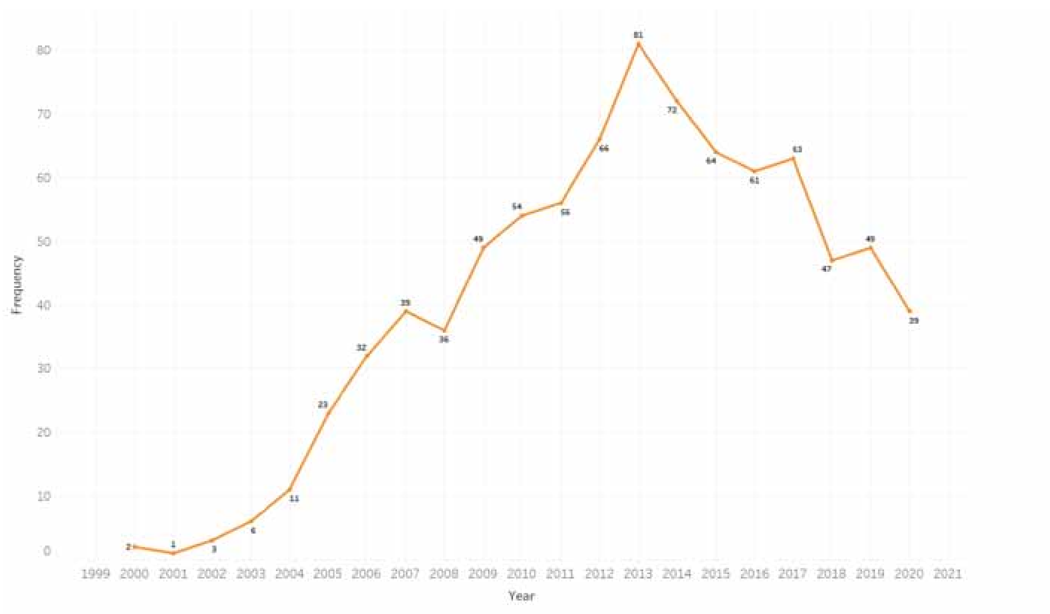


Figure 15. Context awareness keywords trend



or meta-analysis reviews by providing quantitative measures and qualitative interpretations, given that the scope is very large coupled with the high number of related publications (52,037 analyzed publications in this study). We observed an exponential growth in the number of publications per year (Figure 2), which denotes the great importance of the topic in recent years. Our bibliometric study was

