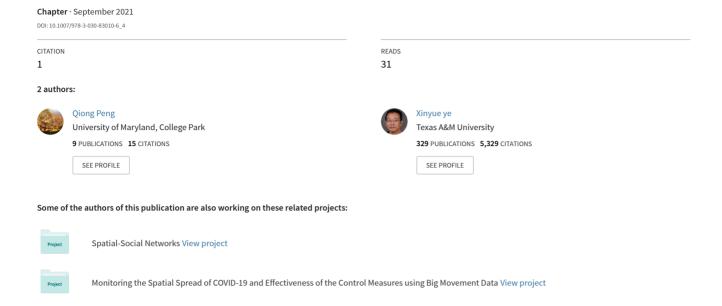
# Research Trends in Social Media/Big Data with the Emphasis on Data Collection and Data Management: A Bibliometric Analysis



# Research Trends in Social Media/Big Data with the Emphasis on Data Collection and Data Management: A Bibliometric Analysis

Qiong Peng and Xinyue Ye

Abstract: Data collection and data management research is a multidisciplinary field that covers a wide range of subjects, each of which serves as a fundamental prerequisite for Human Dynamics Research utilizing Social Media/Big Data. The everchanging academic landscape of this field has been characterized by rapid expansion of various applications and dynamic collaboration across multiple disciplines, yielding an increasing number of publications. This chapter reviews the research trend of such techniques and methodologies over the past ten years (2010-2019). Specifically, we conducted Bibliometric analysis to examine growth of output during 2010-2019, distribution of output in subject categories and journals, most cited documents, geographic and institutional distribution of publications, institution collaboration network, and keywords. The keyword analysis reveals that "big data", "social media", "data collection", "Twitter", "Facebook", and "privacy", were popular throughout the past 10 years. Additional keywords such as "data management", "cloud computing", "machine learning", "data mining", "Internet of Things", "big data analytics", "crowdsourcing", "data analytics", "data science", "big data management", "Hadoop", "MapReduce", "sentiment analysis", "surveillance", "business intelligence", and "IoT" have attracted increasing attention, further reflecting research trends.

## 4.1 Introduction

Advances in social sensing and data acquisition technologies have led to an enormous amount of human dynamics data. Social media data, in particular, have been used extensively in human dynamics research [1]. In many ways, analysis of social media data could prove especially helpful in detecting anomalous events such as panic resulting from natural disasters [2, 3], a pandemic [4], and measuring interaction among cities and regionals [5, 6]. The social media data could also be used to observe shopping behavior [7], travel recommendations [8], political activism [9],

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and business intelligence [10]. However, there are potential drawbacks from relying on these data, such as unrepresentative sample, rumors, and location spoofing [11].

Focusing on the technical aspects of data collection and data management, social media data including text messages, photos, and videos posted on social media platforms can be collected and managed using several techniques. Furthermore, social media may be associated with location information, such as through a checkin function or geo-tagging; this information could offer a solid foundation for geographical analysis Still, there are some strategic decisions that need to be made before data collection methods are established, such as strategic decisions about the period of data collection and search criteria for collecting data (i.e. based on lists of user accounts or filtered by topics and corresponding hashtags) [12]. To access social media data, researchers can fetch the data using Python scrapy and codingfree web tools. Even more, there are free research web tools that enable data collection and visualization, such as the Social Data Analytics Tool (SODATO) and Netlytic [13]. Developed by the Copenhagen Business School, SODATO can fetch data from Facebook and Twitter. Those interested in utilizing this tool may contact the research group, but public access to SODATO is currently limited. Netlytic can capture data from YouTube and Twitter, and the data are geo-coded.

Efficient data management is also critical to handling large quantities of social media data. There are increasing numbers of established data management techniques and techniques vary across data structure. For example, Zheng et al. [14] conclude that there are three common data structures- stream, trajectory, and graph data. Regarding various data structure, Zheng et al. introduce corresponding data management techniques, including data reduction techniques for trajectories<sup>1</sup>, noise filtering techniques for trajectories, techniques for indexing and query trajectories, managing spatiotemporal graphs techniques, hybrid indexing structures techniques that can well organize different data sources [14].

