

Topical Analysis of Telemedicine Studies Using Text Mining Techniques

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Received 10 August 2024; Accepted 1 December 2024

Abstract

The presence of diverse research in the field of telemedicine necessitates the need to analyze the topics of these studies to have a clear and comprehensive vision of this domain. The present study was conducted with the aim of topic modeling the published articles in the field of telemedicine using the PubMed database. This study employed a descriptive approach using LDA and TF-IDF as text mining techniques. Articles in the field of telemedicine were extracted from the PubMed database using the search formula "Telemedicine"[Majr] without any time limitations. A total of 37,181 records were retrieved. After data cleansing, the abstracts of 31,144 articles were analyzed, and topic modeling was performed. The topic modeling of telemedicine resulted in the identification of eight topical clusters, including e-health, interventions, primary care, remote monitoring, COVID-19, telehealth, cardiovascular disease, and research. The highest publication trend was observed for the COVID-19 topic, followed by primary care. Findings demonstrate the satisfactory performance of the LDA algorithm in topic classification in the field of telemedicine. Also, the results provide a better foundation for developing policies and research programs, as well as increasing awareness and utilization of emphasized topics. Modeling the topics of global telemedicine articles and comparing different algorithms with the current one is recommended for future research. Further studies in this field can lead to improved effectiveness, quality, and accuracy of telemedicine services.

Keywords: Topic modeling Text mining, Telemedicine

1. Introduction

Telemedicine has emerged as a solution to address the unequal distribution and scarcity of medical resources, emphasizing the geographical separation between healthcare providers and recipients of medical information. In other words, its goal is to provide access to healthcare regardless of geographical location [1]. Telemedicine is considered a strategy aligned with the era of Industry 4.0, where information systems have permeated social life [2]. Furthermore, telemedicine can collect and manage patient data, enabling timely and remote clinical decision-making without needing in-person encounters with patients [2]. In other words, telemedicine is the convergence of medicine and remote information and communication technologies, facilitating communication between healthcare professionals and patients through telephone, wireless communication, fax, remote conferences, and the internet [3]. The role and benefits of telemedicine, particularly during widespread outbreaks such as COVID-19, are noteworthy so that it leads to increased workforce stability, limited direct contact between physicians and patients, the establishment of physical distance for the continued treatment of patients with various allergic and immunological conditions, reduced reliance on personal protective equipment, decreased physician burnout, and facilitating the work of personnel who are under overwhelming pressure due to patient influx related to the pandemic [4]. The points mentioned above highlight the

importance of this field and confirm the presence of diverse studies in this area.

The research history in telemedicine dates back to 1990, and since then, numerous articles have been published in this area [5]. The existence of many research studies in this field necessitates their analysis and categorization to provide a clear roadmap for future research and inform researchers about the topics and issues addressed in this field. The analysis of the conducted research in any scientific field reveals the scientific trajectory of that discipline and facilitates policymaking and investment in that area [6]. The prioritization of research topics based on the needs of the stakeholders in each scientific field is crucial in scientific and research policymaking, which can be achieved by investigating various dimensions and aspects of each scientific field and identifying research gaps [7].

Senel and Demir conducted a study in 2015 to analyze the literature on telemedicine and teledermatology using the Web of Science database. The analysis was performed on published documents from 1980 to 2013, examining the correlations between economic productivity, human development index, technological advancements, and the performance of countries in both fields. The study concluded that the majority of published works originated from high-income and developed countries [5]. Armfield et al. conducted a study in 2014 to provide bibliometrics of telemedicine and telehealth texts and analyze the changes in content themes. They used Medline entries and considered two time periods for analysis: 1970-1995 and 2009-2013. The findings revealed that most published documents in the field of telemedicine were disseminated through channels other