Figure 16. Usability and evaluation keywords trend

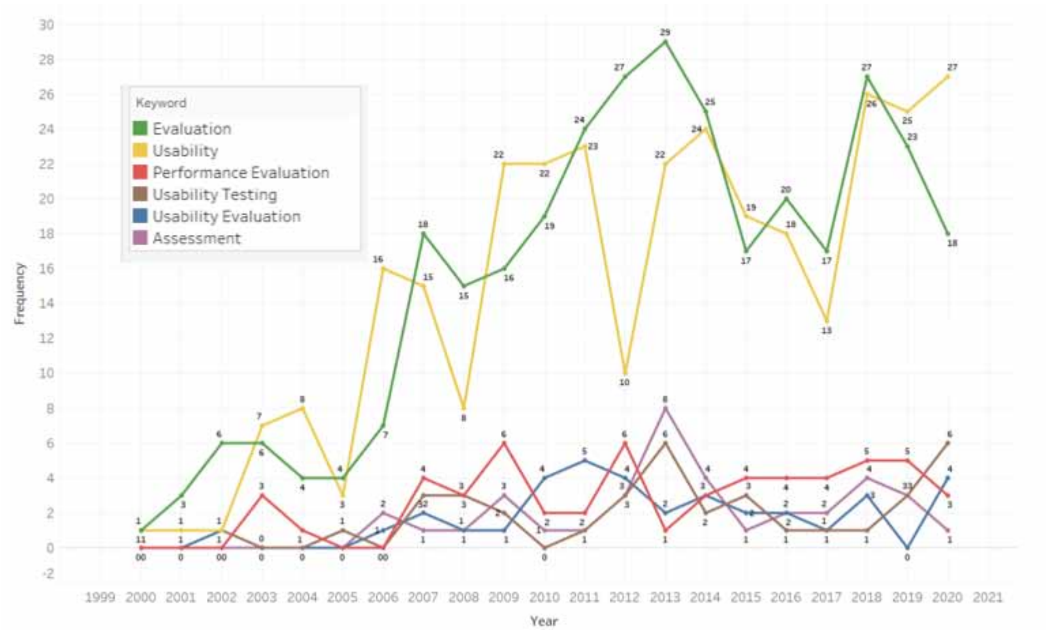


Figure 17. Big data, cloud computing and IoT keywords

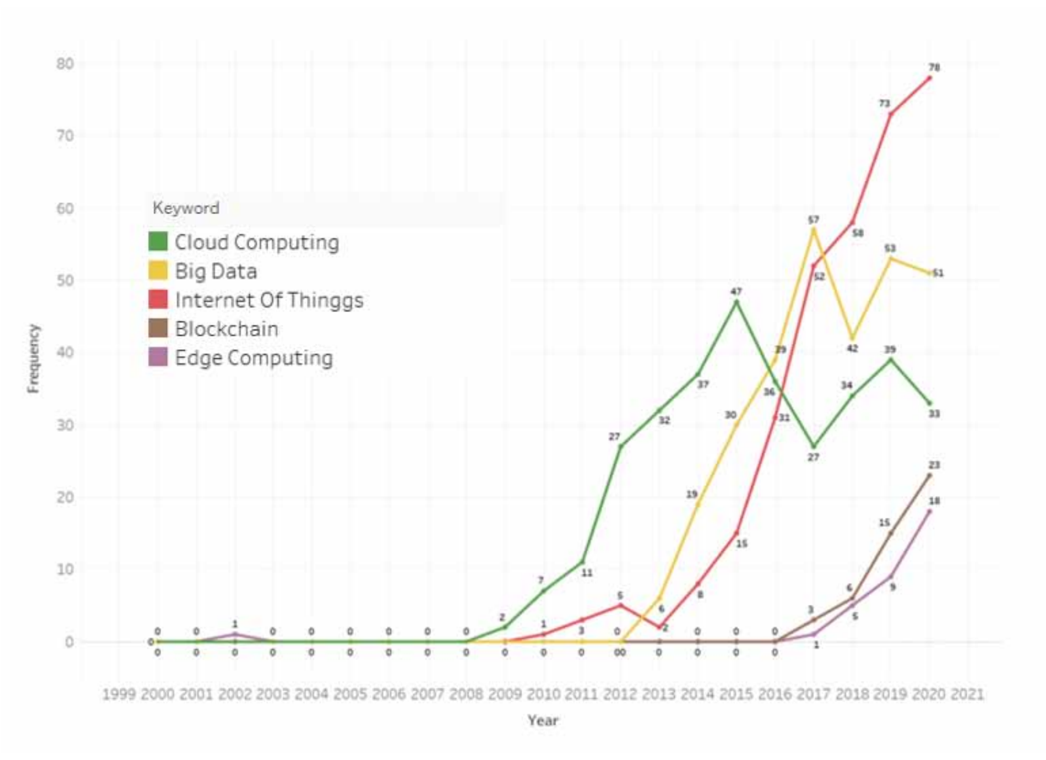
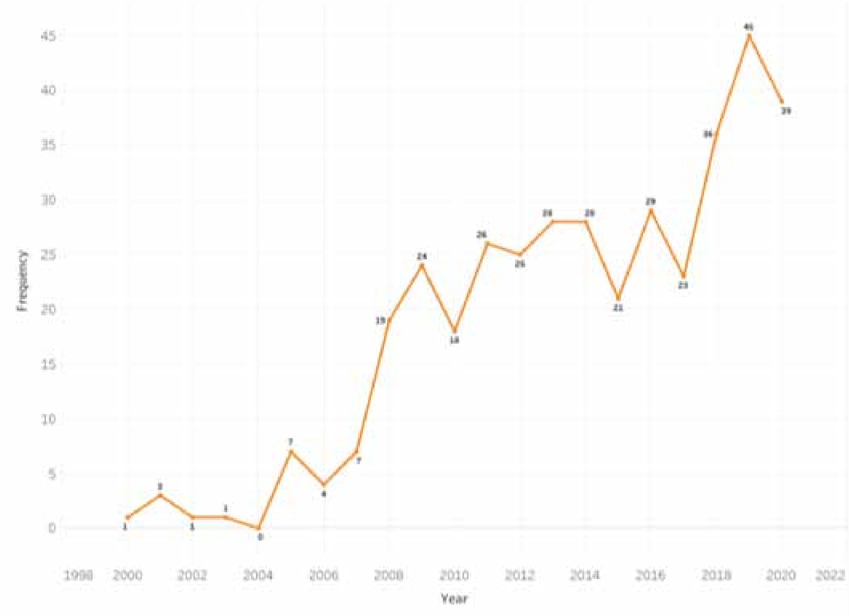


Figure 18. Technology acceptance model keywords trend



centered on three main research questions: (i) Concerning user profiling, what are the most relevant authors, sources of publications, institutions, countries, and their collaboration?, (ii) What are the main related research topics and their trends?, (iii) What are the potential future research directions?