Social data collection and data management research comprise a multidisciplinary field that covers a wide range of subjects including information science, computer science, and geography. It is necessary to identify the cutting-edge trends related to this research. Although there is increasing interest in big data and social media data-particularly data collection and data management-there is still limited research on the "big picture" of social media data collection and data management. In addition, human dynamics research spans multiple disciplines of study. Hence, it is necessary to examine global development and research trends comprehensively when discussing social media data collection and data management. A systematic review of social media data collection and management techniques could help readers gain a better understanding of research achievements, directions, and development of research methods.

Bibliometric analysis incorporates both visual and quantitative analytics that can be used to summarize trends in selected research fields [15, 16]. This type

<sup>&</sup>lt;sup>1</sup> A spatial trajectory is a trace indicating a moving vehicle or induvial in geographical spaces.

of analysis can reveal temporal dynamics of scholarly outputs, spatial and institutional distributions of publications, scientific collaborations, and major research trends [17]. Furthermore, bibliometric network analysis, such as co-word analysis [18], co-citation analysis [19], co-authorship analysis [20], and co-publication analysis [21]), can be conducted to shed light on relationships between keywords, as well as other identifiers such as country, research institute, and author.

In this study, we used a bibliometric method to examine global research trends of big data and social media data research in the last decade with an emphasis on data collection and data management. The purposes of this study are to (1) evaluate research performance by country, institute, journal, subject category, and keywords; and (2) briefly identify future research directions in big data and social media data research with an emphasis on data collection and data management.

## 4.2 Methodology, Data Collection, and Analysis

# 4.2.1 Applications

Bibliometric analysis was carried out in order to evaluate the characteristics and trends in big data and social media data research. Bibliometric analysis was introduced by Pritchard [16] as a mathematical and statistical approach to analyze pertinent literature and understand the global research trends in a specific area. It has been applied to environmental engineering and science, soil science, ecology, food safety, new energy utilization, and other aspects. Bibliometric indicators analyzed in this study include publication number, subject categories, source journals, countries, institutions, journals, and keywords.

### 4.2.1 Data Collection

The dataset was derived from the database of the Science Citation Index (SCI) and Social Science Citation Index (SSCI) publications by Web of Science. The following keywords were used, including Topic= ("social media\*" OR "big data\*") AND ("data collection\*" OR "data management\*") to search all archived documents. The publications that contain any of those keywords and their variants (with \*) in their titles, abstracts and keyword lists were included. The following information was downloaded: title, authors, institutions, abstract, keywords and cited references. The studies period spanned 2010 to 2019. Our bibliographic search resulted in 1,436 records.

## 4.2.3 Analysis Tools

In order to conduct bibliometric analysis, an R package 'Bilbiometrix' [22], VOSviewer [23], Ucinet [24], or other packages can be applied (see [25]) for a review on bibliometric software). In this study, we use the R package "Bibliometrix" and VOSviewer. VOSviewer is a freely available texting software for generating bibliometric maps and analyzing trends in scientific literature. Natural language processing techniques are built in the VOSviewer package to enable one to create term co-occurrence networks based on English-language textual data. State-of-the-art techniques for network layout and network clustering are available in the software. VOSviewer software uses a circle and label to represent an element, in which the circle size represents importance, and circles with the same color belong to the same cluster. In the following section, we will focus on aspects that describe global scientific production for big data and social media data research:

- (1) Growth of output during 2010-2019
- (2) Distribution of output in subject categories and journals
- (3) Most cited documents
- (4) Geographic and institutional distribution of publications
- (5) Institution collaboration network analysis
- (6) Keywords analysis

## 4.3 Results and Discussion

# 4.3.1 Characteristics of Article Outputs

1,436 publications have been identified as being data collection and data management of social media and big data-related during 2010-2019. A total of 1,436 documents includes 1,233 articles, 154 reviews, 10 book chapters, 28 early accesses, 30 proceeding papers, two letters, 39 editorial materials, one software review, and one book review. After removing records that do not have completed authorship and publication year information, we were left with 1,408 records. The characteristics of the article outputs are shown in Figure 4.1 and Table 4.1. The number of annual publications rose from four in 2010 to 362 in 2019, illustrating a dramatic rise and upward growth of this are of the research in the past decade. The average annual growth rate of all SCI and SSCI publications in the field was 56.74%. In addition, Figure 4.1 shows that the annual growth rate of publication has accelerated since 2014.

