Social Media Recommender Systems (SMRS): A Bibliometric Analysis Study 2000–2021

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ABSTRACT The increasing popularity of social media resources such as blogs, bookmarks, chatrooms, forums and video portals in recent years has attracted diverse users. Following the rise of the Internet, online content has become overloaded, prompting the introduction of recommender systems on social media. As a result, research on the dynamic growth of recommender systems in social media has gained significant traction since the year 2000. Social media recommender systems (SMRS) utilize multiple recommendation fields such as item, user, location, tag, event, tour and game in searching for preferred recommended information. Thus, young research fellows, academic scholars and practitioners must understand the need for SMRS to be complemented with recommendation fields. This requirement underlines the significance of a bibliometric analysis that focuses on social media based on existing publications. Hence, using the Web of Science (WoS) database, this study aimed to gather statistical information on SMRS to help researchers acquire an extensive understanding of such systems. The analysis was conducted by identifying SMRS-related publications and scientometric indicators to assess the growth rate, including the relative growth rate (RGR), doubling time (DT) and the field-normalized citation score (NCSf)—for citation analysis. Overall, this bibliometric study provides relevant measures for comparing and improving the citation rate of publications for new researchers.

INDEX TERMS Social media, social network, recommender system, bibliometric, doubling time, relative growth rate.

I. INTRODUCTION

Since the 1960s, social media has been key to studying the relationship between groups of people within a system. Social media offers channels; its advancements involve user-generated content, information sharing, user interactions, a sense of community, real-life event circulation, message exchanges through virtual communities, as well as private and public networks [1]. Modernization has engendered the rapid spread of information technology, leading to significant changes in various knowledge domains and asynchronous sharing on social media.

People use different social media platforms for various purposes like education, news, business, shopping,

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discussions, and other activities [2]. Users involved in these activities produce huge volumes of data online. Based on assorted user generated content, social media encompass digital libraries (e.g., Wikipedia) [3], social networks (e.g., LinkedIn, Facebook) [4], e-commerce platforms (e.g., Amazon) [5], travel reviews (e.g., Trip Advisor) [6] microblogs (e.g., Twitter) [7], entertainment services (e.g., MovieLens, YouTube) [8], as well as forums (e.g., Stack Overflow, Yahoo!) containing discussions, questions, and answers [9], [10].

The explosive increase of social media platforms both spurred development and overburdened information systems, signaling a major challenge. This overburdened content information makes identification tasks even more frustrating when irrelevant information is included on social media websites. The solution is to extract preferred information from a huge

volume of data, especially from different resources like text content, images, videos, discussions, reviews, search histories, and documents [11]–[13].

One possible solution is the "recommender system" which is an architectural approach for accessing relevant and reliable information from overloaded content. Generally, in the past there was a lot of research on recommender systems for information searches; users prefer them due to narrowed down recommendation fields, focusing two entities on various resources. These entities are the "user" and the "items" which provide ratings for recommender systems [14]. Recommendations denoted by a set of users $U = \{u1, u2,\ldots un\}$ i.e., $|U| = n$, where n is the number of users. The set of items being recommended is represented by $I = \{i1, i2,\ldots im\}$, with $|I| = m$, where m is the number of items. Rating denoted by $R (i, u) \in T$, where T is the total number of ratings U x I; i.e., each user rates a possible number of items recommended to users [15], [16].

Social media recommender systems (SMRS) are new innovations offered on a variety of social media platforms. Initially, SMRS were content-based (CB) and entailed collaborative filtering (CF) and hybrid (HB) filtering for various domains, with specific recommendation fields in terms of users or items [17]. However, in recent research on SMRS, terms for recommendation fields have been described in different ways. Recommendation fields could involve any information that implicitly or explicitly exists on social media websites rooted in users' experiences, which in turn serve as the key points for recommendation fields [18]. For recommending user preferred items or content, the items should be rated and ranked based on numerous attributes. For example time, location, history, tags, topic, user activity, interactions, popularity, trust, and reviews are considered while rating computations for recommendations [19]. Further, other research on recommender systems (e.g., e-commerce, online communities, and entertainment) utilizes various aspects- not only users and items. These studies on SMRS have increased nowadays based on behavioral approaches related to social media platforms in a broad array of domains [20], [21].

Many studies or review articles have examined SMRS since the year 2000. Notwithstanding, the number of studies is limited, especially in terms of quantitative assessments, which require a nuanced understanding of the Web of Science (WoS) data source [22]. This bibliometric study analyzed the growth of SMRS and current trends from multiple angles using scientometric indicators via WoS data. None of the studies contain quantitative results based on the literature growth rate and citation analysis. Quality is defined based on recommendation field categories found to be useful for understanding current trends, and being aware of different recommendation aspects is important for choosing the future research direction of SMRS. For this study, WoS data were employed for bibliometric analysis; all types of documents that facilitate understanding of the popularity of social media were used and derived from top organizations,

funding agencies, cited articles, conferences, research areas, and prominent journals [23]–[25].

In recent years, the research on SMRS has expanded as numerous social media outlets have become widely popular. Thus, this study compiled recommendation fields such as user, item, location, tag, event, tour and game from past studies in the search for preferred information. Specifically, this bibliometric study aimed to narrow the present gap in knowledge by obtaining quantitative outcomes to enable and support the understanding of research growth by publication, citation, and the analysis of recommendation fields of SMRS in an improved manner. Regarding publication growth, if the number of publications increases, so does the growth rate. Grounded in scientometric techniques, the growth rate analysis showed that the RGR increases, while the DT of publications decreases. Citation analysis revealed contemporary SMRS field popularity using the field-normalized citation score (NCSf), which measures the citation impact (i.e., the more articles tend to be cited, the more active studies will be on SMRS). This interpretation allows scholars to have options for SMRS research using a variety of social media platforms. Additionally, the bibliometric analysis indicates the scope for SMRS from different perspectives. Hence, the present aimed to:

1. quantitatively analyze published research articles as publication growth per year, publication growth per country, author co-citations, and keyword co-occurrences in WoS between 2000 and 2021.
2. compute the growth rate of publications using scientometric indicators (e.g., relative growth rate (RGR), doubling time (DT) and field-normalized citation score (NCSf) based on recommendation field categories.
3. identify the current popularity of SMRS by looking at top organizations, funding agencies, citation, conferences, research areas, and journals.

This paper is organized into eight sections. Section Two presents related literature on SMRS. Section Three addresses the data collection and methodology of the bibliometric study. Section Four covers the scientometric indicators based publication growth and the citation rate between 2000 and 2021, briefly tabulated. Subsequently, Section Five involves the additional results of analysis rooted in literature growth, countries, organizations, and funding agencies. Section Six deals with the future implications of SMRS based on the quantitative analysis. Finally, Sections Seven and Eight refer to the limitations and conclusion.

II. RELATED WORK

This section provides an overview of recommender systems, existing recommendation approaches, and different aspects of existing recommendation field categories in constructing user profiles in social media- related researches. Recommender systems were broadly investigated in the middle of the 1990s using traditional algorithms to extract information tied to users and relevant information depending on the user's

need [26]. Since the year 2000, the need to predict recommendations for various domains has facilitated the rapid growth of research on social media resources and platforms [27]. SMRS have been employed to examine users' issues to identify new items or services and knowledge, which in turn can be used to provide target users with recommendations [28]. Assorted data mining techniques are used to analyze large quantities of data in patterns and rules. The effect of decisions is predicted, thereby improving the performance of the recommender system using different recommendation approaches on social media [29]–[31]. The three traditional approaches— content-based (CB), collaborative (CF) and hybrid (HB) filtering are harnessed to focus on rating calculations via specific structured methods or frameworks for recommendations. Hybrid achieves better recommendation outcomes by overcoming the issues of CF and CB [32], [33]. The traditional recommender system utilizes information retrieval (IR) which entails keyword matching and retrieval to provide information in accordance with user preferences [34]. Recently, numerous studies have emerged on diverse recommender systems, including those that are knowledge-based (KB), semantic aware, tag-based, and location-based. Novel approaches are viewed as contemporary, examining user behavior with other attributes from website content explored through a multidimensional approach. The attributes may be implicitly or explicitly available, obtained from the content of social media websites [35]. Thus, the rating or ranking computation is heavily based on the user's implicit or explicit information for user profile construction to suggest recommendations to users [36]. In this case, implicit information refers to observed user behavior and information collected based on a specific observation [37]. In contrast, explicit information is acquired from the user's webpage on social media. Different recommendation fields are employed in different domains grounded in user preferences [38].

