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Mapping the big data analytics in sharing economy: A bibliometric literature review

Yuxue Yang[1]*, Xiang Su[1], Shuangliang Yao[1] and Chen Tao[2]

[1]Department of Information Management, School of Economics and Management, Jiangsu University of Science and Technology, Zhenjiang City, China, [2]Zhenjiang Financial Bureau, Zhenjiang City, China

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Atif Saleem Butt,
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Hamed Fazlollahtabar,
Damghan University, Iran

*CORRESPONDENCE
Yuxue Yang,
yangyuxue1224@163.com

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This paper offers a holistic review of the role of big data analytics in sharing economy (SE). Academic literature in this field is analyzed to show the theoretical foundation, important papers, and key themes underlying the field by using various bibliometric analysis tools. We conduct a citation and co-citation analysis on literature concerning big data analytics in sharing economy, which published in the 12-year period from 2010–2021. A total of 205 papers were screened from Web of Science (WoS) database for our analysis. In the citation analysis, we depend on the degree centrality and betweenness centrality to identify 48 important papers. In the co-citation analysis, four major research themes are identified: sustainable business model, efficient match-making, trust building and innovation and value cocreation. The research also highlights future research directions and critical areas for the application of big data analytics in the SE context, which may help to produce in-depth studies.

KEYWORDS

big data analytics, sharing economy, bibliometric analysis, digital technology, sustainable development

1 Introduction

In recent years, increasing sharing economy (SE) platforms are built to resolve the issue of idle social resources by connecting the supply and demand sides (Constantiou et al., 2017). The sharing economy, as an essential practice of the digital economy, has exhibited fast growth (Constantiou et al., 2017; Mocker and Fonstad, 2017). This rapid growth of SE is strongly related to the big data analytics in pursuit of better value creation and resource distribution (Hamari et al., 2016; Laurell and Sandström, 2017; Liang et al., 2017). In the SE context, big data analytics is the often a complex process of examining big data to uncover information to achieve that social resources can be quickly integrated. Fast matching of resources between supply and demand is applied in the process so as to decrease the consumption of undeveloped resources and reduce pollution emissions, which serves as a new path to achieving sustainable development (Martins et al., 2021; Li et al., 2022). Many SE firms have invested heavily in developing big data analytics with the aim of improving decision making process, increasing user base and customer loyalty, creating business value (LaValle et al., 2011; Kaya et al., 2022). Incorporating big data analytics into the SE brings opportunities as well as new challenges, and researchers have discussed how big data analytics influences organizational performance. However, literature concerning SE, particularly in relation to big data analytics, has been relatively modest. As such, it is highly necessary and appropriate time to undertake a review article on SE to advance the field.

Prior literature on big data analytics has synthesized the adoption of big data applications in SE domain, such as match-making (Carroll and Bellotti, 2015), scaling user base (Bauer and Gegenhuber, 2015), demand prediction (Westland et al., 2019), improving service quality (Krishna et al., 2016; Ranjbari et al., 2020), etc. Remarkably, none of these studies has systematically analyzed the models and theories of big data analytics in SE context. This paper will shed new light on the theoretical underpinnings and important topics that support SE in general, as well as their relevance to big data analytics. By adopting the bibliometric and visualization method, this study attempts to cover this gap by integrating the core information from 205 papers to provide a comprehensive review. Researchers may gain a grasp of the structure and knowledge base of big data analytics in the SE context by using frequency analysis, citation and co-citation network analysis. Several visualization figures are provided to present the relation between publications. As a result, integrating these methodologies allows for a comprehensive understanding of the fundamental knowledge base and important subjects that compose the sharing economy area, which aids in identifying research gaps for big data analytics in the sharing economy.

This bibliometric study intends to bring to light the many assumptions regarding big data analytics that are prevalent in SE research, and so address the issues of big data analytics. We introduce bibliometric methods to conduct this research. Afterward, the results are discussed *via* a series of visual representations. Then, with identified important papers and main research topics, relevant insights are presented by discussing the logic and interrelation of studies on different topics. Research gaps and areas for future research then follow. This study concludes with a summary of the contributions and limitations of this study.

2 Methodology

2.1 Systematic literature review

A comprehensive literature review is conducted during the initial analyzing step. Systematic literature reviews enable researchers to assess the strength of published evidence while staying objective, so contributing to the growth of existing knowledge bases (Tranfield et al., 2003; Buchanan and Bryman, 2009). We follow the steps of systematic literature review process: 1) identification of research; 2) selection of studies; 3) quality assessment of studies; 4) data extraction and examining progress; 5) synthesis of data. The detailed operation processes in our study are as follows.

The data of this paper is mainly from the web of Science (WOS) database, a comprehensive database that includes more than 8,700 core academic journals across 170 disciplines. The WoS is one of the most often utilized scholar citation databases for field delineation since it has been the dominating citation database in most citation analysis research to date. To get a full-scale result, we use not only the keywords but also the related words regarding big data analytics (big data OR volume data OR vast data OR artificial intelligence OR data mining OR text mining OR sentiment analysis etc.) coupled with a term concerning sharing economy (sharing economy OR collaborative consumption OR gig economy OR on-demand platform OR access economy OR digital platform etc.). Without considering time limitation, a total of 1,108 articles were obtained. To assure the quality and relevancy of article, we re-checked them individually. Besides, only full-length articles are included in our sample, and book review, reports, short communications, research notes and viewpoints are excluded from the analysis. Further, to ensure the comprehensiveness of the article selection, we also searched the source journals to identify if there are related literature that did not included in our dataset, and carefully read the selected literature to find new related articles. Finally, a total of 205 articles are selected in this study. We record the important attributes of each article, such as title, author names, year of publication, keywords, source title etc.

2.2 Bibliographic network analysis

In the second analysing phase, a bibliographic network analysis is conducted (Guan et al., 2019). In particular, citation and co-citation analysis are adopted to understand the intellectual structure of big data analytics research in the SE field.