The average number of authors and references increased from three and 50 in 2010 to 4.439 and 59.948 in 2019, respectively (Table 4.1). The growth of an average number of authors per article indicates that collaboration in the field has

increased. The growth of average references per article indicates that there is increased knowledge about this topic. It is interesting to see that the average number of citations per article has decreased overall since 2010.

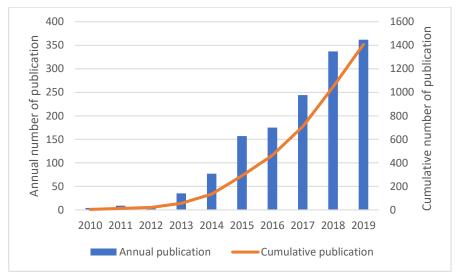


Figure 0.1. Growth of publication outputs. (Horizontal axis: year; Vertical axis: number of publications)

Table 0.1. Scientific outputs descriptors during 2010-2019

| PY   | TP  | AU   | AU/TP | NR    | NR/TP  | TC   | TC/TP   |
|------|-----|------|-------|-------|--------|------|---------|
| 2010 | 4   | 12   | 3.000 | 200   | 50.000 | 453  | 113.250 |
| 2011 | 9   | 35   | 3.889 | 301   | 33.444 | 555  | 61.667  |
| 2012 | 8   | 25   | 3.125 | 329   | 41.125 | 792  | 99.000  |
| 2013 | 35  | 102  | 2.914 | 1476  | 42.171 | 1793 | 51.229  |
| 2014 | 77  | 326  | 4.234 | 3128  | 40.623 | 3123 | 40.558  |
| 2015 | 157 | 600  | 3.822 | 7616  | 48.510 | 3123 | 19.892  |
| 2016 | 175 | 813  | 4.646 | 9053  | 51.731 | 3119 | 17.823  |
| 2017 | 244 | 1017 | 4.168 | 13739 | 56.307 | 2626 | 10.762  |
| 2018 | 337 | 1622 | 4.813 | 19529 | 57.950 | 1769 | 5.249   |
| 2019 | 362 | 1607 | 4.439 | 21701 | 59.948 | 442  | 1.221   |

PY: year; TP: number of publications; AU: number of authors; TC: total citation count; NR: number of cited references; AU/TP, NR/TP, and TC/TP: an average of authors, references, and citation per paper.

# 4.3.2 Subject Categories and Major Journals

Based on the classification of the Web of Science categories, the sample documents covered 194 subject categories. The research domain covered a wide variety of themes and disciplines. The top 20 subject categories were presented in Table 4.2. The results show that data collection and management for big data and social media research spanned a wider range of disciplines, but such studies mainly stemmed from computer science information systems, engineering electrical electronics, telecommunications, computer science theory methods, computer science interdisciplinary applications, and information science library science.

Table 0.2. Distribution of the top 20 subject categories.

| Subject Category                                | TP(%) |       |
|---|-------|-------|
| Computer science information systems            | 233   | 16.19 |
| Engineering electrical electronic               | 158   | 10.98 |
| Telecommunications                              | 126   | 8.76  |
| Computer science theory methods                 | 108   | 7.51  |
| Computer science interdisciplinary applications | 90    | 6.25  |
| Information science library science             | 90    | 6.25  |
| Computer science software engineering           | 76    | 5.28  |
| Health care sciences services                   | 68    | 4.73  |
| Medical informatics                             | 60    | 4.17  |
| Environmental sciences                          | 51    | 3.54  |
| Public environmental occupational health        | 51    | 3.54  |
| Computer science artificial intelligence        | 50    | 3.47  |
| Communication                                   | 49    | 3.41  |
| Management                                      | 49    | 3.41  |
| Computer science hardware architecture          | 44    | 3.06  |
| Business  | 43    | 2.99  |
| Medicine general internal                       | 40    | 2.78  |
| Multidisciplinary sciences                      | 34    | 2.36  |
| Environmental studies                           | 33    | 2.29  |
| Green sustainable science technology            | 29    | 2.02  |
| Engineering civil                               | 28    | 1.95  |
| Operations research management science          | 28    | 1.95  |

The top 20 active journals are summarized in Table 4.3. This table shows that *IEEE* (*The Institute of Electrical and Electronics Engineers*) Access is the most productive journal, followed by *Future Generation Computer Systems - The International* 

Journal of eScience, Journal of Medical Internet Research, ISPRS (International Society for Photogrammetry and Remote Sensing) International Journal of Geoinformation, Sensors, and Sustainability. Regarding average citation number per article, IEEE Transactions on Knowledge and Data Engineering, Computers in Human Behavior, and Big Data are the three most highly cited journals, with a magnitude of 112.4, 70, and 44.429, respectively.