For example, e-commerce websites (e.g., Amazon.com) customize their interfaces for large-scale visual searches of information about products, sharing online shopping experiences, and review ratings of a desired product. These aspects are considered factors for research using recommendation techniques to identify suitable products for users [39]. Social media entertainment platforms (e.g., online games, YouTube) that utilize hybrid filtering yield highly accurate predictions in filtering results in combination with a desired item [40]. Frequently used entertainment platforms include movie websites on social media. The researchers explored online movie platforms and relevant web services for data collection by using classification algorithms [41]. The collaborative filtering algorithm entailed several parameters based on movies and their ratings to provide pertinent recommendations to users via a ranking model. Zhao *et al.* proposed the user ranking model approach and grouped user feedback about an item for recommendations [42].

Another familiar area where recommendations are essential is tourism. Shen *et al.* [40] and Lim *et al.* [41], suggested tourism attractions to both single and community users based on their travel interests. They obtained results on classic approaches to generate recommendations to individual users and groups. Trip planning of tour itineraries and numerous areas of interest centered on the distinctive choice of tourism places with geolocations. This recommendation incorporated real-life factors such as weather, touring time limits, group travel, tentative traffic situations, crowdedness, and queuing times.

The discussion forum area is familiar for technical queries, which involve academic and programming people. Forum users employ titles, archived content, and tags to express their specialization in terms of keywords that indicate their interests. The user's interests and behavior from his/her past history of answering are observed for scoring computation based on tags. Hence, users realize that unfamiliar resources from related users could signal interest in a target user through tags expressed as tag-based recommendations [7], [43].

Social media offer opportunities for sharing suggestions for geolocation, which provide locations to users; that is, location-based recommendations that enable use of the global positioning system (GPS) in travel domains (Bao *et al.* [86]) based on the user's preferences. The locations, usually derived from the user's check-in spots, are considered part of the historical collection of human movement in reality. The social recommendation systems extract the user's raw data such as tags, comments, reviews, friends, and attributes on social networks. Many social recommenders have proposed a personalized system to enhance collaboration and users' experiences on social media [44].

All of the above studies are based on the two types of recommendation aspects: two-dimensional (2D) or classical and multidimensional or contextual. Generally, type 2D falls under traditional recommendation approaches, which only encompass two fields [45]. For example, the two recommendation fields in terms of user and item include User X Item, Item X User, or User X User. The MD type utilizes dimensions such as User $\times$ Tag $\times$ Items or User $\times$ Item $\times$ Tag. Thus, the resultant rating (R) represents $R = \text{MD1} \times \text{MD2} \times \text{MD3} \times \text{MD4} \times \ldots \ldots \times \text{MDn}$. This approach uses more than one attribute for recommendations [46]; for instance, entities in the online shopping domain (item id, name, manufacturing year, and remark). Hence, a recommendation function will turn to multiple attributes or be multidimensional in the matrix format, which will lead to more accuracy in a recommendation.

Generally, for recommender systems, a user profile is usually compiled and personalized with a score of item/user/information from a large amount of content data for recommendations [47]. This score determines user ratings in developing recommendations on social media websites. Based on the rating, the highest ranking users are recommended by the recommender system as experts. Recently, several scholars have concentrated on the multiple forms of implicit and explicit information as significant factors from social media websites in generating user profiles to quantify users' ratings or rankings for recommendations [48], [49].
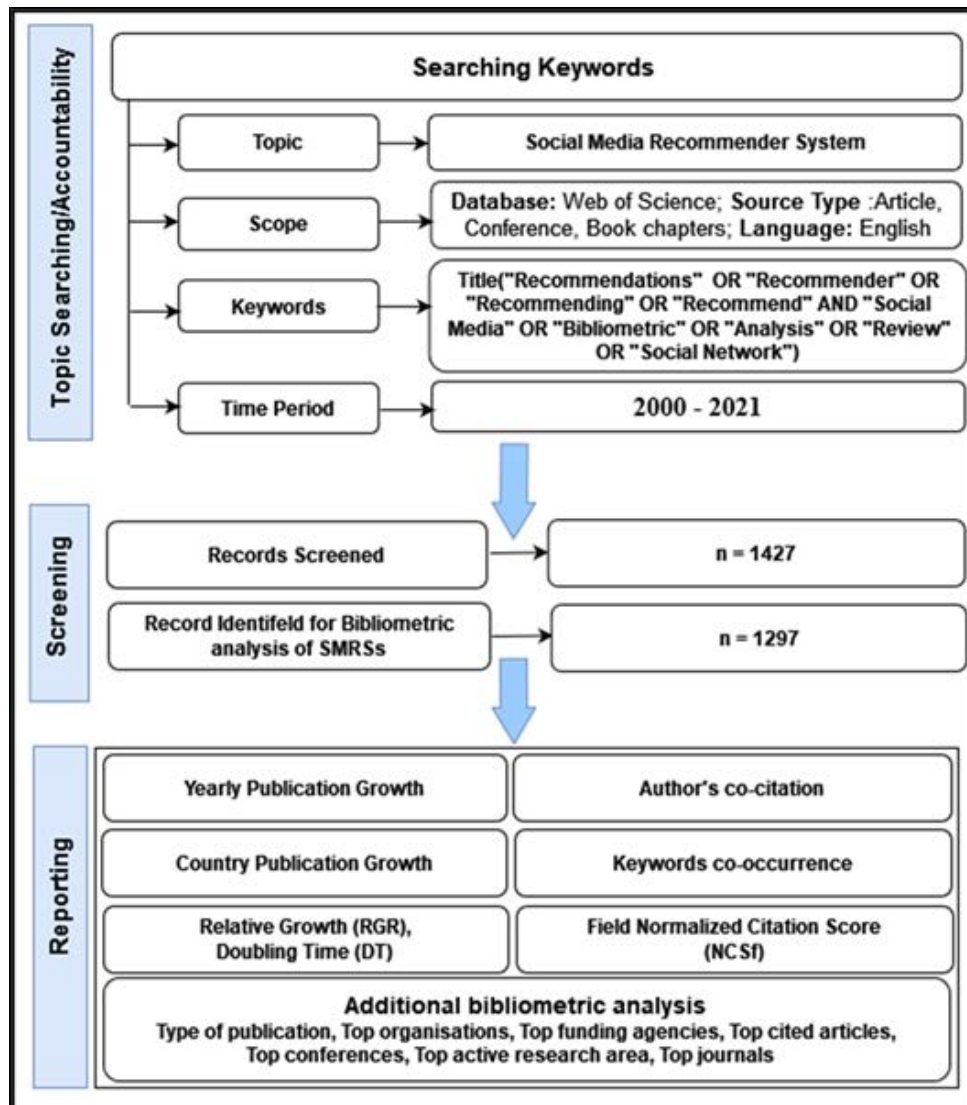
FIGURE 1. Research design.

III. METHODOLOGY

This section covers the collected data, regulated by the query and sequential steps of the research design. Social media comprise an upcoming research area in various domains, as evident in the growing number of publications. The Web of Science (WoS) is a verified, reliable database used to collect research publications [53], [54]. The collection on WoS mainly consists of scholarly journals, conference proceedings, and book chapters with a traditional science citation index between 2000 to 2021 related to recommender systems in social media are considered for this study. A graphical representation of the current study's research design is shown in Figure 1.

This bibliometric study involved scholarly works published between 2000 and 2021 on WoS where information such as authors, file name, publication type, version, citation,

DOI, organization(s), funding, and other relevant details were analyzed using the functions available on Microsoft Office Excel. WoS was selected as a data source since it is a reservoir of data spanning multiple disciplines, and links to full-text articles are available [50]–[52]. The first step in the data collection procedure was to create a query to extract appropriate articles: [TS = ("Recommendations" OR "Recommender" OR "Recommending" OR "Recommend" AND "Social Media" OR "Bibliometric" OR "Analysis" OR "Review" OR "Social Network")]; Timespan = 2000 - 2021; Indexes = SCI-EXPANDED, A&HCI, SSCI, CPCI-S, CPCI-SSH". Different keywords were used in the data collection process where they mostly involved different definitions associated with SMRS. The articles extracted from the above query and the subsequent set of articles considered serve as a comprehensive dataset to achieve this paper's objectives.