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doi:10.25103/jestr.176.02

than specialized journals, and content analysis indicated that the literature had emphasized clinical and evaluation applications of this field. [8]. Yang et al. performed an investigation in 2015 on the published resources related to telemedicine from 1993 to 2012 in the Science Citation Index – Expanded database. The findings indicated significant growth in telemedicine literature, but publication activity varied across countries and over time. The study also identified research interests in neuroscience and nursing for telemedicine [9]. Viswanathan, Elango, and Yugapriya analyzed telemedicine research using publications indexed in the Scopus database between 1992 and 2016. The retrieved data underwent bibliometric analysis, including co-authorship lists, multi-authorship lists, average citations per article, relative citation index, highly-cited articles, and relative uncitedness index. The findings indicated that the highest number of telemedicine publications occurred in 2015, with most research being conducted by collaborative authors. In addition, approximately one-third of the publications received no citations [10]. Leena et al. analyzed the growth of telemedicine, its applications, and its benefits using the Web of Science Core Collection database. The years 2016 to 2019 had the highest number of studies in the field of telemedicine, and the United States, followed by Australia and the United Kingdom, had the highest volume of remote-oriented publications. Several records focused on analyzing telemedicine research and its applications, describing the advantages of remote healthcare services along with wireless technologies or the use of telemedicine for preventive care and disease management [11]. Sikandar et al. examined telemedicine and eHealth research from 2011 to 2020 using the Scopus database. The findings of their study included a descriptive analysis of influential authors, journals, institutions, countries, and top articles, as well as bibliometric analysis, such as co-authorship, co-occurrence of keywords, and bibliographic pairs. The study also discussed limitations and future directions for researchers in this field [12]. Zulfikar and Setyonugroho conducted a bibliometric analysis of telemedicine from the perspective of healthcare workers. Their study examined indexed articles in Scopus between 2010 and 2022; the findings illustrated the subject structure and patterns of main topics in the studied field [13].

The objective of the present research is to analyze and examine studies in the field of telemedicine, with the difference that the current research aims to categorize telemedicine studies and provide a topic modeling; most studies have utilized bibliometric tools for analyzing telemedicine studies. Text classification is one of the methods of text mining. Text mining is the process of extracting information, knowledge, or patterns from unstructured text resources. From a technical view, text mining uses automated methods to exploit the vast knowledge available in textual documents [14]. In other words, the main purpose of text mining is to understand the underlying structure of a collection of documents. In topic modeling models, this structure is observed as a set of topics or categories based on the words present in the documents [15]. Therefore, in the present study, text mining, especially topic modeling, and the Latent Dirichlet Allocation (LDA) algorithm were employed. No study has addressed the topic classification of the telemedicine field using text mining. However, topic modeling has been used in other health-related research. For instance, Ni Ki et al. conducted research on topic modeling in precision medicine with its applications in personal diabetes management [16]. Moreover, Joe et al. conducted research on online information analysis about pancreatic cancer in Korea

using structural topic modeling [17]. In another study, Asadi Qadiklaei et al. performed topic modeling of Iranian researchers' papers in the field of endocrine and metabolism in the Web of Science database [18]. Moreover, Shokouhian et al. presented a model for topic-based categorization of scientific outputs in the field of health using text mining methods [19].

Another feature of the present research was that the text mining was performed on the documents available in PubMed, which is a specialized medical database. Due to the utilization of Big Data software, unlike other studies that have selected a timeframe for their research, the present investigation has no time limitations and includes all relevant documents in the PubMed database related to telemedicine. This feature allows for a comprehensive view of this field because it utilizes all relevant documents. In general, this research aims to examine the most common words in scientific outputs in the field of telemedicine based on the bag-of-words (BOW) approach, extracted topics using text mining in the field of telemedicine, the frequency of formed topics in the field of telemedicine, the correlation between telemedicine topics, and the trend of scientific publications in each of the formed topics in this field.

2. Methodology

A quantitative approach was used for performing the present investigation, and this study is an applied research conducted using text mining methods. The research population includes all articles in the field of telemedicine, which are searched based on the topics of the Medical Subject Headings (MeSH). For this purpose, a search was conducted using the strategy "Telemedicine"[Majr] on March 11, 2023.

After retrieving 37,181 records, the abstracts of the articles were saved in text format and converted to structured Excel format for analysis.

The present research was conducted in four stages:

I. Preprocessing

Since the data is unstructured, it usually contains a significant amount of irrelevant information that must be removed before transferring it for training and analysis. This stage includes the following steps for preprocessing the articles' abstracts and titles:

- Removing NULL records: In this step, records with NULL abstract and title fields are deleted.
- Punctuation removal: In this step, punctuation marks are removed as some word embedding models do not support them.
- Tokenization: This is a method of breaking down the text into smaller units called tokens.
- Stop word removal: Stop words are generally words that do not contribute much to the meaning of the content and are therefore removed in the preprocessing stage.
- Lemmatization: This stage reduces words to their root form and helps extract valid and essential words (20). In this stage, words are transformed into their root form.