Considering the h-index, we found that the top-5 most influential authors by the h-index are BRUSILOVSKY Peter (USA), WHITE Ryen W. (USA), RICCI Francesco (Italy), MOBASHER Bamshad (USA), CANTADOR Iván (Spain) and SHIN Donghee (United Arab Emirates). With the same criterion (h-index), the following journals form the top-5 most influential: User Modeling and User-Adapted Interaction; Expert Systems With Applications; Computers in Human Behavior; Knowledge-Based Systems; and Information Sciences. Moreover, by the number of publications, China and the USA are the venues for the top-5 affiliations, which include: Tsinghua University (China), Beijing University of Posts and Telecommunications (China), University of California (USA), Carnegie Mellon University (USA), Zhejiang University (China). Exploring the number of publications also enabled us to determine the top-5 countries, namely China, the USA, South Korea, the United Kingdom and Germany. We also found that the country collaboration network shows four clusters of collaboration. The first one is led by the USA and China. The second cluster mostly contains European countries and is led by Germany, the United Kingdom and Italy. The third cluster mostly contains France and some countries from the Maghreb (Algeria, Tunisia, Morocco). The last cluster is made up of Egypt and many countries from the Middle East (Pakistan, Iran, Malaysia, Saudi Arabia, Indonesia). Overall, we can also see that all continents are concerned with this research field, even though the contribution of a few geographical areas such as sub-Saharan Africa is marginal.

From the most frequent authors' keywords, we identify 12 different topics related to user modeling or user profiling (Figures 5 and 6). These topics present a wider and global picture of this research field, compared to existing specific literature reviews (e.g., Eke et al. 2019; Piao and Breslin 2018; Zanker at al. 2019; Gao et al. 2010). They are summarized by order of importance in Table 7 with their overall trend, the 10 most frequent subtopics, trending subtopics, and emerging subtopics. Based on

Table 7. Summary of topics, related frequent subtopics and emerging subtopics

Topic	Main objective	Global trend	10 most frequent subtopics	Trending subtopics	Emerging subtopics
Recommender systems	Generating meaningful recommendations to users for items or products that might interest them	Very increasing	Collaborative filtering; Matrix factorization; Cold start problem; Music Recommendation; Social recommendation; News recommendation; Service Recommendation; Group Recommendation; Location recommendation; Hybrid recommendation	Collaborative filtering; Matrix factorization; Cold start problem; Social recommendation; News recommendation.	Point of interest (poi) recommendations; Session-based recommendation; Sequential recommendation.
Learning methods	Algorithms used for building user profiles or for associated mechanisms	Very increasing	Data mining; Machine Learning; Clustering; Neural networks; Web usage mining; Web mining; Fuzzy Logic & Fuzzy Sets; Classification; Association Rules; Multi-Agent systems	Machine learning; Deep learning; Neural networks; Opinion mining; Genetic algorithms; Reinforcement learning; Game theory.	Reinforcement learning; Transfer learning; Representation learning
Personalized systems and information retrieval:	Avoiding information overload problem by personalizing the result of the search according to his profile (e.g. search engine)	Decreasing	Information retrieval; Information filtering; Search engines; Image retrieval; Web personalization; Information extraction		
Applications fields	Application fields where user profiling is used	Very increasing	E-commerce; E-learning; Virtual/ Augmented Reality; Ubiquitous computing; Eye-Tracking; Anomaly detection; Intrusion Detection; Smartphones; Education; Pervasive computing	Virtual and augmented reality; E-commerce, Anomaly detection; Eye-tracking applications; Mobile applications; Health	Virtual and augmented reality; Smart homes; Tourism; Sustainability; Smart cities.
Social networks	Social data sources or methods from social network analysis used in user profiling or associated mechanisms	Very increasing	Social networks; Social Media; Tags; Twitter; Online Social Networks; Web 2.0; Social Networks Analysis; Facebook; Social Networking; Social Influence;	Social networks; Social Media; Twitter; Online Social Networks; Facebook; Social Influence; Instagram	Social Influence; Instagram; Facebook; Twitter; Online social networks
Privacy, security and trust	Take into account the handling of sensitive data when building or using user profiles	Very increasing	Privacy; Security; Trust; User Authentication; Access Control; Information security; Network security; Computer security; Anonymity; Reputation	Privacy; Security; Trust; User Authentication; Cybersecurity	Cybersecurity
Semantic web and ontologies	Representing or sharing users' profiles as web resources easily interpretable by machines	Decreasing	Ontologies; Semantic Web; Folksonomies; Linked Data; RDF		