The research design outlines the steps of searching the topics, scope, keywords, and time period, along with the number of selected and rejected articles.

A total of 1427 publications were initially found where 1297 relevant publications contained an indicator of higher quality based on the citation index. These high-quality articles were then selected based on their concerning recommendations and the use of social media resources and platforms. The remaining 130 articles were rendered irrelevant and subsequently excluded. The findings of this bibliometric study are discussed in the following subsections, along with results and charts.

IV. ANALYSIS AND FINDINGS

This section covers current SMRS trends through a quantitative analysis of yearly publication growth, with percentage and country ranking based on publications between 2000 and 2021. Further, the relative growth rate (RGR), doubling time (DT) and field-normalized citation score (NCSf) are based on the citation score for each SMRS field category using mathematical expressions. These scientometric indications were employed to identify the citation gains of publications.

A. NUMBER OF PUBLICATIONS PER YEAR

This section analyzes the overall growth of SMRS research by counting the number of articles published in a given period of time. The publication growth of articles on SMRS, consisting of 1297 SMRS-related papers from 2000 to 2021, is presented in Figure 2. Between 2000 and 2005, about 4-17 articles were published annually, charting a publication rate of 1% only. Between 2005 and 2015, a gradual increase in publications was reported, which is considered satisfactory. This gradual increase, beginning in 2008, culminated in 2015 with 173 publications, accounting for 10.32% of the publication rate.
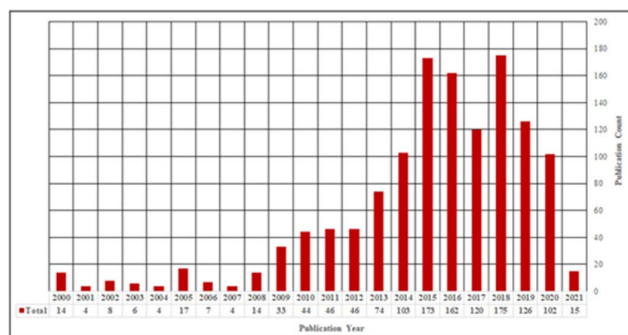
FIGURE 2. Publications per year.

Despite the fluctuation between 2016 and 2021, there was a stable rate of publications each year from 9% to 13% in the total publications on SMRS; in 2018, the publication count once again achieved a record high at 13.49% (175 articles) of the annual publication rate. This shows large-scale growth. However, in 2019, there was a notable reduction, which continued into 2021, when only 15 articles were published.

The results indicate the fluctuating trend of perceiving the research interest rate as the total number of articles according to year, documenting the saturation and peak publication periods where the percentage of differences in publications on SMRS is evident in these years.

B. NUMBER OF PUBLICATIONS PER COUNTRY

Based on the selected WoS data source, this section analyses the total number of publications and citation frequency according to countries between 2000 and 2021. The 10 most active countries were ranked according to the estimation of the total number of publications on SMRS. The People's Republic of China and the USA lead the chart by occupying the first two spots of the 10 most active countries.

The People's Republic of China produced 343 publications, approximately 26.43% of all articles besides having a higher number of citations. On the other hand, the USA published 156 (12%) of SMRS-related articles, followed by Spain with 108 (8.41%) publications. The SMRS concept was also researched in Germany and Taiwan, which published 89 (6.86%) and 80 articles (6.16%), respectively. The remaining countries of England, Australia, India, and Italy published 51 to 62 (4%) articles, while the rest of the countries on the list published less than 50 (2%) publications, indicating the trend of SMRS in those countries. South Korea ranked last on the list, where it comparatively published 33 articles less than the other countries in the list of top active countries.

The comparative assessment of the total publication growth count and the corresponding citation count exploitation of SMRS of these 10 countries is depicted. The total citation count for each country is represented by the line chart, while the corresponding values of the total publications denoted by bars during the selected period. The notable changes in this visualized citation count include 3824 citations for 343 published articles by the People's Republic of China while the USA recorded 4018 citations for the 156 publications between 2000 and 2021.

The number of publications from the People's Republic of China (3824 citations) was twice the number of publications from the USA (4018 citations), which got less citations. Ranking second, the USA clearly published fewer articles and possessed more citations, which indicates the quality of SMRS articles published in this country compared to other nations. In order to acquire a better representation of quality- which impacts the number of articles and the total citations of the published articles—the results of total publications, total citations, average citations per publication (C/P), and average citations per cited publication (C/CP) were computed per country in Table 1.

The rest of the countries on the list imply the strength of the results of recommendations based on the technology development in a particular country [55], [56]. The fewer publications in the remaining countries published are perhaps due to the weak influence of studies in the SMRS field, as the total number of articles on SMRS determines each respective country's research productiveness and development of future

TABLE 1. Publications per country for SMRS.

Country	TP	NCP	TC	C/P	C/CP
China	343	197	3824	11.14	19.41
USA	156	141	4018	25.76	28.50
Spain	108	97	2533	23.45	26.11
Germany	89	70	2165	24.33	30.93
Taiwan	80	74	2343	29.29	31.66
England	62	56	1425	22.98	25.45
Australia	54	49	766	14.19	15.63
India	53	39	473	8.92	12.13
Italy	51	41	1133	22.22	27.63
South Korea	33	27	578	17.52	21.41

Note: TP=total number of publications; NCP=number of cited publications; TC=total citations; C/P=average citations per publication; C/CP=average citations per cited publication

research interests, which are often reflected in the productivity distribution.

Figure 3 reveals the chart which shows the statistics of the number of papers published and total number of citations for top 10 countries. The total number of publications and Total citations are combined in the following figure, bar chart represent total publications and line chart represent total citations. This shows the growth of publications as well as total citations for top countries.
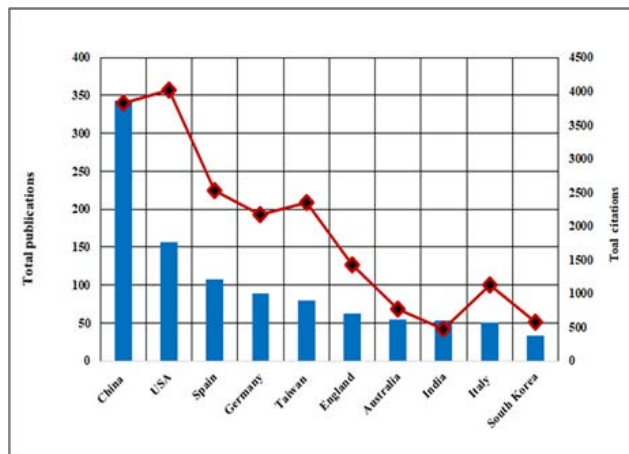

FIGURE 3. Publication per country versus citation.

C. RELATIVE GROWTH RATE (RGR) AND DOUBLING TIME OF PUBLICATIONS (DT)

Based on the outcomes and discussion of the current study, the prominence of the research output was measured by metrics. This form of quantification is important in charting the growth of the research level used in this bibliometric analysis. The research outcome, comprising the total number of publications, was measured using two scientometric techniques:

Relative Growth Rate (RGR) and Doubling Time (DT) [57]. These metrics are employed to compute the growth rate of research productivity during the period of 2000–2021, which is described in this section.

1) RELATIVE GROWTH RATE

The Relative Growth Rate (RGR) and Doubling Time (DT) model are scientometric indicators used to gauge the overall production growth rate of publications [58]. In this case, the growth of SMRS publications was identified by RGR and DT, since both scientometric indicators are interrelated in analyzing growth rate computations for a specific timeframe. The RGR for the published articles during the set period was computed using the following formula:

Relative Growth Rate (RGR) of publications

$$\mathbf{R\,(P) = P2 - P1/T2 - T1} \tag{1}$$

where P1, P2 = Cumulative number of publications in T2 & T1

R = Mean relative growth rate over the specific period of intervals

W1 = LogP1 (natural log of the initial number of contributions)

W2 = LogP2 (natural log of the final number of contributions)

T1 = the unit of initial time; T2 = the unit of final time.