II. Conversion of Text to Numerical Vectors

In the next step, considering that most machine learning methods can be executed on numerical data, it is necessary to convert textual data into a set of numbers for their utilization

and execution on textual data, which is achieved through vectorization. In this stage, unstructured textual data is transformed into structured matrix data using TF-IDF. The TF-IDF is a BOW paradigm, but it differs from a regular corpus since it weights the terms, meaning that the words that appear frequently in the corpus are given higher weights. During the initialization, it requires a training dataset with correct values, similar to a BOW model that has been pre-obtained. In other words, in order to obtain the TF-IDF scores, it is first necessary to train the corpus and then apply it to the model mentioned above [20].

III. Topic Modeling

Topic modeling is an unsupervised machine learning strategy that can examine a collection of documents, identify words, discover patterns within them, and consequently cluster words and phrases in the best possible way to determine a set of topics. In summary, topic modeling algorithms generate a set of phrases and words that they believe are related and allow the reader to understand the meaning of those relationships while categorizing topics [21].

In this stage, the input obtained from the previous TF-IDF step is fed into the LDA algorithm to model the topics. The LDA is a probabilistic approach to topic modeling. In other words, it is a hierarchical Bayesian probabilistic model for collecting discrete data that works based on the assumption of coherence between words and topics in a document. It models

the corpus as a whole distribution of topic models and the subsequent topics as a distribution of word models in the document. This is an improvement over other models that also employ competitive scattering as it resolves the balance at the document level. In the present study, the implementation of LDA is performed through Gensim, a Python library used for topic modeling, document indexing, and retrieval of similarity with large corpora.

IV. Visualization

In the next step, the correlation chart and the trend of topics are determined. It should be noted that the coding for this task was carried out using Python programming language with the help of packages such as Pandas, Gensim, Scikit-learn, NumPy, NLTK, and WordCloud.

3. Results

As mentioned, 37,181 articles in the field of telemedicine were retrieved from the PubMed database; 31,144 articles among them were analyzed after cleansing.

In Figure 1, using the word cloud module, a cloud of the top 200 words with the highest weights based on TF-IDF is generated. Therefore, larger-sized words have higher weights in telemedicine-related research.



Fig. 1. Words cloud of research in the field of telemedicine.

Afterward, topic modeling was performed using the LDA algorithm. The topic clusters comprised eight groups, and topical experts labeled them as the topic clusters/groups in the field of telemedicine. Table 1 displays the eight clusters mentioned above, and Figure 1 indicates the distribution of published articles in the field of telemedicine based on these eight clusters.

Cluster 1: eHealth

According to Figure 2, the eHealth cluster accounts for the highest percentage, precisely 25%, of the published articles. The eHealth is generally considered an umbrella term encompassing all events at the intersection of healthcare,

information, and communication technology. This cluster includes several applications related to medicine and information and communication technology, including telemedicine [22]. Telemedicine and eHealth represent the manifestation of new technological participation, enabling the exchange of knowledge among healthcare professionals and providing access to quality services for patients [23]. As observed in Table 1, the keywords associated with the eHealth cluster include health, care, technology, information, mobile, network, data, etc.

Cluster 2: Intervention

The second cluster is dedicated to the topic of intervention, which accounts for 13% of the published articles. By considering the keywords in this cluster (Table 1), which include intervention, control, trial, mHealth, participants, diabetes, health, mobile, patients, app, randomize, management, depression, message, etc., it can be understood that interventions are discussed in two ways. One way is related to the tools used for intervention, such as mobile and messaging, and the other focuses on interventions in diseases like diabetes, depression, and remote care. Since intervention research often involves experimental trials, keywords related to this aspect are also mentioned in this cluster.

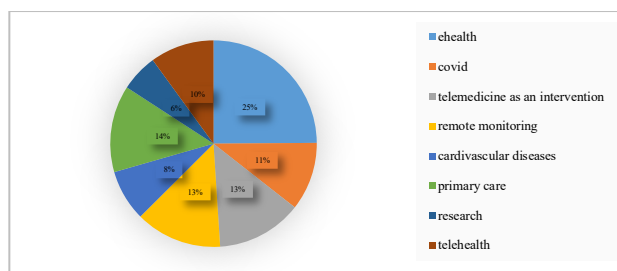


Fig. 2. Distribution of published articles in the field of telemedicine based on eight topic clusters.

Table 1. Eight topic clusters obtained from implementing the topic modeling algorithm in the field of telemedicine.