2.2.1 Citation analysis

Citation analysis has been extensively used to identify the source papers, influential papers and inheritance relationships among related papers (Garfield, 1979; Wang et al., 2016). A citation occurs when a paper refers to another paper (also known as a source paper). Adopting citation analysis, the information of papers that refer to or receive citations as well as the total number of citations are provided (Osareh, 1996). In this research, we conduct citation analysis to identify important studies in our dataset, and the key measurements are degree centrality and betweenness centrality (Freeman, 1978).

Degree centrality is the total of a node's direct links in the network. As a result, the more ties a node has, the more central the node is. Those with less ties will suffer when compared to the key nodes. Furthermore, there are two kinds of degree centrality: in-degree centrality and out-degree centrality. We use in-degree centrality to demonstrate a paper's importance, which represents the extent to which a paper is recognized by researchers, because

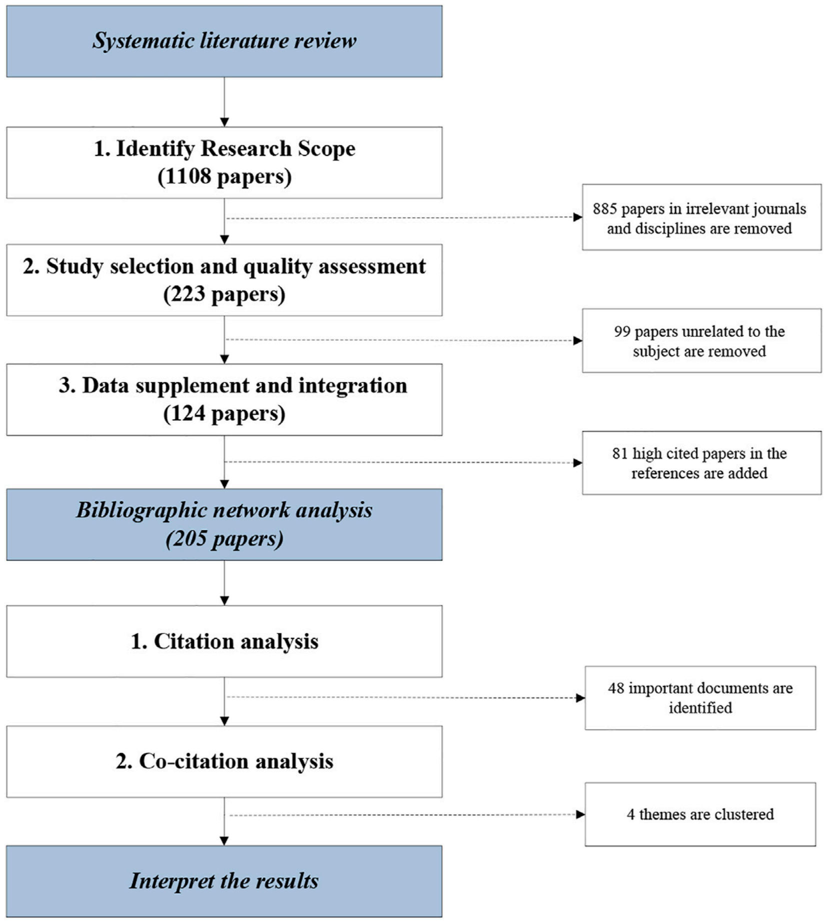

FIGURE 1
Research procedure.

in-degree centrality refers to the number of papers that cite the focal paper and out-degree centrality measures the number of papers that the focal paper cites.

Betweenness centrality refers to the extent to which one node exists on the shortest path among other nodes (Freeman, 1978). It is the amount of times a node requires the focus node to reach any other node using the shortest path. In communication network, the node with a higher betweenness value shows a strong ability for information dissemination, which also indicates that the node is often viewed by other researchers in the citation network. The betweenness centrality scores of 205 papers were computed following the approach of prior research (White and Borgatti, 1994).

2.2.2 Co-citation analysis

Co-citation analysis is commonly used as a credible way of examining the intellectual structure of a research topic (Cheng, 2016). In particular, it evaluates the semantic similarity of papers that share citations by examining the frequency of two publications cited in a pair as references (White and Griffith, 1981). As such, it enables the researchers to discover the structure, theoretical foundations and pattern within a focal research territory. To visibly identify the theoretical foundations and research streams within the focal field, we also use grouping algorithms embedded in CiteSpace to uncover clusters of relevant publications and visualize their network results. Figure 1 summarized the overall procedure of our study.

3 Results and discussion

3.1 Frequency analysis

Frequency analysis presents the descriptive results of our sample of 205 articles. We first analyze the type of articles across sources. The result is presented in Figure 2, which indicates that journal articles contribute 92 percent with 189 out of 205, and the

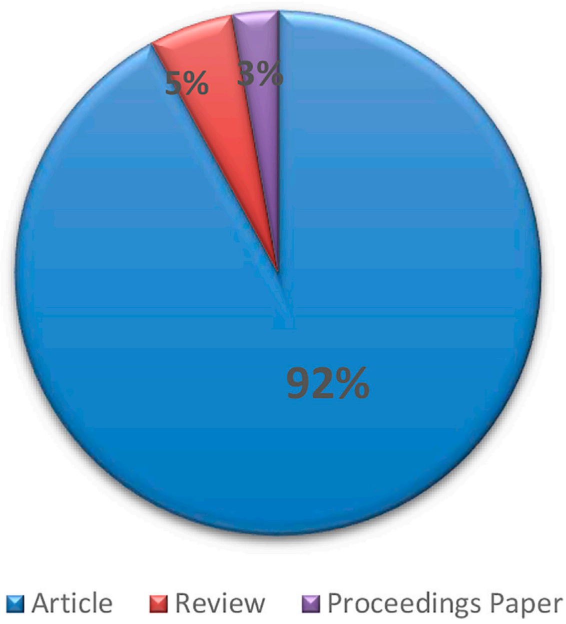

FIGURE 2
Type of articles.