Table 0.3. The 20 most active journals

| Journals   | TP | (%)   | TC   | (%)   | TC/TP   |
|--|----|-------|------|-------|---------|
| IEEE Access  | 43 | 3.054 | 234  | 1.315 | 5.442   |
| Future Generation Computer Systems - The International Journal of eScience     | 29 | 2.060 | 399  | 2.242 | 13.759  |
| Journal of Medical Internet Research   | 29 | 2.060 | 384  | 2.158 | 13.241  |
| ISPRS International Journal of Geo-information                                 | 14 | 0.994 | 46   | 0.258 | 3.286   |
| Sensors  | 14 | 0.994 | 124  | 0.697 | 8.857   |
| Sustainability   | 14 | 0.994 | 51   | 0.287 | 3.643   |
| BMJ Open   | 13 | 0.923 | 42   | 0.236 | 3.231   |
| PLOS ONE   | 12 | 0.852 | 235  | 1.321 | 19.583  |
| Cluster Computing - The Journal of Networks Software<br>Tools and Applications | 10 | 0.710 | 24   | 0.135 | 2.400   |
| Concurrency and Computation: Practice and Experience                           | 10 | 0.710 | 63   | 0.354 | 6.300   |
| IEEE Transactions on Knowledge and Data Engineering                            | 10 | 0.710 | 1124 | 6.316 | 112.400 |
| International Journal of Information Management                                | 10 | 0.710 | 118  | 0.663 | 11.800  |
| Transportation Research Record   | 10 | 0.710 | 39   | 0.219 | 3.900   |
| IEEE Internet of Things Journal  | 9  | 0.639 | 222  | 1.248 | 24.667  |
| Computers in Human Behavior  | 8  | 0.568 | 560  | 3.147 | 70.000  |
| IEEE Transactions on Industrial Informatics                                    | 8  | 0.568 | 274  | 1.540 | 34.250  |
| SIGMOD Record  | 8  | 0.568 | 56   | 0.315 | 7.000   |
| Big Data   | 7  | 0.497 | 311  | 1.748 | 44.429  |
| Computer Law & Security Review   | 7  | 0.497 | 54   | 0.303 | 7.714   |
| Frontiers in Psychology  | 7  | 0.497 | 17   | 0.096 | 2.429   |
| International Journal of Distributed Sensor Networks                           | 7  | 0.497 | 20   | 0.112 | 2.857   |
| Online Information Review  | 7  | 0.497 | 38   | 0.214 | 5.429   |

TP: number of publications; TC: total citation count; TC/TP: an average of citations per paper

### 4.3.3 Most Cited Documents

Based on the number of citations, we list the 10 most cited documents relating to data collection and data management in Table 4.4. The citation number has updated base on Google Scholar figures. If audiences wish to heavily research big data collection and data management, it might prove worthwhile to read those highly cited documents first to gain an overview of the topic. For example, one could read Chen & Zhang [26] to learn more about challenges, techniques, and technologies as they relate to big data. In order to learn how to process and generate large datasets, it could prove beneficial to learn more about a programming model- MapReduce- by reading Dean & Ghemawat [27].