2) DOUBLING TIME

A direct equivalence between the RGR and Doubling Time (DT) was identified by calculating the variation in the logarithms involving the numbers from the start to the end of the time period [59]. The logarithm (ln) 2 must be employed if the total count of contributions of the subject doubles within a specific period. The value of ln (2) was computed using the Napier logarithm, which has a value of 0.693 [60]. On the other hand, the corresponding doubling time of publications was computed using the formula:

$$\mathbf{DT\,(P) = 0.693/RGR}$$

Table 2 presents the RGR and DT of publications contributed by the WoS database between 2000 and 2021; the data were sorted based on the number of publications concerning SMRS trends. The values are slightly ups and downs in that time period. The RGR value declined in 2005 (0.12), and a slight deviation of values between 0.12 and 0.35 was recorded from 2006 to 2009.

Likewise, the subsequent set of RGR values between 2010 and 2014 recorded inconsistencies between 0.26 and 0.34. In 2015, this value reached 0.24 and experienced a slight discrepancy in values between 0.01 and 0.24 for the next five years. For better understanding of RGR and Mean figures are averaged for each five years are recorded in that time period.

TABLE 2. Relative growth rate and doubling time of publications.

Publication Year	Number of Publications	Cumulative Sum	W1	W2	RGR	Mean (R)	DT (P)	Mean (DT)
2000	14	14	0	2.8	2.8		0.2	
2001	4	18	2.89	3.26	0.36		1.88	
2002	8	26	3.26	3.47	0.20		3.34	
2003	6	32	3.47	3.58	0.11		5.88	
2004	4	36	3.58	3.97	0.38	0.79	1.79	2.62
2005	17	53	3.97	4.09	0.12		5.59	
2006	7	60	4.09	4.16	0.06		10.74	
2007	4	64	4.16	4.36	0.19		3.50	
2008	14	78	4.36	4.71	0.35		1.96	
2009	33	111	4.71	5.04	0.33	0.21	2.08	4.77
2010	44	155	5.04	5.30	0.26		2.67	
2011	46	201	5.30	5.51	0.20		3.36	
2012	46	247	5.51	5.77	0.26		2.64	
2013	74	321	5.77	6.05	0.27		2.49	
2014	103	424	6.05	6.39	0.34	0.27	2.03	13.18
2015	173	597	6.39	6.63	0.24		2.89	
2016	162	759	6.63	6.78	0.14		4.72	
2017	120	879	6.78	6.96	0.18		3.82	
2018	175	1054	6.96	7.07	0.11		6.14	
2019	126	1180	7.07	7.17	0.08		8.36	
2020	102	1282	7.16	7.17	0.01	0.15	52.61	78.52
2021	17	1299	7.17	0.00	0.00		0.00	

D. FIELD-NORMALIZED CITATION SCORE (NCSf) OF SMRS FIELD CATEGORIES FOR TOP COUNTRIES

This section expands on the field-normalization citation score by comparing the set (country/journal/researchers) of publications with the global average citations using similar works published in the same year or in the same research field. Based on the global average citations, the active and current trends of recommendation field categories were identified.

A more recent method proposed by Van den Besselaar and Sandstrom [54] utilized the NCSf as an indicator to measure the level of independence in terms of productivity and impact equality for publications [61], [62]. In the current study, the NCSf was computed using two parameters—citation per paper (CPP) and citation impact (CI)—where the resultant score determined the publication significance. The computed NCSf score decides significance of 1.4 and higher ="excellent"; 1.2 and higher ="very good"; 1.0 and higher is the international average, which is "good"; below that is considered "weak." The formula for measuring the significance includes CPP and CI can be expressed as follows [63].

Field − Normalized Citation Score (NCSf) = CPP/CI;

where CPP=citation per paper, CI=citation impact (CI).

The Citation Impact (CI) of a journal for a specific recommendation field refers to the journal's impact factor, which evaluates its rate of publication and rate of citations. This parameter involves the ratio between the number of times a published article is cited in the given "collected" years before the analysis, and the total number of articles published during the same allocated "collected" years [64], [65]. The value of the CI for the 1297 selected articles was 13.323, computed from the WoS data source. Table 3 summarizes the NCSf performance indicators for the top 20 countries based on SMRS fields such as *item*, *user*, *location*, *friend*, *mobile*, *tag*, *event*, *tour*, and *game*.

Greece's high performance can be attributed to the consideration of user behavior, comments, similarity, interactions, trust relationships, and the user's activeness in research. The adoption of a multidimensional perspective in computing the degree of trust between users for efficient recommendations on social media also contributed to this performance [67].

Rooted in the item-based recommendation system field, four other countries also recorded significant influence: England, the USA, Australia, and South Korea all exceeded the international level benchmark with NCSf scores of 3.79, 2.13, 1.83, and 1.62, respectively. England's high score is due to the expanding technological upgrade in social

TABLE 3. Top 20 countries NCSf for SMRS field categories.

	Item	User	Location	Friend	Mobile	Tag	Event	Tour	Game
China	0.21	0.83	0.54	0.40	0.11	5.60*	0.22	---	---
USA	1.54*	2.13*	3.56*	1.61*	---	0.14	0.50	2.15*	---
India	0.05	0.17	0.50	0.17	---	0.33	0.00	0.00	---
Canada	1.98*	0.60	1.15	0.04	1.56*	0.45	0.20	---	---
Iran	0.34	0.38	---	0.71	---	---	---	---	0.11
South Korea	---	1.62*	1.04	0.71	0.57	8.84*	0.00	---	---
Australia	---	1.83*	0.09	1.00	3.56*	---	0.33	0.20	---
Taiwan	0.96	0.57	---	---	0.45	---	---	0.47	---
England	0.16	3.79*	3.96*	0.19	---	---	---	---	0.40
Italy	1.74*	1.01	0.95	---	0.71	---	---	0.27	---
Greece	2.73*	---	0.36	---	---	---	---	0.18	---
Turkey	---	---	0.27	---	---	---	---	---	---
Bangladesh	---	---	---	0.10	---	---	---	---	---
Belgium	---	---	---	0.00	---	---	---	---	0.00
Finland	---	---	---	---	0.00	---	---	---	---
Saudi Arabia	---	---	---	---	0.00	5.70*	---	---	---
Egypt	---	---	---	---	0.00	0.22	---	---	---
Singapore	---	---	---	---	---	0.65	---	---	---
United Arab Emirates	---	---	---	---	---	0.30	---	---	---

Note: * - Excellent

communication among peers in a specific network, where the item field is analyzed using a new dimension to seek item similarities, especially in e-commerce, multimedia, and travel recommendations since it holds key information [68].

For the location-based field category, two countries (England and the US) recorded more influence compared to other countries, with scores of 3.96 and 3.56, respectively based on disciplinary peer review. The familiarity of location-based research through the use of geographic neighborhoods is grounded in factors such as user activity, global map-based tools, and exploration in terms of geographic points for location identification of users on social media [69]. For the friend field category, the USA recorded the highest performance due to its observation of social friendships, social influence, location-based geo-friends, and mutual friends in crowded data for better recommendations [70]–[73]. Additionally, the mobile field category reported two countries—Australia (3.56) and Canada (1.56)—as having the most influence. The influence exerted by these two countries can be explained in terms of the technological development in communication among users, as mobile devices can achieve a high ratio of delivery of information. Moreover, mobile devices are fairly easy to use and offer opportunities in various domains such as learning, online shopping, geo sharing, and gaming, contributing to their high performance in mobile-based recommendations [74].

As for the tag-based category, three countries exceeded the international level benchmark, namely, South Korea, Saudi Arabia, and the People's Republic of China scored an NCSf of 8.84, 5.60, and 3.71, respectively. These high scores are due to tag utilization in diverse sharable web-based content such as news, videos, articles, and bookmarks [75]. Researchers may also account for advanced tag features from websites involving the probability matrix trust score, cross-domain tag similarities, and hashtags in blogs based on implicit and explicit information in analyzing the user's specialization/interests [76].