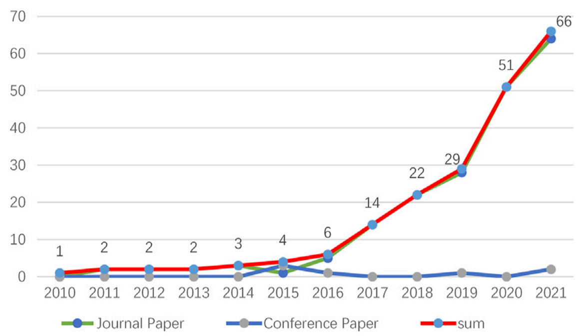

FIGURE 3
Annual distribution of sample paper.

review paper and conference articles only account for 5 percent and 3 percent, respectively. Furthermore, the allocation of the reviewed publications across years is depicted in Figure 3. There is a growing trend in the number of related articles since 2010, with a sudden steep increase in the number of articles in 2020. The results also imply that more and more scholars start to pay attention to this field, indicating the popularity of research on big data analytics in sharing economy.

Figure 4 shows the distribution of publications concerning big data analytics in sharing economy across journals. The top 11 journals with the largest number of published articles are presented and contribute to about 36% of the publications with 73 out of 205 articles. Further, we find big data analytics in SE context has received attention from various disciplines. As the statistics show, hospitality and information management are frequently concerned in this field. To our surprise, we also find this topic of research also appears in journals that focus on production and decision-making such as International Journal of Production Economics and Decision Support Systems. The analysis by country gives a more comprehensive understanding of the regions where the articles were published. Figure 5 shows the 12 most productive countries chosen by the sample articles. The majority of publications concern United States (65), China (64), and United Kingdom (41), the top three in the research field of big data analytics in sharing economy, followed by Germany (14) and France (13). This result is consistent with the development of big data technology and sharing economy in each country.

3.2 Citation analysis

We used UCINET to plot the citation network on the sample of 205 articles (Figure 6). The nodes in the network graph represent the article, and the arrow direction represents the citation relationship between the articles. An important indicator of citation networks is density, which denotes the connection between nodes. Intuitively, when we see a dense arrow around a node, such as article 54, it means that the article has a great influence in this field. According to prior research, if a score is higher than 0.5, it indicates the high density of the network and below 0.5 indicates low density (Abrahamson and Rosenkopf, 1997). For the citation network of big data analytics in SE, the network density is 0.0076. The low network density indicates research concerning big data analytics in SE, as an emerging research field, is still in the early stage and the connection between papers is sparse.

As previously explained the differences between degree centrality and betweenness centrality, we combine these two indicators to identify important research. In our study, the paper with in-degree centrality of 5 and above, or betweenness centrality is 50 or above is considered as important papers. Using UCINET to calculate these two indicators, a total of 48 papers meet the above criteria. Particularly, 48 important papers account for 23% of the total articles, which meet the “80/20 rule” (Nisonger, 2008). In this sense, it can be inferred that 80% of the relevant information in the field of big data analytics in sharing economy comes from 20% of the important papers. Therefore, by analyzing the 48 important papers, we keep the most valuable information in this field, and eliminate the complexity of the analysis of all research.

Table 1 shows the basic information of 48 identified important research. It can be noticed that in-degree and

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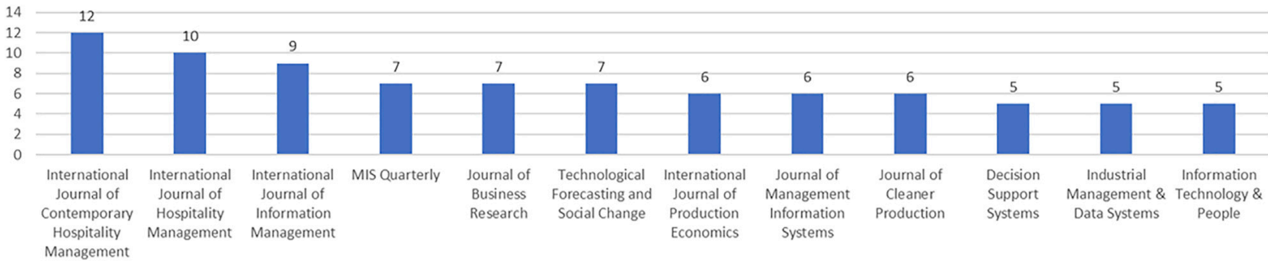

FIGURE 4
Number of articles published in top 11 journals.

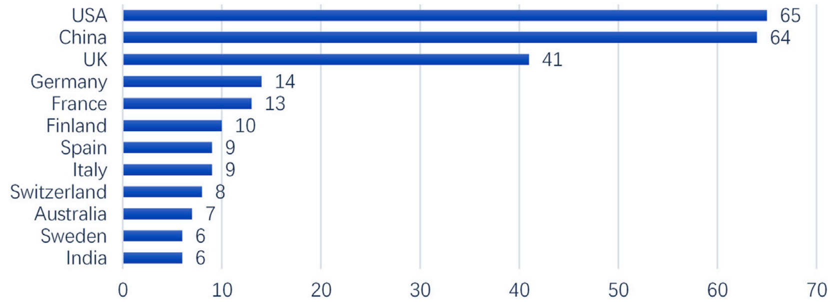

FIGURE 5
Number of articles across countries.