continued on following page

Table 7. Continued

Topic	Main objective	Global trend	10 most frequent subtopics	Trending subtopics	Emerging subtopics
Adaptive systems and Human–Computer Interaction	Adapting contents to the user in Human Computer Interaction systems (e.g. adaptive user interface, adaptive hypermedia, adaptaive learning systems)	Decreasing	Adaptive systems; Human-Computer Interaction; Adaptive Hypermedia; Human-Robot Interaction; Content Adaptation; Adaptive Interfaces; Adaptive Learning; Brain-Computer Interfaces		Brain-Computer Interfaces
Context awareness	Using contextual information for improving user profiling or associated mechanisms (e.g. temporal context, spatial context, emotional context).	Decreasing	Context; Context-awareness		
Usability & Evaluation	Evaluating the performance of user profiling or associated mechanisms	Very Increasing	Evaluation; Usability; Performance Evaluation; Usability testing; Usability Evaluation; Assessment	Evaluation; Usability;	
Big Data, Cloud computing and Internet of Things	Technological trends that make more data or resources accessible for user profiling and their usages	Very increasing	Cloud computing; Big Data; Internet of Things; Blockchain; Edge computing	Cloud computing; Big Data; Internet of Things; Blockchain; Edge computing	Blockchain; Edge computing
Technology Acceptance Model	Providing some specific frameworks to measure users' perceptions (or intentions) of using technologies.	Increasing	Technology Acceptance Model		

the overall trend (Figure 6), the fast-growing topics include recommender systems, learning methods, application fields, social networks, privacy (along with security and trust), usability and evaluation, big data (along with cloud computing and the internet of things).

The goal of a recommender system is to generate meaningful recommendations to users for items or products that might be of interest for them (Kembellec et al. 2014). Trending related subtopics (Figure 7) are collaborative filtering, matrix factorization, cold-start problem, social recommendation and news recommendation. Collaborative filtering is one method in recommender systems that makes recommendations to users based on the behavior of other similar users (Herlocker et al. 2004). Matrix factorization, which is one of the most popular collaborative filtering techniques, works through a decomposition of the user-item interaction matrix into the product of two lower dimensionality rectangular matrices (Koren et al. 2009). The cold-start problem appears when the system cannot draw any inferences on users about which it has not yet gathered enough information (Lika et al. 2014). Social recommendation refers to recommender systems that target the social media domain (Guy 2015). As for news recommendation, it refers to recommender systems that make reading suggestions to users in a personalized way (Karimi et al. 2018).

Learning methods here include learning algorithms or techniques for building users' profiles or associated mechanisms. We observed that trending methods (Figure 13) currently include, by order of importance: machine learning, deep learning, neural networks, opinion mining, genetic algorithms, reinforcement learning and game theory.

For the purpose of our study, applications fields are considered the applications fields for user profiling. We observed that trending applications fields (Figure 14) currently include the following by order of importance: virtual and augmented reality, e-commerce, anomaly detection, eye-tracking applications, mobile applications and health. We can particularly note the explosion of virtual/augmented reality applications, which are currently the most frequent applications (in front of e-commerce).

Social networks here refer to social data sources or methods from social network analysis used in user profiling (Piao and Breslin 2018; Tchuente et al. 2013). We observed that trending subtopics related to social networks (Figure 9) mostly include social media platforms or online social networks (Twitter, Facebook, Instagram) and social influence modeling in user profiling.

Building user profiles or associated mechanisms (e.g., recommendation, personalization, adaptation) commonly means manipulating users' sensitive data. This usually raises many privacy, security and trust issues (Chellappa and Sin 2005; Toch et al. 2012; Zhang and Sundar 2019). We observed that trending subtopics related to privacy, security or trust (Figure 10) mostly include user authentication and cybersecurity.

Usability and evaluation studies are mainly related to empirical studies that evaluate the performance of proposed methods for user modeling or associated mechanisms such as recommender or personalized systems. Even if there is no identified trending related subtopic, the most frequently related keywords (Figure 16) are performance evaluation, usability testing, and assessment.