The People's Republic of China was the only country in the event-based category that acquired a high NCSf score, since the PRC utilized factors related to user requirements in their research methodology, as well as in their recommendations for new research directions [77]. In fulfilling the user's requirements, new dimensional approaches are considered in travel information such as particulars, opinions, traffic conditions, group travel, and the crowdedness of places. The final category, gaming, requires more publications to overcome the limitation in this domain. The NCSf results discussed in this section are limited to 20 countries, as the remaining countries had a low score and were deemed non-applicable. The table covering NCSf performance demonstrates that countries whose scores are listed with (∗)—awarded the performance level of "excellent"—produced research articles
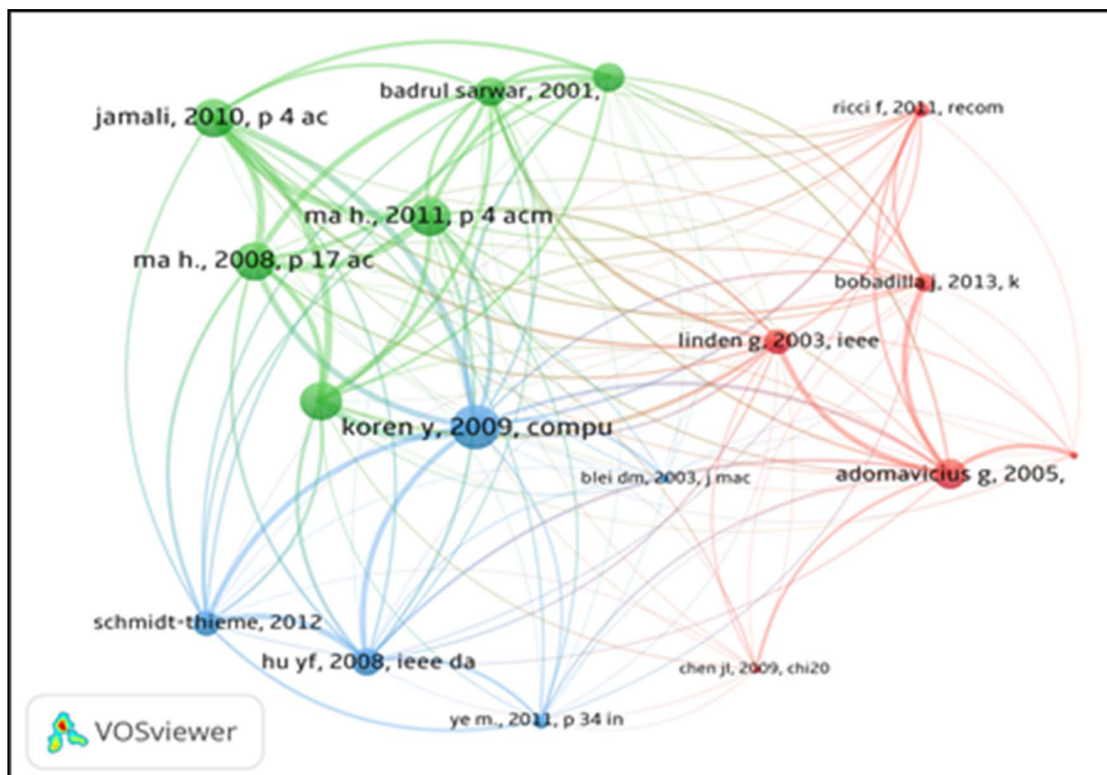
FIGURE 4. Co-citation SMRS knowledge map.

for each category. The findings of the normalization score performance contribute to current knowledge trends in the SMRS recommendation field categories of a particular country, in addition to addressing the knowledge gap concerning social media resources.

E. NUMBER OF AUTHOR'S CO-CITATION

This section expands on the analysis of author co-citations, which entail incidents where two works simultaneously appear in other literature, reflecting a co-citation relationship. This analysis established the connections among authors by identifying authors who are co-cited by a set of publications [78]–[80]. The co-citation network for this bibliometric analysis is shown in Figure 4, where it consists of the top three clusters among 1095 nodes and 250 links. The VOSviewer tool provides an in-depth visualization network of the analysis of author co-citations [81].

The link between two nodes reflects two co-cited works, while the size of the node denotes the frequency of citations. McCain [71] proposed identifying the similarity of articles using the number of author co-citations [82]. Therefore, the current study selected SMRS-related articles with citations from three notable clusters differentiated by color for easy visualization. The analysis of author co-citations Figure 4 accounts for the 20 citations visualized by VOSviewer. Accordingly, 53 co-cited authors with

publications between 2001 and 2021 were then grouped into three clusters.

These three clusters are differentiated by green, blue, and red. Similar colors highlighted in the network map represent authors who are co-cited in publications and frequently occur together. The top three clusters are differentiated by green, blue, and red respectively based on the top citation numbers. Similar colors, highlighted in the network map, denote authors who are co-cited in publications and appear closely together. These significant findings—from the limited number of the top 3 clusters of author co-citations— were observed in the results. Each circle is labelled with the name of the first author, followed by the year of publication for the article. The size of each circle refers to normalized publication citations, while the thickness of a line indicates the strength of the co-citations. More thickness shows more strength and its association by different color for easy understanding. The circle size is varying based on co-citations of authors. Further, the color of a bubble shows the cluster with which an article is associated. The main cited references of an article, total citations, links, and article title are documented in Table 4.

Adomavicius (2005), Koren (2009), Ye (2011), Ma (2011) and Linden (2003) are the authors with the highest co-citations in the red, green and blue clusters respectively. This implies that the literature of co-citations represents the

TABLE 4. Co-Citation literature of SMRS.

Author	Citation	Link	Title
Adomavicius, G., Tuzhilin, A. (2005)	59	67	Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions
Koren, Y., Bell, R., Volinsky, C. (2009)	36	98	Matrix factorization techniques for recommender systems
Ye, M., Yin, P., Lee, W. C., Lee, D. L. (2011)	29	32	Exploiting geographic influence for collaborative point-of-interest recommendations
Ma, H., Zhou, D., Liu, C., Lyu, M. R., King, I. (2011)	28	85	Recommender systems with social regularization
Linden, G., Smith, B., York, J. (2003)	26	57	Amazon. com recommendations: Item-to-item collaborative filtering

knowledge base of current trends in SMRS-related research, which is preferred by researchers to move forward for finding the novel way.

F. NUMBER OF KEYWORD CO-OCCURRENCES
This section analyzes the co-occurrence of keywords identified from the titles, keyword sections, and abstracts of the retrieved publications. The graph for the keyword co-occurrence network consists of 250 connections where the threshold level was set at a minimum number of 7 keyword occurrences for the analysis. The keywords for the top four clusters are demonstrated in Table 5. The graph for the keyword co-occurrence network consists of 250 connections where the threshold level was set at a minimum number

of 7 keyword occurrences for the analysis. The co-occurrence of keywords was also examined using the VOSViewer for visualization.

The prominent clusters that emerged in this network map, which presents a subfield of research in SMRS, are differentiated by the green, blue, violet, orange, and yellow clusters. The color, font size, frame size, and thickness of the lines in the network visualization map indicate the degree of relatedness between the nodes, while the visualized keywords are frequently used keywords for SMRS research in the selected articles.

The keyword "recommender systems" was the most frequently used as it has a larger frame size where it can occur as the full/short form or as singular/plural. While the results show co-occurrences for keywords from 2000 to 2021, there are some limitations in attributes or keywords that are useful for identifying the characteristics of answering in a specific domain. The visualization map achieved for the keyword network was constructed based on the frequency of co-occurrence for the top 20 keywords out of a total of 1135 retrieved keywords. The 10 most frequently co-occurring keywords were "social network" (69), "recommender system" (69), "social media" (65), "algorithms" (64), "model" (63), "trust" (60), "algorithm" (58) and, "network" (48). Their occurrences indicate that these keywords are central to research and help to reinforce the influence of SMRS studies, as shown in Figure 5. Each node illustrates a keyword, where keywords connected by lines are frequently used, in addition to representing the keywords employed by SMRS studies published from 2000 until 2021.