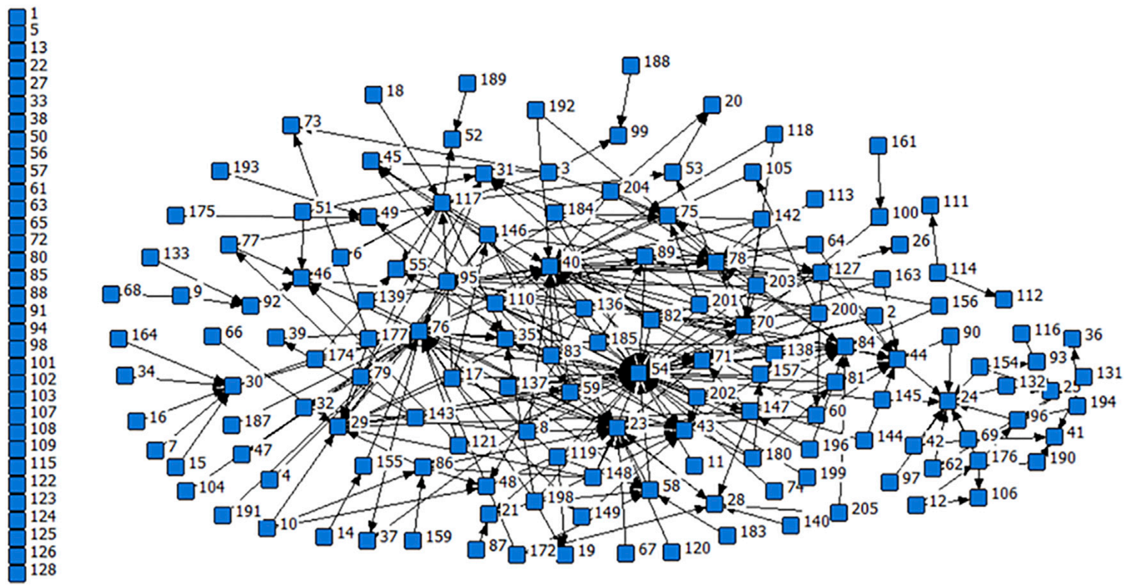

FIGURE 6
Citation network of the 205 papers.

TABLE 1 Important papers of citation analysis.

No.	Author	Title	Research type	In degree	Betweenness centrality
54	Zervas et al. (2017)	The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry	Quantitative, survey	38	619.34
40	Ert et al. (2016)	Trust and reputation in the sharing economy: The role of personal photos in Airbnb	Quantitative, survey	29	376.44
23	Bardhi and Eckhardt (2012)	Access-Based Consumption: The Case of Car Sharing	Qualitative analysis, case study	19	152.41
76	Sutherland and Jarrahi (2018)	The sharing economy and digital platforms: A review and research agenda	Literature review	17	357.81
29	Cohen and Kietzmann (2014)	Ride On! Mobility Business Models for the Sharing Economy	Conceptual	15	128.93
24	Chen et al. (2012)	Business intelligence and analytics: From big data to big impact	Conceptual, literature review	11	299.83
78	Bridges and Vásquez (2018)	If nearly all Airbnb reviews are positive, does that make them meaningless?	Qualitative analysis, case study	11	157.78
44	Tussyadiah and Zach (2017)	Identifying salient attributes of peer-to-peer accommodation experience	Quantitative, survey	10	79.21
43	Camilleri and Neuhofer (2017)	Value co-creation and co-destruction in the Airbnb sharing economy	Qualitative analysis, case study	9	140.85
84	Cheng and Jin (2019)	What do Airbnb users care about? An analysis of online review comments	Quantitative, case study	9	63.74
46	Edelman et al. (2017)	Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment	Experiment	8	80.77
30	Lee et al. (2015)	Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers	Qualitative analysis	7	140.73
70	Mauri et al. (2018)	Humanize your business. The role of personal reputation in the sharing economy	Quantitative, survey	7	122.22
75	Zhang et al. (2018)	A computational framework for understanding antecedents of guests' perceived trust towards hosts on Airbnb	Quantitative, survey	7	102.83
31	Ikkala and Lampinen (2015)	Monetizing Network Hospitality: Hospitality and Sociability in the Context of Airbnb	Qualitative analysis	6	0.00
35	Einav et al. (2016)	Peer-to-Peer Markets	Theoretical, modeling	6	40.87
71	Lutz and Newlands (2018)	Consumer segmentation within the sharing economy: The case of Airbnb	Mixed method	6	172.79
28	Belk (2014)	Sharing Versus Pseudo-Sharing in Web 2.0	Conceptual	5	153.35
58	Lee et al. (2018)	Why people participate in the sharing economy: an empirical investigation of Uber	Quantitative, survey	5	121.29
110	Xu (2020)	How do consumers in the sharing economy value sharing? Evidence from online reviews	Quantitative, survey	0	584.13
198	Nadeem et al. (2019)	The Role of Ethical Perceptions in Consumers' Participation and Value Co-creation on Sharing Economy Platforms	Quantitative, survey	0	443.41
117	Gerwe and Silva (2020)	Clarifying the sharing economy: Conceptualization, typology, antecedents, and effects	Conceptual	4	287.61
205	Serrano et al. (2021)	Exploring preferences and sustainable attitudes of Airbnb green users in the review comments and ratings: a text mining approach	Quantitative, survey	0	216.95
142	Zhang et al. (2020)	A text analytics framework for understanding the relationships among host self-description, trust perception and purchase behavior on Airbnb	Quantitative, survey	0	175.76
133	Guidon et al. (2020)	Expanding a(n) (electric) bicycle-sharing system to a new city: Prediction of demand with spatial regression and random forests	Modeling	0	155.00
190	Tofangchi et al. (2021)	Handling the Efficiency-Personalization Trade-Off in Service Robotics: A Machine-Learning Approach	Modeling	0	154.00
49	Cachon et al. (2017)	The Role of Surge Pricing on a Service Platform with Self-Scheduling Capacity	Modeling	3	142.53
157	Ranjbari et al. (2020)	A big data approach to map the service quality of short-stay accommodation sharing	Mixed method	2	142.44

(Continued on following page)

TABLE 1 (*Continued*) Important papers of citation analysis.