Big data, cloud computing or internet of things represent some technological trends that produce more data and computing resources available for user profiling and its various uses. We observed that trending related subtopics (Figure 17) also include blockchain (Y. Chen et al. 2019) and edge computing (Zeng et al. 2019).

Among the twelve identified subtopics, five of them show a decreasing trend, thus illustrating the fact that they have been less important over the past recent years. These include personalized systems and information retrieval (Figure 8), semantic web and ontologies (Figure 11), adaptive systems and human-computer interaction (Figure 12), and context-awareness (Figure 15).

Concerning the Technology Acceptance Model topic, it shows a relative upward trend (Figure 6 and Figure 18). The technology acceptance model provides some specific frameworks to measure users' perceptions (or intentions) of using technologies (Davis 1989; Venkatesh et al. 2003).

5. FUTURE RESEARCH DIRECTIONS, IMPLICATIONS AND LIMITATIONS

If weak signals can provide a lot of information for future trends, they are by nature not always easy to detect. As they are generally defined, weak signals appear as a set of premature and imperfect information that is usually obfuscated by confounding factors announcing discrete shocks or new developments in powerful trends (Mendonça et al. 2012). In our study, section 3 discusses some figures about subtopics, which provides analytical views that can be used to quickly identify weak signals or emerging themes. For instance, despite their recent development, they show an increasing trend. Such topical issues represent potential future research directions related to user profiling and their usages (Table 7). Recommender systems nurture potential avenues for future research, including the development and improvement of point of interest (poi) recommendations, session-based recommendations (that uses short-term users' profiles during single sessions) or sequential recommendations (that combines long-term users' profiles and short-term tendencies). With regard to learning methods for building user profiles or associated mechanisms, emerging methods include reinforcement learning, transfer learning, and representative learning. Emerging applications fields include virtual/augmented reality, smart homes, tourism, sustainability, and smart cities. The field of human-computer interaction (HCI) systems also provide new angles of research for the future including brain-computer interfaces: systems capable of decoding neural activity in real time, thereby allowing a computer application to be directly controlled by thought (Pillette et al. 2021).

Blockchain and edge computing are also emerging recent technologies with an undeniable value for future applications of user modeling. Furthermore, future research studies can well mix some of the emerging technologies in order to come up with interesting findings. For instance, this may include using reinforcement learning techniques for modeling social influence in user profiling, or relying on social media data. Even if there are many studies related to privacy (along with security and trust) and cybersecurity, there is a need to keep tackling several ethical and moral implications that impede technological progress (Pandit and Lewis 2018). Laws often try to reflect the shifting values of social perception, and this is the case of the General Data Protection Regulation (GDPR) which is trying to explicit consent over personal-data use, though actions may still be legal without being perceived as acceptable.

Concerning practical and research implications, this study provides some of them. Practically, its findings can help interested novices, scholars, experts or industrials identify both potential research collaborators and suitable sources for their publications. The science mapping that is provided can also help novices in the field to quickly have an overview of existing research as well as hot applications fields. For research, the identified gaps, topics, subtopics, emerging subtopics, can provide many interesting directions for future research.

Finally, the two main limitations of this study relate to the use of keywords for the search, which may not have covered all published papers, as well as to the use of a single database (Scopus) to perform the keyword search. Thus, some documents may not have been retrieved from our search, thus impacting the analysis. To address these limitations, future bibliometric studies could extend the number of keywords (or limit the scope to a specific application field, for instance) or combine multiple databases (e.g., Web of Science and Scopus).

6. CONCLUSION

In this paper, we conducted a bibliometric analysis on user modeling and user profiling, and their usage in information systems. The analysis was made with 52,027 related publications extracted from the world reputed Scopus database. Our findings identify (i) the most relevant authors, sources of publications, institutions, countries, and their collaboration; (ii) twelve main related research topics along with their subtopics and their trends; (iii) the potential future research directions and some research gaps. To the best of our knowledge, this is the first bibliometric study on user modeling or user profiling that analyzes a very large number of related publications. The findings obtained through the use of this approach can complement existing literature reviews and provide a lot of insights into performance analysis and science mapping to novices, scholars, industrials or experts interested in this research field.

ACKNOWLEDGMENT

We would like to thank the anonymous reviewers of this paper for taking the time and effort necessary to review the manuscript. We sincerely appreciate all valuable comments and suggestions, which helped us to improve the quality of the manuscript.

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

FUNDING AGENCY

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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