Table 0.4. The 10 most cited documents

| Title   |      | Publication   | Author                                       | Citation<br>Count <sup>2</sup> |
|---|------|---|--|--------------------------------|
| Users of the world, unite! The challenges and opportunities of Social Media                           | 2010 | Business horizons                                       | AM Kaplan, M<br>Haenlein                     | 17,762                         |
| MapReduce: Simplified data processing on large clusters   | 2004 | usenix.org  | J Dean, S<br>Ghemawat                        | 12,758                         |
| Big data: A revolution that will transform how we live, work, and think                               | 2013 | Houghton Mifflin<br>Harcourt                            | V Mayer-Schön-<br>berger, K Cukier           | 5,340                          |
| Big data: The next frontier for innovation, competition, and productivity                             | 2011 | McKinsey  | J Manyika                                    | 5,319                          |
| Business intelligence and analytics: From big data to big impact.                                     | 2012 | MIS quarterly   | H Chen, RHL<br>Chiang, VC Storey             | 4,620                          |
| Big data: the management revolution   | 2012 | Harvard Business<br>Review                              | A McAfee, E<br>Brynjolfsson, TH<br>Davenport | 4,130                          |
| Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon | 2012 | Information, com-<br>munication & soci-<br>ety          | D Boyd, K Craw-<br>ford                      | 3,254                          |
| Big data: A survey  | 2014 | Mobile networks and applications                        | M Chen, S Mao, Y<br>Liu                      | 2,403                          |
| Data-intensive applications, challenges,<br>techniques and technologies: A survey on<br>Big Data      | 2014 | Information sci-<br>ences                               | CLP Chen, CY<br>Zhang                        | 2,255                          |
| Beyond the hype: Big data concepts, methods, and analytics  | 2015 | International jour-<br>nal of information<br>management | A Gandomi, M<br>Haider                       | 2,212                          |

<sup>&</sup>lt;sup>2</sup>The citation count is updated based on Google Scholar on January 9, 2020.

## 4.3.4 Geographic and Institutional Distribution of Publications

The geographic and institutional distributions of publications were generated based on author affiliation information. We summarized the 10 most productive countries in Figure 4.2, in terms of the number of total publications, single country articles, and international collaborations, respectively. Out of these 10 countries, five were from Europe, two from North America, one from Australia, and two from Asia. The U.S. was the most productive country with a total of 506 articles. China ranked second with 234 articles, followed by the UK with 195 articles. Figure 4.2 also reveals that some countries achieved higher rates of international collaboration. These countries include France (collaboration rate: 65.00%), Spain (collaboration rate: 63.16%), Canada (collaboration rate: 62.65%), Australia (collaboration rate: 60.31%), and Germany (collaboration rate: 60.32%).

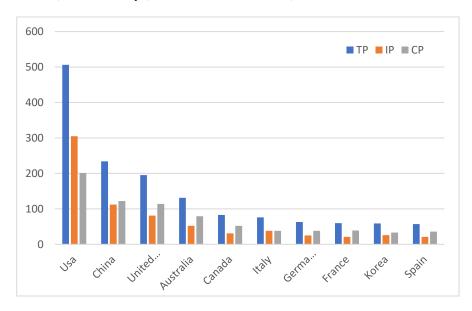


Figure 0.2. Most productive countries during 2010-2019 (TP, total publications; IP, the number of independent publications by country; CP, the number of internationally collaborative publications)

Co-authorship analysis enabled the study of the most influential countries' cooperation network, as plotted in Figure 4.3. The size of nodes reveals the productivity rate of each country, while the thickness of curved lines between countries demonstrates the strength of collaboration. The U.S., China, and the U.K. had the largest number of papers with co-authorships. As we can see from Figure 4.3, there are clusters that demonstrate inter-country collaboration. European Countries cluster together, whereas Asian countries and Australia cluster together. This suggests that countries from the same continent tend to collaborate more with one another than

with countries from distant continents. Note that the U.S. is at the center of the collaboration network, which illustrates that U.S. researchers conduct an enormous amount of collaborative research with researchers from both Asian and European countries.

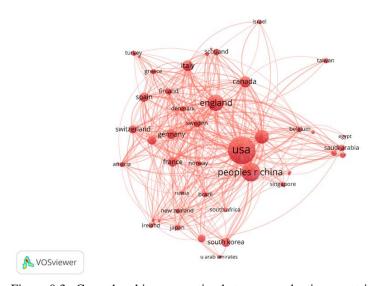


Figure 0.3. Co-authorship cooperation between productive countries

# 4.3.5 Institution Collaboration Network

A collaboration network of the 80 most productive institutions is visualized using the VOSviewer (Figure 4.4). The most productive institution proved to be the University of Michigan with 21 papers, followed by both the Chinese Academy of Science and the University of Sydney, each of which produced 17 papers (Table 4.5). Each node in Figure 4.4 indicates an institution. The size of each node indicates the institution's productivity. The bigger the node is, the more productive the organization is. The distance between two organizations in the visualization approximately indicates the relatedness of the organizations in terms of co-authorship links. The closer two organizations are located to each other, the stronger their relatedness. The co-authorship links between organizations are also represented by curve lines. The institutions are clustered into two groups: each group has a unique color. Asian institutions are represented by the green group, while North America institutions, European institutions are represented by the red. Institutions that are working on