No.	Author	Title	Research type	In degree	Betweenness centrality
25	Demirkan and Delen (2013)	Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud	Conceptual	3	132.83
5	Braesemann et al. (2020)	ICTs and the urban-rural divide: can online labour platforms bridge the gap?	Quantitative, survey	0	125.00
6	Eichhorn et al. (2020)	Dimensions of digital inequality in the sharing economy	Quantitative, survey	0	125.00
174	Dwivedi et al. (2020)	Impact of COVID-19 pandemic on information management research and practice: Transforming education, work and life	Conceptual	0	113.10
62	Lehrer et al. (2018)	How Big Data Analytics Enables Service Innovation: Materiality, Affordance, and the Individualization of Service	Theoretical, modeling, case study	2	100.81
21	Buhrmester et al. (2011)	Amazon's Mechanical Turk: A New Source of Inexpensive, Yet High-Quality, Data?	Quantitative, survey	3	97.07
13	Song et al. (2021)	Big data analytics in digital platforms: how do financial service providers customise supply chain finance?	Quantitative, survey	0	93.00
14	Vakeel et al. (2020)	Impact of network effects on service provider performance in digital business platforms	Theoretical, modeling	0	93.00
22	Banker et al. (2011)	The effects of digital trading platforms on commodity prices in agricultural supply chains	Quantitative, survey	0	77.50
86	Ma et al. (2019)	Value Co-creation for sustainable consumption and production in the sharing economy in China	Conceptual	4	74.00
52	Chang (2017)	The economic effects of Uber on taxi drivers in Taiwan	Quantitative, survey	2	71.63
189	Willis and Tranos (2021)	Using 'Big Data' to understand the impacts of Uber on taxis in New York City	Quantitative, survey	0	67.45
36	Erevelles et al. (2016)	Big Data consumer analytics and the transformation of marketing	Conceptual	1	67.00
100	Zamani et al. (2019)	Trust in the sharing economy: the Airbnb case	Qualitative analysis, case study	1	67.00
92	Westland et al. (2019)	Demand cycles and market segmentation in bicycle sharing	Quantitative, modeling	2	65.00
41	Martens et al. (2016)	Mining Massive Fine-Grained Behavior Data to Improve Predictive Analytics	Quantitative, survey	3	64.50
45	Heylighen (2017)	Towards an intelligent network for matching offer and demand: From the sharing economy to the global brain	Conceptual	4	62.11
55	Constantiou et al. (2017)	Four Models of Sharing Economy Platforms	Conceptual	4	54.28
37	Banning (2016)	Shared entanglements - Web 2.0, info-liberalism and digital sharing	Conceptual	2	50.30
38	Liou et al. (2016)	Investigating information sharing behavior: the mediating roles of the desire to share information in virtual communities	Quantitative, survey	0	50.30

betweenness centrality of Paper 54, 40, 23, 76, 29 and 24 are relatively high, indicating that these papers contribute to the major knowledge sources for research in big data analytics field. Although the in-degree of literature 110, 198, 205, 142 is low, the betweenness centrality is relatively high (> 150), revealing that these papers are critical to the dissemination of knowledge in this field by playing a bridge role. To further analyze the features of these important papers, we categorize the papers based on the research type. As shown in Table 1, there are 21 non-empirical studies, including 11 conceptual studies, 6 qualitative analysis, 3 theoretical modelings and 1 literature review, suggesting that researchers are still trying to clarify big data analytics in SE by elaborating on the basic model and fundamental mechanism of the relationship between big data analytics and sharing economy. Additionally, there are also 25 empirical studies, including 20 quantitative surveys, 4 modeling and 1 experiment study. It is found that many of them focused on the cases of Airbnb and Uber, two sharing economy giants. Furthermore, two papers used a mixed methods approach that combines qualitative content analysis and quantitative methods.

3.3 Co-citation analysis

Co-citation analysis is used to identify and illustrate the knowledge groups of big data analytics in SE. Specifically, by analysing 48 important articles using CiteSpace, we obtain the co-citation network of the references from the focal articles, which was visualised in Figure 7. As shown in the Figure 7, the monolithic network is not dominated by a specific study. And the important studies have been identified. After careful scrutiny of the articles in the primary 7 clusters, we compared and combined

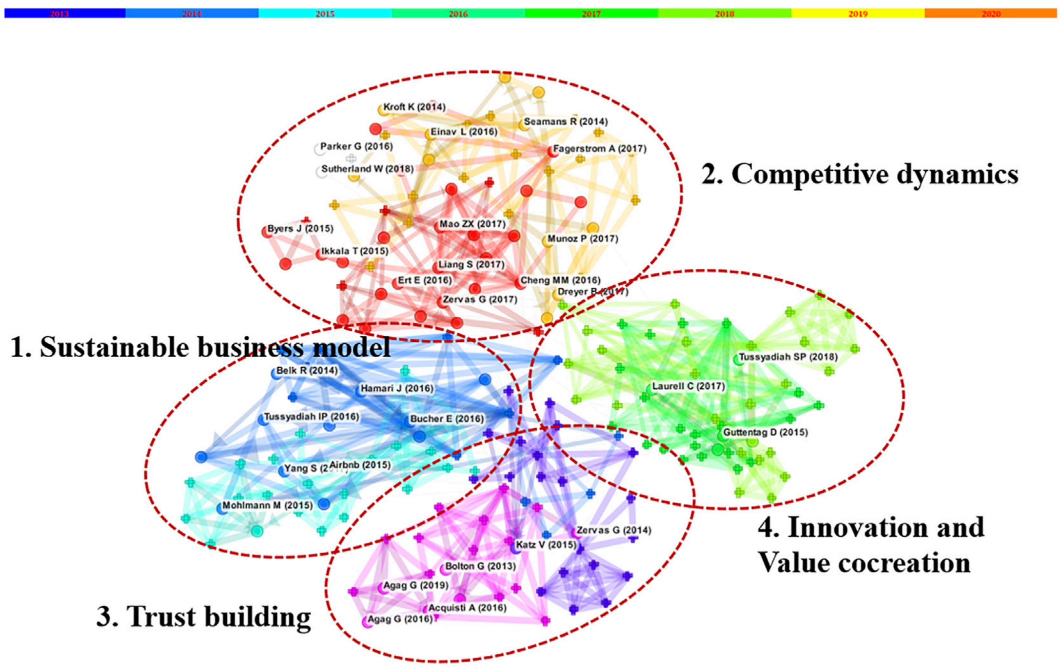

FIGURE 7
Visualized co-citation network.

some of the articles, resulting in the final four clusters. The four clusters identified are 1) sustainable business model; 2) efficient match-making; 3) trust building; 4) innovation and value co-creation.