The prominent clusters that emerged in this network map, which presents a subfield of research in SMRS and is differentiated by the green, blue, violet, orange, and yellow clusters. Different colors are used in the map for easy understanding of the keyword groups. The color, font size, frame size, and thickness of the lines in the network visualization

TABLE 5. Co-occurrences of keywords for SMRS.

| #	Subject	Keywords	References
1	Social network	Collaboration, information retrieval, internet of things, link prediction, text mining, recommendations, social network analysis, big data analytics, data mining, machine learning	Mazhari, Fakhrahmad & Sadeghbeygi, 2015; Katarya & Verma, 2017, Lopes, Fidalgo-Neto & Mota, 2017; Wu et al., 2015; Zhang el al., 2017; Rawashdeh et al., 2017; Xiao et al., 2017; Fang et al., 2018; Margaris et al., 2019; Zhao et al., 2020;
2	Recommender system	Group recommendations, data models, context modelling, data models, personality, social influence, social recommendations, trust, social networks,	Zhang et al., 2013, Maniktala et al., 2015; Chen et al.,2016; Yang & Huang, 2017; Alam & Ismail, 2017; Zheng et al., 2018; Missaoui et al., 2019; Yang et al., 2016; Noor et al., 2020
3	Algorithms	Design, algorithms, experimentation, human factors, measurements, performance, personalization, topic model, tensor factorization, user modelling	Hong et al., 2014; Zhao et al., 2015; Li, Ngai & Chai, 2015; Hasan et al., 2015; Liu et al., 2018; Shukla, Singh & Verma, 2019; Beheshti et al., 2020; Chang et al., 2020
4	Social networking services	Twitter, Facebook, online communities, entertainment videos, games	Huang, 2016, Sharma et al., 2017; Liu & Zhong, 2018; Zheng et al., 2018; Neshati, Fallahnejad & Beigy, 2017; Roy et al., 2018; Chen et al., 2019; Liu & Ma, 2020
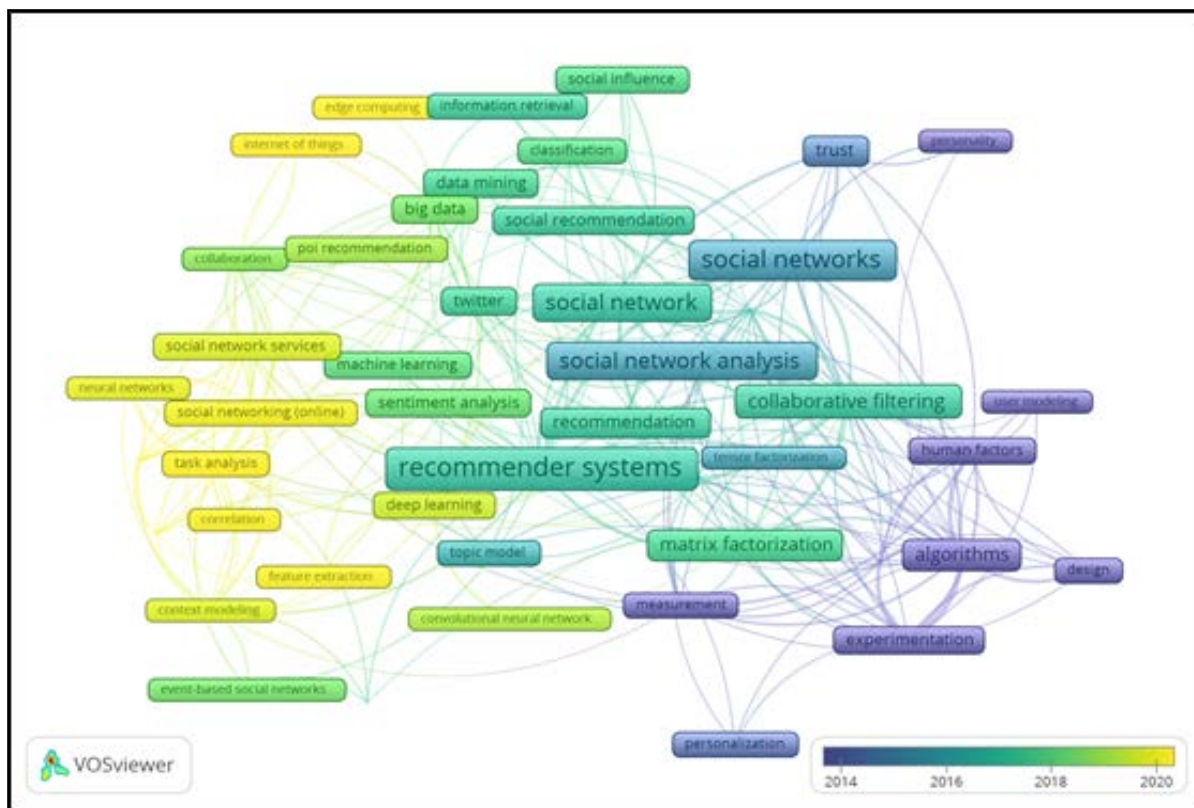
map demonstrate the degree of relatedness between the nodes in the map, while the visualized keywords are frequently used keywords for SMRS research in selected articles. Thus, the keyword "recommender systems" is the most frequently used as it has a larger frame size where it can occur in the full/short form or as singular/plural. While the results suggest the co-occurrences for keywords from 2000 to 2021, there are some limitations in attributes or keywords that are useful for identifying the characteristics of answering in a specific domain.

The VOSViewer tool utilising for creating visualization map of the keyword network was developed based on the frequency of co-occurrences for the top 20 keywords out of a total of 135 retrieved keywords. Also, the visualization map helps in understanding of co-occurrences in a clear way. The 10 most frequently co-occurring keywords in publications are "social network" (69), "recommender system" (69), "social media" (65), "algorithms" (64), "model" (63), "trust" (60), "algorithm" (58) and, "network" (48). This shows the growth and trends of SMRS particularly in that time period.

Their occurrences indicate that these keywords are central to research and help to strengthen the influence of especially in recommender systems in social media studies for new researchers. Each node illustrates a keyword, where keywords connected by lines are frequently used, in addition to

representing keywords used by SMRS studies published from 2000 until 2021.

V. ADDITIONAL RESULTS OF BIBLIOMETRIC ANALYSIS

Additional bibliometric analysis was conducted on SMRS-related studies, namely the type of publication, the top publishing organizations, the top funding agencies, the top conferences, the top active research area, and top journals from 2000 to 2021. The significance of additional bibliometric analysis based on citations, publications, and popularity—which helps young researchers of SMRS literature—and top numbers are outlined in the following subsections. For each category the results are documented for top items in the following sections.

A. TYPES OF PUBLICATION

The dataset of the current study was also examined based on document type with total publication percentage; three main categories were identified: journal articles, conference papers, and book chapters. These publication types, which comprise the full sample for this study, are listed in Table 6. The data source, WoS, was the only comprehensive database to provide citation data and freely available full texts from preprint servers or personal websites, as well being freely available for all users. The family of ISI citation indexes makes up the core of WoS. References are automatically

extracted from the full text of the indexed items and include all references cited by papers in the primary (source) documents. The WoS continuously includes journals in its indexes regularly for all types of documents [83]. Based on the above keywords discussed in Section III, three types of documents were selected from 2000 to 2021. The most salient type of document was journal article, with 847 (65.25%) articles, which is a high number, indicating that the authors are most likely researchers who document their findings in published articles.

TABLE 6. Publication type.

Document Type	TP	Percentage (%)
Article	847	65.25
Conference Paper	457	35.20
Book Chapter	35	3.69

Notes: TP=total number of publications;

WoS had more research papers in recommender systems-related research, but especially while filtering SMRS-related conference papers published between 2000 and 2021 using set of keywords especially related to "recommender system" and "social media". The search keywords yields the result count is amounted to 457 (35.20%) as the second most common type of document. The selected articles were indexed in WoS during this period. As for the remaining documents, they fell under the book chapter type, at 35 (3.69%). The findings suggest that most SMRS-related articles examined for this bibliometric analysis and published between 2000 and 2021 can be classified either one of these three document categories.

B. TOP ORGANISATIONS

Table 7 outlines the top institutions involved in publishing SMRS-oriented work, with most of them located in the People's Republic of China and the USA. Aspects such as country, total publications (TP), total citations (TC), and average citations per publication (C/P)—covering the period between 2000 and 2021—are also listed. The first top four institutions are from the People's Republic of China while the fifth institution is from the USA. The Chinese Academy of Sciences leads the list as it is responsible for publishing nine SMRS articles with 104 citations. Peking University occupies the subsequent spot with nine articles, followed by Wuhan University, which published 6 articles in the SMRS field. On the other hand, Huazhong University produced seven articles while the University of Florida produced five publications.