social media data collection and management within the same continent are clustered closer together and have more connections than institutions scattered across different continents. This means that institutions from the same continents are more likely to collaborate with one another than institutions from different continents.

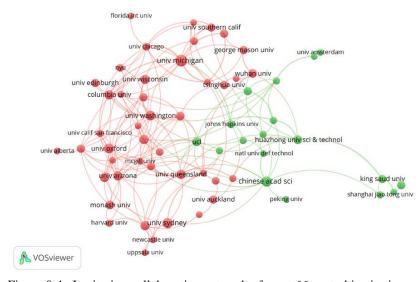


Figure 0.4. Institution collaboration network of most 66 central institutions

Table 0.5. Top 17 institutions based on the total publications

| Rank | Organization                | Country   | Number of publications | Total citations |
|------|-----------------------------|-----------|------------------------|-----------------|
| 1    | University of Michigan      | USA       | 21                     | 226             |
| 2    | Chinese Academy of Sciences | China     | 17                     | 370             |
| 3    | University of Sydney        | Australia | 17                     | 266             |
| 4    | University of Washington    | USA       | 15                     | 350             |
| 5    | University of Oxford        | UK        | 15                     | 177             |
| 6    | University of Arizona       | USA       | 14                     | 230             |
| 7    | University of Cambridge     | UK        | 14                     | 312             |
| 8    | Columbia University         | USA       | 14                     | 178             |
| 9    | University of Melbourne     | Australia | 14                     | 502             |
| 10   | University of Toronto       | Canada    | 14                     | 84              |
| 11   | University of Queensland    | Australia | 13                     | 105             |
| 12   | University of Wisconsin     | USA       | 13                     | 243             |

| 13 | University of College London             | UK        | 12 | 443 |
|----|--|-----------|----|-----|
| 14 | Huazhong University Science & Technology | China     | 12 | 54  |
| 15 | University of Maryland                   | USA       | 12 | 379 |
| 16 | Monash University                        | Australia | 12 | 56  |
| 17 | Wuhan University                         | China     | 12 | 72  |

# 4.3.6 Keywords Analysis – Network Analysis

Keywords supplied by the authors provide a very basic idea of the topics covered within the article. The 30 most frequently used keywords in the study period are calculated and ranked in Column (1) of Table 4.6. Co-occurrence links indicate the frequency whereby keywords occur simultaneously in a study. The co-occurrence relationships between keywords can be shown by the co-occurrence links in the cooccurrence word network. In this study, the co-occurrence relationships between the top 86 high-frequency keywords were examined, and the co-occurrence word networks were visualized by VOSviewer software (Figure 4.5). The nodes represent high-frequency keywords, and the size of each represents the degree of frequency the keyword is used. The high-frequency keywords are selected based on how many times keywords have. A higher value for a keyword represents a higher frequency at which the word was referenced as a keyword in the last 10 years. The distance between two keywords in the visualization approximately indicates the relatedness of the keywords in terms of co-occurrence links. The closer two keywords are located to each other, the stronger their relatedness. The strongest co-occurrence links between keywords are also represented by curved lines.