3.3.1 Sustainable business model

The first cluster, "business model", reflects the research aiming at clarifying how SE business model is built on the basis of big data analytics. They depart from specific managerial applications and attempt to identify and classify the literature concerning the organizational and market mechanisms of SE. Sutherland and Jarrahi (2018) point out that the core of SE concept is the role of big data analytics, which is efficient and scalable and bring a large network of people together to match them with the goods and services they need. Vakeel et al. (2020) propose that SE business models are driven by network effects, and growing user base is critical in their initial development stage. Therefore, SE firms use liminal moves to attract and manage users based on various big data analytic technologies. For example, Uber uses "heat maps" showing high-demand locations on the user and driver versions of its app (Garud et al., 2020). Amazon and eBay also provide product recommender systems to achieve better performance by analyzing and predicting the preference of their users with large amount data from multi sources (Chen et al., 2012). Platform features like rating systems also enable the users to establish a reputation within a network (Einav et al., 2016; Zheng et al., 2022).

Further, studies tried to classify different SE business models. For example, Constantiou et al. (2017) categorize the sharing economy into four models, i.e., "Franchiser", "Principal", "Chaperone", and "Gardener" based on the tight or loose control over participants, and high or low rivalry between participants. Most studies agree that SE platforms could benefit from these business models in different ways *via* online mediated platforms (Bardhi and Eckhardt, 2012). Specifically, SE platforms contribute to the increase of employment by providing more flexible and diverse work opportunities without limitation of distance with the support of distributed intelligent networks and big data algorithms (Asghari and Al-e, 2020; Braesemann et al., 2020; Huang et al., 2020). To some extent, the big data algorithms embedded in SE platforms optimize the utilization of idle resources to decrease the cost to users and society as a whole to achieve sustainable development (Cohen and Kietzmann, 2014; Heylighen, 2017). The traditional economic business model is based on the continuous investment of resource elements to create new products or services to generate revenue, while the allocation object of the sharing economy is the idle resources in stock, which do not need to invest in resource elements and fundamentally maximizes the resource utilization rate. In this sense, sustainable nature of sharing economy helps to achieve the sustainable development goals of society. However, there are also some critics of the business models of SE. For instance, Belk (2014) and Banning (2016) both point out SE as pseudo-sharing because of profit motives. Chang (2017) found that SE business model has intensified the market competition, which decreases the income of employees in the incumbent industry. With these flaws, the SE business model still thrives and expands globally (Hossain, 2020).

3.3.2 Efficient match-making

The second cluster, "efficient match-making", refers to those papers that attempted to provide empirical insights into big data analytics for venture development and competitive purpose. This, therefore, analyzed the big data analytics for improved performance in terms of service quality and motivating user participation. Many emerging SE ventures compete fiercely with firms in the traditional accommodation industry (Zervas et al., 2017), and they survived and thrived by taking advantage of big data analytics to achieve a fast scale. A careful scrutiny of these papers reveals three topics: match-making, marketing and pricing.

Match-making is a major way that achieves the viability of large-scale sharing or collaborative networks. SE platforms are characterized by Web 2.0 of digital production and participation without limiting by distance but only by the problem of classifying through a large group of people (Banning, 2016), which also close relates to the experienced quality of service that affects the overall satisfaction of users. Therefore, it enables applications to connect people in real-time through algorithms (Sutherland and Jarrahi, 2018). For instance, Uber assigns passengers to drivers on the platform based on the attributes of passengers' locations, and all users could classify and evaluate each other using digital features such as ratings (Lee et al., 2018). In this sense, platforms need to pay extra effort into algorithmic management to ensure the flexibility and effectiveness of their service to facilitate user satisfaction (Lee et al., 2015). Further, sociotechnical approaches considering the interpersonal dynamics of matching based on personal traits are used to attract user participation. For instance, the well-known sharing economy giant, Airbnb, allows users to carry out their own evaluating and matching through pleasant and meaningful social encounters. Specifically, the host in Airbnb could select the matched guests who are like-minded, which motivates hosts to participate (Ikkala and Lampinen, 2015).

Furthermore, since online reviews have been found to be significant in guiding consumer decisions, it is also widely used for marketing purpose (Martens et al., 2016). Zervas et al. (2021) found that ratings of properties on Airbnb are often higher than similar rental hotels on other accommodation platforms, which attributes to the reciprocity of the review system that enables both host and guest to advertise themselves (Bridges and Vásquez, 2018). Mauri et al. (2018) find the storytelling narratives in profiles can significantly boost the popularity of their offer. Besides, target marketing is also used by SE platforms based on customer segmentation through analyzing customer data (Lutz and Newlands, 2018). Additionally, big data analytics is also used by researchers to prevent customer loss (Erevelles et al., 2016). With large structured and unstructured data, SE firms use big data analytics (e.g., machine learning) to effectively and accurately predict service demand (Westland et al., 2019) and factors that lead to negative decision-making of customers (Shirazi and Mohammadi, 2019). It is also noted that this type of analysis as a service (AaaS) in SE firms requires decision support systems processing in cloud in order to process big data in a short time and produce accurate and operable results.