Organizations in the People's Republic of China are leading the game as they explore advanced technology and deploy different perspectives of talented key features in social media research. In addition, China is a progressing nation where rapid technological growth is prioritized in organizations.

TABLE 7. Top 5 productive organisations on SMRS.

Organization	TP	TC	C/P
Chinese Academy of Science (RPC)	9	104	11.55
Peking University (RPC)	9	218	24.22
Wuhan University (RPC)	6	278	46.33
Huazhong University (RPC)	7	173	24.71
University of Florida (USA)	5	163	32.60

Notes: TP=total number of publications; TC=total citations; C/P=average citations per publication

TABLE 8. Top funding agencies.

Funding Agency	TP	Percentage (%)
National Natural Science Foundation of China (NSFC) (RPC)	168	12.94
National Science Foundation (NSF) (RPC)	22	1.69
Fundamental Research Funds for the Central Universities (RPC)	16	1.23
National Basic Research Program of China (RPC)	16	1.23
National High-tech R&D Programmes of China (RPC)	11	0.84

Notes: TP=total number of publications;

In the case of the USA, the country supports new innovation and creativity in SMRS research.

C. TOP FUNDING AGENCIES

A total of five hundred and seventy eight funding agencies supported approximately 64.09% of the 1297 SMRS publications from 2000 to 2021. Table 8 presents the list of the top five funding agencies that supported more than 100 studies.

This information is especially useful for SMRS researchers. Leading the ranking list is the National Natural Science Foundation of China (NSFC), which funded 168 publications (12.94%). The NSFC funded 1.69% more publications than other agencies, which funded fewer than 20 publications. Most active funding agencies consist of Asian organizations where the top five funding agencies are located in the PRC, facilitating the knowledge transformation of future researchers. The results outline the top funding agencies that support SMRS research, with the PRC being in the lead.

D. TOP-CITED ARTICLES

Table 9 presents the SMRS articles with the highest citations from the pool of 487 cited articles included in this study under a single document type category. The most ten popular papers have the highest citations which were published between 2000 and 2020.

TABLE 9. Top-Cited articles on SMRS.

Authors	Article Title	Year	TC	TP	C/P
Ma, TH; Zhou, JJ; Tang, ML	Social Network and Tag Sources Based Augmenting Collaborative Recommender System	2015	1732	173	38.57
Bao, J; Zheng, Y; Wilkie, D;	Recommendations in location-based social networks: a survey	2015	1731	173	44.50
Wang, ZB; Liao, JL; Cao, Q	Friend book: A Semantic-Based Friend Recommendation System for Social Networks	2015	1731	173	42.33
Bonilla, CA; Merigo, JM; Torres-Abad, C	Economics in Latin America: a bibliometric analysis	2015	1230	173	107
Majid, A; Chen, L; Chen, GC;	A context-aware, personalized travel recommendation system based on geotagged social media data mining	2013	1125	74	61.00

Notes: TC=total number of citations; TP=total number of publications; C/P=average citations per publication

TABLE 10. Top conferences on SMRS.

Conference Title	TP	Percentage (%)
17th Conference of the International Society for Scientometrics	23	1.77%
12th Conference of the International Society for Scientometrics	16	1.23%
16th Conference of the International Society for Scientometrics	14	1.08%
15th Conference of the International Society for Scientometrics	13	1.00%
13th Conference of the International Society for Scientometrics	13	1.00%

Notes: TP=total publications

TABLE 11. Most active research area on SMRS.

Research Area (Computer Science)	TP	Percentage (%)
Information Science/ Library Science	715	55.08
Engineering	116	8.93
Telecommunications	87	6.70
Business Economics	17	1.31
Educational Research	13	1.00
Other	349	26.98
Total	1297	100

Notes: TP=total publications

The article with the most citations is entitled "Social network and tag sources based on augmenting a collaborative recommender system," which recorded 1732 citations. Its popularity can be linked to the implementation of software for factorization machines in terms of modelling and innovation, utilizing in-depth expert knowledge. These highly-cited articles account for more than 1000 citations, where the popularity of the article is determined by its yearly citation rate. These findings also reflect the recommendation approaches and various SMRS domains, while the high number of article citations between 2002 and 2015 demonstrate the development of SMRS.

E. TOP CONFERENCES

The current study also analyzed conference proceedings on SMRS. Conference proceedings are not widely cited compared to journal articles, highlighting the significance of the document type. The citations and percentage details of these documented conference proceedings are included in Table 10. Conference proceedings were deemed a less popular publication type when compared to journal articles in the SMRS field. This situation is due to the smaller proportion of research works presented as conference papers since the article document type is preferred, which awarded low in citation numbers.

F. TOP RESEARCH AREA

The distribution of research fields in this study, collected from computer science, includes information science/library science, engineering, telecommunications, business economics, and education research on SMRS, collected from the WoS data source and spanning 2000 to 2021. As illustrated in Table 11, out of these tabulated results, more than 50% of the documents originated from the field of information science/library science and computer science (55.08%); the remaining ones comprised less than 10% of publications from 2000 to 2021.

G. TOP JOURNALS

In the current study, the journal articles were also analyzed based on their total number of publications collected and the number of publications in journals. This outcome of the analysis also provides insight into journal popularity. Table 12 illustrates the five most popular journals that are responsible for publications where the details of percentage and total number out of 1297 articles on SMRS are listed. The Scientometrics and IEEE Access journals are scholarly journals obtained top two places shows that are more on particular researches. Those are more focused on information and scholars who are experts respected on SMRS field.

Journal Name	TP	TC
Scientometrics	43	1767
IEEE Access	23	205
Information Processing & Management	10	323
Information Sciences	10	306
Multimedia Tools and Applications	10	70

Notes: TP=total publications; TC=total number of citations;

Scientometrics is the most popular journal, publishing over 43 articles (1767 citations), followed by IEEE Access (23 articles with 205 citations) within the timeframe set for this study. The remaining journals hold a publication count of around 10 articles on SMRS from 2000 to 2021.

VI. DISCUSSION

In this study, 1297 articles regarding SMRS were selected from among 1427 articles derived from WoS using various filters such as year, language and category. This study included journal articles, reviews, and conference papers related to SMRS. This study revealed various notable information and provides a scope for different factors for extending the research further.

Searching pattern using set of keywords used for selecting articles related to recommendation in social media includes "recommendations", "recommender", "recommending" and "recommend" between the selected time periods in this study. This bibliometric study have performed analysis and an extensive analysis based on the global average citations, the active and current trends of recommendation field categories were identified using information retrieval platform WoS. Additionally, the organisation analysis, funding agencies and author analysis are documented. The documented findings provided valuable information about SMRSs researchers that can be easily understand the research status and current trends in social media are expressed in each section of this study.

As seen in Figure 2 and in Figure 3, for publication growth in the year 2000, only 14 articles were produced; this figure remained unstable until 2008. After 2008, SMRS publication growth started increasing and reached 175 publications in 2018.The gradual increase in publications from 2000 to 2021 confirms the trend of the SMRS field. The main reason for this trend, especially on social media, is the channel for gathering and sharing information in real time among users [83], [84]. This is due to the easy accessibility of social media websites for different domains (which are growing and are easily available online) [85], as well as the accessibility of the internet through different digital devices in recent years; around a billion people use social media every day [86].

Additionally, the exponential growth from a low to a high level of development in the SMRS field is the upcoming research since the early 21st century. The growth in publication can be attributed to the increase in research interests in SMRS on various platforms. Recommender systems have evolved in different fields across diverse trends in recent studies on recommender systems, including machine learning [87], big data [88], text mining [89], and location-based [90]. Moreover, there is a new direction for scholars using different metadata from social media websites for research in SMRS.