As shown in Figure 4.5, the 86 most frequent author keywords are grouped into four clusters. The red cluster mainly focuses on social media; the green and yellow clusters focus mainly on big data dimensions, and the blue cluster is mainly about data analytics. The keywords that are referenced with highest frequency are "big data", "social media", "data management", "data collection", "cloud computing", "Twitter", "machine learning", "Facebook", and "data mining". Twitter and Facebook are the two most popular social data platforms referenced in human dynamics research. It is not surprising to see these two words occurring in high frequency. We also see that machine learning is frequently referenced, which coincides with the fact that the machine learning approach has been popular and been applied heavily in social media data analysis and human dynamics. Other significant topics over the past 10 years include: "Internet of things", "privacy", "big data analytics", "crowdsourcing", "data analytics", "Internet", "ethics", "data Science", "big data management", and "citizen science". The high frequency of the aforementioned topics suggests that these are critical areas of social media data collection and data management throughout human dynamics research. For example, the keyword "ethics" and "privacy" both occur frequently in the literature, which reflects that privacy and ethics are among the critical concerns relating to social media data collection and management.

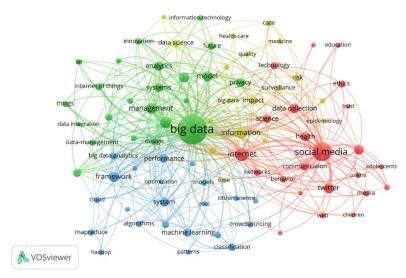


Figure 0.5. Co-occurrence network of top 86 high-frequency keywords.

# 4.3.7 Keywords Analysis – Temporal Evolution

By examining the temporal evolution of these keywords would give us insights on trending areas of research. To closely examine the temporal evaluation, we divide the 10 studied years into three consecutive periods (2010-2012, 2013-2015, and 2016-2019). The 30 most frequently used keywords throughout the entire studies period (2010-2019) are calculated and ranked in Columns (2), (3), and (4) of Table 4.6. We identify keyword trends on the basis of whether or not the rank of a keyword rises upward across the three consecutive periods. Eleven keywords ("data management", "cloud computing", "machine learning", "data mining", "Internet of things", "big data analytics", "crowdsourcing", "data analytics", "data Science", "big data management", "Hadoop", "MapReduce", "sentiment analysis", "surveillance", "business intelligence", and "IoT") are becoming increasingly popular over the past 10 years. For example, the keyword "machine learning" does not occur in articles in the 2010-2012 period, but usage of this keyword increased from 18th in 2013 to 2015 to fifth from 2016 to 2019, suggesting that machine learning rose as a trending research topic in the past years. This dramatic increase coincided with the popularity of AI and machine learning. It is not surprising that the keyword "cloud computing" has also been frequently referenced frequently in recent years. This can be attributed

to the recent advance of cloud computing technology and applications in social data analysis. In addition, "crowdsourcing" and "surveillance" rose in popularity. Human crowdsourcing and surveillance cameras are the two important approaches for sensing and data acquisition. Surveillance cameras generate a huge volume of images and videos while human crowdsourcing generates data via mobile devices. These data acquisition approaches provide information for traffic analysis, human mobility, and urban structure research needs. Another example for treading research topics is the keyword "sentiment analysis". With social media data, researchers are capable of analyzing the change of human sentiments and their mobility pattern as a result of an event (e.g., disaster, pandemic, or presidential candidate campaign).