Pricing is critical in motivating users to participate in SE. By applying big data analytics to analyze online reviews on Tujia, a leading P2P accommodation sharing website in China, Liu et al. (2020) demonstrated that price difference has a significant moderating effect on the competitive effect between commercial and individual hosts. SE platforms commonly provide lower price services to compete with large incumbents, since price constitutes to major reasons for user participation (Ert et al., 2016; Huang et al., 2020). Further, considering the major profit is largely determined by pricing, a dynamic pricing strategy is also used by SE firms to improve their revenue based on the analysis of product attributes and market information (Banker et al., 2011). For instance, Uber uses a surge pricing algorithm to vary the per-mile price of a taxi ride as supply and demand conditions change (Einav et al., 2016; Cachon et al., 2017).

3.3.3 Trust building

The third cluster, "trust building", hints that the adoption of big data analytics also helps SE platforms to build trust which constitutes a critical factor in mitigating risk precepted by users (Lee et al., 2018; Nienaber et al., 2021). In the process of sharing and transactions, distrust is a large obstacle since sharing often involves personal interactions with strangers (Sutherland and Jarrahi, 2018). For the trust between users, a number of digital features embedded in SE platforms are designed for building trust, such as a rating system and user reviews (Ikkala and Lampinen, 2015). Song et al. (2021) also found that financial service providers (FSPs) assess the supply chain credit of small and medium-sized enterprises (SMEs) and offer them supply chain finance (SCF) through SE platform using big data analytics. Moreover, research has shown that a trustworthy-looking photo in one's profile can substantially improve the perceived trust of others (Ert et al., 2016). For instance, Zhang et al., 2018 use text mining and face recognition method to investigate the antecedents of trust in Airbnb, and either self-descriptions or profile photo is helpful in trust formation. In all cases, these features face difficulties of integrating themselves into existing social norms for which users may have different understandings (Sutherland and Jarrahi, 2018).

Another perspective considers trust between the user and the platform, as users' trust to platform significantly affects their participation motivation (Eichhorn et al., 2020). SE platforms provide specific regulating rules to facilitate user trust, such as restricting the entry of service providers and verifying the service quality through autonomously analyzing the users' feedback information (Einav et al., 2016). Further, matching and searching algorithms constitute a significant part of user trust. Specifically, a user's trust in the matches depends on the perception of platform capabilities or wisdom in making trustworthy connections (Deng et al., 2016). However, discrimination still occurs in sharing economy under the current matching algorithm. For instance, Celata et al. (2017) provided an experiment on Airbnb and found orders from guests with distinctively African American names are less likely to be accepted relative to identical guests with distinctively white names, indicating discrimination and undermined civil rights gains. In this sense, SE platforms should offer timely intervention to reduce the occurrence of discrimination and create a fair transaction environment (Edelman et al., 2017). Besides, trust is also improved by mobilizing a sense of community among users (Liou et al., 2016).

3.3.4 Innovation and Value co-creation

Finally, while cluster 2 and cluster 3 cover a wide range of managerial issues in various aspects of SE platform, the fourth cluster, "innovation and value co-creation", refers to the research that explains the mechanisms of how big data analytics enable innovation and value co-creation in SE. the sharing economy platform combines the location sharing of idle resources, the application of big data algorithms and other accurate matching and connection to achieve mutual benefit between the supply side and the demand side. The platform can provide the same level of services, increase the use time of products, reduce the production of goods, and thus reduce the related resource exploitation and waste generation.

On the one hand, research has investigated the theoretical model of the value co-creation process. For example, Nadeem et al. (2020) studied the antecedents of consumers' value co-creation intentions at SE platforms and evaluate them empirically. The results indicate that social support is essential in arousing value co-creation intentions of users. Shah et al. (2021) identified privacy-safety risk and trust as influential for the customer participation in value co-creation. Moreover, Ma et al. (2019) proposed a framework to conceptualize the emerging patterns of value co-creation between governments, sharing business firms, and consumers in the sharing economy. They found that the sharing economy platform achieves the location sharing of idle resources and increases the use time of products, thus reducing the production of goods, and the related resource exploitation and waste generation. Lehrer et al. (2018) developed a theoretical model and highlighted the role of big data analytics serving as generative digital technologies that provide a key organizational resource for service innovation.

On the other hand, the value co-creation between actors in SE context is also empirically examined. In the era of big data, consumers have generated various types of data in their consumption process, such as user-generated ratings and comments. SE firms collect these data for prediction so as to gain insights into the consumers' characteristics and needs. Through analyzing user-generated big data such as online reviews and leaving messages, Casais et al. (2020) discovered in the Airbnb context that the host could advance their service in order to offer better experience for guests. Additionally, scholars have used big data analytics to identify user preferences based on the reviewing system embedded in SE platforms. For instance, Cheng and Jin (2019) spot key influencers (i.e., "location", "amenities", and "host") in the decision of guests using text mining and sentiment analysis. Tussyadiah and Zach (2017) also find the critical role of host-guest relations in affecting consumer satisfaction by applying big data analytics to online user reviews. In the meantime, Camilleri and Neuhofer (2017) confirmed the dominance of guest views on value co-creation in Airbnb. These findings can help hosts to better differentiate and highlight their service attributes, thus providing more value to the customers (Nadeem et al., 2020).

4 Future research directions

In this section, we discuss the future directions in big data-driven SE research based on the findings of co-citation analysis. With a critical reading of prior research focusing on various topics of SE, we find that little attention has been given to the evaluation of how varying levels of big data analytics impact SE firm performance. Besides, previous work has also tended to only examine big data analytics as a tool embedded in the platform (Krishna et al., 2016; Sutherland and Jarrahi, 2018), without considering it into the value cocreation mechanism. Hence, there is a dearth of literature that has identified the prominent role that big data analytics play in facilitating value co-creation. Moreover, the big data analytics method used in SE needs to be improved to supplement for value co-creation process and the algorithms need to be managed to mitigate ethical and regulatory concerns in this emerging market. We explain them in detail as follows.