The country-wise distribution of SMRS-related articles and citations, shown in Table 2, help scholars to understand the international position in SMRS research. The top country is China (343 publications), followed by the USA (156 publications); the remaining countries produced fewer publications. Due to the popularity of social media, the majority of authors in China have produced vast publications on social media [91]. China is more focused on empirical and quantitative research on SMRS; the literature has gradually become enriched with content types such as e-commerce, digital library, location, and entertainment compared to other countries [92]. The USA produced fewer publications but cited more studies (4018 citations) than China (3824 citations). The most cited article from the USA is entitled, "Recommendations in location-based social networks: A survey" by Bao *et al.* [86], which identified 287 citations (average: 35.88%). The reason is the more theoretical research and practical application in the USA [93]. As for China and the USA, both countries are leading in terms of the number of articles and citations compared to other countries. To fill the gap, other countries can enroll research methods and rely on their recommender system fact-finding achievements to enhance SMRS research.

The scientometric indicators are interrelated for analyzing the growth rate in a specific time frame [94], [95]. Initially, the publication number was not as high as in later years. The overall average mean of the RGR was between 0.79 (2000) and 0.15 (2020), where the DT increased from 2.62 to 78.52, computed every five years from 2000 to 2021. As seen Table 3, the RGR is relatively high and DT is steady with mild changes, especially the development of SMRS from 2000 to 2021, with the average annual growth rate at 12.5%. In this period, the number of SMRS-related publications increased; RGR slowed down while DT grew immensely. The production of academic papers related to SMRS kept rising year by year; RGR and DT demonstrated that the quantity of research kept expanding in the growth rate, and speed declined in 2021. This is due to the publications of 2021, which were in progress or under review, and previously published articles were cited more.

The NCSf results were limited for the top 20 countries as the remaining countries had a low citation score and were deemed non-applicable, as seen in Table 4. The NCSf analysis of each country prompted the global average citations, which show the active and current trend of SMRS field categories on social media. The benchmark countries for more effective learning in SMRS are based on average citations, which means that more cited high-quality articles. This highlighted international benchmark countries, which

indicates the significance of the publication by the aspect of different recommendation fields for the top 20 countries. The top country was the US, which produced more SMRS research articles with high performance in all research fields. These are more frequently used recommendation fields with significant levels such as item (1.54), user (2.13), location (3.56), friend (1.61), and tour (2.15). This NCSf score is greater than 1.4, deemed "excellent" based on disciplinary peer review. The US, in promoting SMRS research, focused on social development based on user behavior; another factor is the user's influence in social networks [96], [97]. Consistently increasing publications with citations indicate that there is growing attention and interest in this SMRS research area.

The tabulated results in table confirm the highly cited articles produced by the USA on SMRS-related studies, with more recommendation fields getting more citations. The remaining countries produced SMRS publications, but fewer citations and a low number of recommendation field categories compared to the USA. There is also a limited number of research citations for publications on SMRS that do not meet the significance level, and can move forward for research in the SMRS field with different recommendation fields in the future.

The results of co-citations help to identify authors who are co-cited frequently in a set of publications, visualized in Figure 4. This also helps to identify related literature of co-authors with more citations from the top three clusters, which confirms the quality of the publications from the SMRS knowledge map results. Similar colors in the knowledge map indicate frequently co-cited publications and co-authors who have deep knowledge in SMRS research, suggesting future directions from their research work. Despite that the top three clusters, with a high number of nodes and links, lead to more co-authors and their literature collection, the remaining clusters hold the lowest number of co-authors. The cooperation among the clusters formed by the researchers working on SMRS learning is high in the top 3 clusters. In addition, the number of active SMRS researchers is more than 50 links in most of the clusters, which shows its research strength. Co-author analysis is mainly for the measurement of author collaboration [98]–[100].

The high citation used to measure the influence and the article is noteworthy for SMRS research. Further, the high number of citation articles may be used as a reference for future research on SMRS for better understanding. The co-occurrence of keywords is the bibliometric methodology where each node is a keyword, while an edge between a pair or two nodes implies the co-occurrence of two words [101], [102].

The evolution of trending keywords and hot topics related to SMRS supports the trendy keywords in different periods, shown in the visualization map in Figure 5. The most frequently used keywords are "social network" and "recommender system", which appeared frequently in 69 occurrences. The next level keywords, "social media" and

"algorithms", appeared in more than 64 occurrences. This indicates that most of the articles focused on social media recommender systems. The visualization of high frequency keywords reflect the scope of the SMRS studies listed in Table 5. Further, the co-occurrences of keywords are very important and help researchers to become familiar with SMRS fields such as big data, machine learning, text mining, social recommendations, and social networks. The research methodologies of text analytics and text mining techniques or classification methods with hybrid approaches may be used for both text and visual data for several types of social media platforms in future studies.

Another set of results focusing on publication type and the top results of organizations, funding agencies, cited articles, conference papers, and journals for SMRS was discussed between 2001 and 2021. This includes the three types of searched documents such as articles (847, or 62.25% of all publications). The conference type is 457 (35.2%), which is less than the article document type. The common terms "recommendation" are used in a different way like "recommender," "recommending," and "recommend" with the term "social media" being used apparently in searching for documents for this study. These keywords might be too impactful to find SMRS-related articles, which is the best present of the analysis of this study. Articles and conferences are selected with full documents with cited references. Top organizations (Table 7) and top funding agencies (Table 8) are both located in China. The Chinese Academy of Science and Peking University both produced 9 publications on SMRS with more than 100 citations on SMRS. The National Natural Science Foundation of China (NSFC) (RPC) supported 168 SMRS publications.

The top cited article produced by Ma *et al.* [93] proposed two recommendations such as user-generated tags and social friend relationships (Table 9). Using the collaborative filtering approach to verify initial performance led to 1732 citations. The conferences are smaller proportion for research works on SMRS, which are conducted by the journal Scientometrics, as shown in the Table 10.

The results of V-G indicate that the most active research area is information science/library science, and VI demonstrates that the most active journal is Scientometric for SMRS research. Further, this analysis can help future scholar master SMRS information, and new researchers can get knowledge and stay tuned in to current trends on a variety of social media platforms. There is still a lot of possibility for further exploration of new research in different directions in the field of SMRS.

VII. CONCLUSION
In this bibliometric study, the WoS was used as a data source; 1297 published papers were selected from 2000 to 2021 to analyze research trends in SMRS. 2000 and 2021, the publication growth increased gradually, with an average publication number of 20 per year. The yearly growth increased 45% on average with more citations. The results also demonstrate

the decline of RGR from 2000 (0.21), with the highest RGR in 2021 (0.15). This value fluctuated between 2006 (0.06) and 2021 (0.15). On the other hand, the mean DT rose gradually from 2.62 to 78.52 between 2000 and 2021. Similarly, there were fluctuations within this timeframe, implying the steady growth rate of SMRS multidisciplinary research. The NCSf for each SMRS field category, co-citation author, and co-occurrences of keywords reflects the trends of relevant SMRS articles. The author co-citations and co-occurrences keywords of articles provide the author citation rate per year and frequently used keywords to refine future research. The People's Republic of China and the USA lead the production of publications related to item-based category research. The organization analysis, funding agencies, and author analysis are also documented to provide insightful information on current research status and trends on social media.

VIII. RECOMMENDATIONS, LIMITATIONS, AND SIGNIFICANCE OF THIS STUDY

The results of this bibliometric study reflect current SMRS trends, where these basic trends can be used by future researchers to boost the impact of their work. Considering the novelty of this study, further research is necessary to determine the role of SMRS in robustly identifying different criteria and facts. More bibliometric patterns, including the analysis of abstract content, can be investigated in the future. The dynamic nature of technological innovation implies constant change in the field, reinforcing the need for an SMRS bibliometric analysis. As for the limitations of this study, this bibliometric study arrived with the articles from the WoS data source only. Also, a limited number of keywords used for article extraction in data collection via WoS is another limitation. Moreover, the citation count used for assessing impact in this bibliometric analysis might not reflect the quality of each article on SMRS.

Hence, it would be better to conduct some more experiments to gain broader insight into bibliometric data from other data resources, which can be used to improve the bibliometric analysis. The significance of this study can help researchers in establishing future research directions and in implementing systems development in real practice. Further, this bibliometric study helped us to determine current trends and covers recommendation fields in existing studies on SMRS for establishing recommendation systems effectively. However, the high citation in recommendation fields may be used by researchers in the future to influence their research and this study covered many aspects of bibliometric analysis across the SMRS literature.

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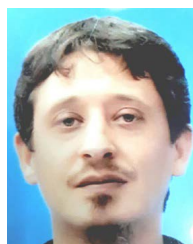
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