Table 0.6. Temporal evolution of the 30 most frequently used keywords

|                     | Periods   |    |           |   |           |    |           |     |                 |      |
|---------------------|-----------|----|-----------|---|-----------|----|-----------|-----|-----------------|------|
| Keywords            | 2010-2019 |    | 2010-2012 |   | 2013-2015 |    | 2016-2019 |     | Rising<br>Trend |      |
|                     | N         | R  | (%)       | N | R         | N  | R         | N   | R               | Henu |
| Big data            | 383       | 1  | 5.75      |   |           | 69 | 1         | 314 | 1               |      |
| Social media        | 155       | 2  | 2.33      | 7 | 1         | 42 | 2         | 106 | 2               |      |
| Data management     | 61        | 3  | 0.92      | 1 | 22        | 9  | 7         | 51  | 3               | X    |
| Data collection     | 58        | 4  | 0.87      | 1 | 19        | 14 | 3         | 43  | 4               |      |
| Cloud computing     | 43        | 5  | 0.65      |   |           | 8  | 9         | 35  | 6               | X    |
| Twitter             | 42        | 6  | 0.63      | 2 | 3         | 11 | 5         | 29  | 8               |      |
| Machine learning    | 40        | 7  | 0.60      |   |           | 4  | 18        | 36  | 5               | X    |
| Facebook            | 35        | 8  | 0.53      | 2 | 2         | 13 | 4         | 20  | 13              |      |
| Data mining         | 34        | 9  | 0.51      |   |           | 7  | 10        | 27  | 9               | X    |
| Internet of things  | 34        | 10 | 0.51      |   |           | 3  | 32        | 31  | 7               | X    |
| Privacy             | 32        | 11 | 0.48      |   |           | 9  | 8         | 23  | 11              |      |
| Big data analytics  | 28        | 12 | 0.42      |   |           | 4  | 15        | 24  | 10              | X    |
| Crowdsourcing       | 24        | 13 | 0.36      |   |           | 2  | 45        | 22  | 12              | X    |
| Data analytics      | 21        | 14 | 0.32      |   |           | 3  | 26        | 18  | 14              | X    |
| Data analysis       | 20        | 15 | 0.30      |   |           | 5  | 12        | 15  | 16              |      |
| Internet            | 20        | 16 | 0.30      |   |           | 10 | 6         | 10  | 29              |      |
| Ethics              | 19        | 17 | 0.29      |   |           | 4  | 16        | 15  | 18              |      |
| Data science        | 17        | 18 | 0.26      |   |           | 2  | 53        | 15  | 17              | X    |
| Big data management | 16        | 19 | 0.24      |   |           | 1  | 162       | 15  | 15              | X    |
| Citizen science     | 16        | 20 | 0.24      | 1 | 10        | 3  | 22        | 12  | 20              |      |
| Hadoop              | 15        | 21 | 0.23      |   |           | 1  | 420       | 14  | 19              | X    |
| Data                | 14        | 22 | 0.21      |   |           | 6  | 11        | 8   | 36              |      |
| MapReduce           | 13        | 23 | 0.20      |   |           | 2  | 67        | 11  | 24              | X    |

| Sentiment analysis    | 13 | 24 | 0.20 |   |    | 1 | 737 | 12 | 21 | X |
|-----------------------|----|----|------|---|----|---|-----|----|----|---|
| Surveillance          | 13 | 25 | 0.20 |   |    | 2 | 95  | 11 | 26 | X |
| Business intelligence | 12 | 26 | 0.18 |   |    | 2 | 39  | 10 | 28 | X |
| IoT                   | 12 | 27 | 0.18 |   |    | 1 | 491 | 11 | 23 | X |
| Recruitment           | 12 | 28 | 0.18 | 1 | 70 | 3 | 34  | 8  | 40 |   |
| Security              | 12 | 29 | 0.18 |   |    | 3 | 35  | 9  | 34 |   |
| Technology            | 12 | 30 | 0.18 |   |    | 4 | 20  | 8  | 41 |   |

N: the number of articles in the study period; R: the absolute rank of author keywords; ---: no such author keyword in a specific period.

## 4.4 Conclusions

In conclusion, this study social data collection and data management as they are referenced in human dynamics research through a bibliometric approach. We presented an overview and brief picture of existing studies in this area. Audiences looking to understand social media data collection and management as it is referenced in human dynamics can use this study to help determine which articles they should read, which journals they should consider for publication submissions, and which research trends are most significant.

In summary, the number of annual publications about big data and social media research with an emphasis on data collection and data management increased from just four in 2010 to 362 in 2019. The annual growth rate for such publications has accelerated since 2014. The studies covered wide variety of subjects, such as computer science information systems, engineering electrical electronic, telecommunications, computer science theory methods, computer science interdisciplinary applications, and information science library science. The three most productive journals in these areas were *IEEE Access*, *Future Generation Computer Systems* - *The International Journal of eScience*, and *Journal of Medical Internet Research*.

This study suggests that "big data", "social media", "data collection", "Twitter", "Facebook", and "privacy" have been the most popular topics in this area over the past 10 years. Some keywords, such as "data management", "cloud computing", "machine learning", "data mining", "Internet of things", "big data analytics", "crowdsourcing", "data analytics", "data Science", "big data management", "Hadoop", "MapReduce", "sentiment analysis", "surveillance", "business intelligence", and "IoT", attracted increasing attention, reflecting research trends. Furthermore, most of those 30 most frequently referenced keywords in this area were not listed as keywords during the 2010-2012 period; rather, they grew in popularity in the most recent periods.

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