4.1 Impact of big data analytics on firm performance

Big data analytics has the potential to revolutionize and advance the management and performance of SE firms. The results of the review suggest the current research has predominantly referred to big data analytics as technology embedded in the SE platforms, without any distinct characteristics (Cheng et al., 2018). Despite the high operational impacts, there is a paucity of empirical research to assess and prove the business value of big data analytics to SE firms. Specifically, the extant research simply views big data analytics as a tool that can be applied to solve a specific problem based on the objectives of the firm (Krishna et al., 2016). However, it serves by driving the overall process of the SE firms and plays as a core mechanism observed as an algorithmic or mathematical model (Weber, 2014). As big data analytics may have varying impacts on firm performance in the SE context, it is important to investigate to what extent big data analytics affect the SE firm performance and environmental performance. To this end, the factor that could measure the varying level of big data analytics should be developed, such as the big data capability of the top management team and the breadth of functions achieved.

Further, the indicator that can be used to represent performance also needs to be identified, as the goal will be changed across different development stages of SE firm. For example, in the early stage, platforms are knee to address the chicken-and-egg problem, thus firm performance mainly focuses on growing the user base. While in the mature stage, the main performance goal will be transformed into social and environmental impacts. Therefore, the varying level of big data analytics may leverage resources in different ways so as to prove their business value. Additionally, there is also lacks of in-depth analysis of the dilemma of managing such big data for small and medium enterprise because they often lack related resources as well as face fierce competition. In this sense, research needs to examine how to achieve the balance of lowering costs and raising the benefits of higher level of big data analytics.

4.2 Big data-driven user-platform value cocreation mechanism

SE as innovative disruption shows great differences in terms of business model compared with the traditional. As the development of the Internet and big data change the original linear one-way value creation mode, it enables the value cocreation between platforms and users (Sutherland and Jarrahi, 2018). Current literature indicates that the value cocreation has been embedded in the value network of SE firms (Schor and Fitzmaurice, 2015), which helps to improve performance. Prior research predominantly focused on the value cocreation between user groups (Casais et al., 2020), rather than facilitating value cocreation from the perspective of SE platforms. Stimulations could be developed by platforms to encourage innovations from users. For example, to knowledge sharing platforms, a better understanding of the impact of investment in big data infrastructure (e.g., software, hardware, network, interface, user tag) on interactive innovation between users and firms would lead to knowledge that could assist SE platform providers with a better road map for how big data motivates the development of Internet-based products and services. In this sense, stimulation mechanism for investment in related assets and a construction mechanism for the required infrastructure need to be developed.

In addition, the overarching publications did not analyze the impact of different market orientations on value cocreation from the perspective of platforms. Market orientation is mainly categorized into responsive and proactive market orientation (Jaworski et al., 2000). Compared with responsive market orientation emphasizing customer needs, proactive market orientation focuses on dominating behavior by forecasting the demand and preference behavior of users, which enables the innovation of platforms driven by big data. Therefore, future research should investigate the mechanism of how market orientation impacts the value cocreation process considering the existing big data technology.

4.3 Big data analysis method and governance

The growth of a SE platform relies heavily on the algorithms of service and operation optimization and the governance of data, relatively little attention has been given to advancing the understanding of the data governance of SE platforms. Previous studies infer that platforms often actively surveil participants (Deng et al., 2016; Kuhn and Maleki, 2017), either through rating system or through direct data collection to ensure quality. However, user-generated data from different sources have not been fully used despite their rich information and strong association. On the one hand, with careful scrutiny of reviewed research, the big data analytics on SE management and operation is still in its infancy. For instance, the big data used for market forecasting and resource allocation is less in dimensions, such as the one-dimension million level transactions data (Martens et al., 2016). The slow progress in this field can be partially attributed to language issues, that is, language usage in social networks is obviously different from traditional usage. In this sense, in order to extract a more useful message and make full use of the user-generated information, future research needs to investigate the theory and method of acquiring and analyzing user's innovative knowledge from network big data. For example, ontology, knowledge mapping, and deep learning can be used to extract user innovative knowledge to improve the efficiency and utilization of user-generated big data. On the other hand, a user often exists in multiple systems, leaving records that can be founded (Weber, 2014). In order to capture the features of the focal user comprehensively and accurately, a data integration method for matching entities using big data across different system need to be developed.

Besides, there are also some legal and ethical concerns. For example, the regulation asymmetry between regulatory bodies and SE firms could result in severe problems such as privacy invasion, human-machine misfit, distrust, and data leakages.

Further, with the increase in bargaining power, SE firms are enabled to change the model to achieve profitability, resulting in a higher price that may jeopardize the users' interests. Therefore, future research should also examine the way that could overcome these challenges by achieving better big data governance.

5 Conclusion

This paper serves as a basis for future big data analytics research in SE context by systematically reviewing and analyzing the current research status for big data analytics in SE, and effectively mapping its knowledge and intellectual structure. Our review makes several major contributions to big data analytics in SE literature. First, this study offers a clear view of big data analytics in sharing economy by identifying important papers and understanding the main research themes in this field. Potential new directions may be inspired according to the visible analysis. Second, this study identifies four major themes of big data analytics in SE research: sustainable business model, efficient match-making, trust building, and innovation and value cocreation, which also helps the researchers locate their work within the field. Finally, based on the research directions we provided, this research assists the scholars to uncover the research gaps when they step into this area and provides inspiration for exploring the factors that affect the environmental sustainable performance of the sharing economy model. Practically, this study serves as a basis for the rapid development of SE and big data analytics research. In particular, it highlights the critical areas that big data analytics involves in the SE field and offers suggestions that policymakers should focus on measures for enabling advancement in important aspects of big data-driven technology and establishment of related regulation.

We do note certain limitations in this work. First, this study examines only academic journal articles and conference articles. In future research, additional insights may be congregated by reviewing different bodies of literature such as reports and books. Second, future research may add another layer of insights into the big data analytics of SE by adopting qualitative methods through consultation with experts, practitioners, and regulatory authorities.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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