No	Topics	Words
1	ehealth	Health, care, technology, healthcare, information, mobile, network, data, ehealth, medical, mobile, technologies, systems, Service, mhealth, applications, patients, digital, model, management, communication
2	Intervention	Intervention, control, trial, mhealth, participants, diabetes, health, mobile, patients, app, randomize, management, activity, months, control trial, care, depression, effect, message
3	Primary care	Patients, visit, consultations, consultation, satisfaction, clinic, person, telehealth, video, cost, primary care, telephone, survey, follow
4	Remote monitoring	Image, diagnosis, remote, medical, network, diagnostic, digital, data, transmission, surgical, screen, video, accuracy, pathology, tele, quality
5	COVID-19	Covid, covid 19, telehealth, pandemic, care, covid 19 pandemic, Mental, mental health, patients, virtual, coronavirus, rural, state, patient, providers
6	Telehealth	Telehealth, telerehabilitation, participants, rehabilitation, patients, home, train, health, satisfaction
7	Cardiovascular diseases	Patients, stroke, heart, heart failure, failure, telemonitoring, home, monitor, care, hospital, cost, acute, cardiac
8	Research	Review, study, interventions, Systematic, systematic review, Search, article, literature, Evidence, meta, health, trials

Cluster 3: Primary Care

The third cluster is related to primary care, which accounts for a significant number of published articles after eHealth. Research indicates that telemedicine can potentially increase access to primary and specialized care [24]. However, it should be noted that telemedicine requires new technologies, different workflows, modified triage processes, physician commitment, and patient acceptance to provide primary care [25]. The keywords associated with this cluster include patients, visit, consultations, consultation, satisfaction, clinic, telehealth, video, cost, primary care, telephone, survey, etc.

Cluster 4: Remote Monitoring

The fourth cluster allocated 13% of the published articles related to telemedicine (Figure 2). Telemedicine can be classified into five main types, and remote monitoring is one of them (26). As evident from the keywords in this cluster (image, diagnosis, remote, medical, network, diagnostic, digital, data, transmission, surgical, screen, video, etc.), remote monitoring involves the utilization of a wide range of technological devices to remotely monitor patients' health and clinical symptoms [26].

Cluster 5: COVID-19

The fifth cluster represents 11% of the published articles related to telemedicine (Figure 2). The COVID-19 pandemic has promoted and accelerated the implementation of telemedicine and considered it an ideal tool [27] and the first line of defense to reduce the spread of the coronavirus. During an epidemic situation, telemedicine could be used for purposes such as reducing the time for diagnosis and initiating

treatment, patient quarantine or stabilization, precise monitoring, coordination of medical resources in remote locations, prevention of transmission risks, informing the public community, cost savings, training of healthcare professionals, and real-world data surveillance and control [28].

Cluster 6: Telehealth

This cluster focuses on telehealth, accounting for 10% of the published articles in the field of telemedicine. Telehealth and telemedicine utilize information and communication technologies in all areas of healthcare. However, telehealth equipment is a tool that healthcare professionals use to assess disease conditions and enables patients to benefit from immediate specialized consultations [29]. In managing long-term conditions in the community, it is increasingly used for active patient monitoring and quick response to exacerbation indicators [30], and telemedicine is increasingly utilized for remote clinical consultations [29].

Cluster 7: Cardiovascular Diseases

This cluster focuses on cardiovascular disease and includes 8% of the articles in the field of telemedicine. The keywords associated with this cluster include patients, stroke, heart failure, telemonitoring, monitor, care, hospital, etc. Since telemedicine is a tool to provide services to patients who are difficult to reach or need urgent care [31], it is effective in managing cardiovascular diseases and an alternative method to on-site care of these types of diseases [32]. In three areas, including early diagnosis of cardiovascular diseases, second consultation, and secondary prevention and follow-up,

telemedicine has proven effective in managing cardiovascular diseases [33].

Cluster 8: Research

This cluster has addressed various studies in the field of telemedicine. This cluster is based on keywords such as review, study, interventions, systematic review, systematic, search, article, literature, evidence, meta, health, and trials. It should be noted that there is a particular emphasis on reviews,

indicating that researchers are focused on conducting secondary studies and examining relevant literature to establish the effectiveness of telemedicine.

In order to provide a more precise visual representation of the eight topical clusters, a words cloud was created (Figure 3). The larger-sized words in each cluster represent their significance and higher relevance within the respective cluster.



Fig. 3. Words cloud in each topical cluster in the field of telemedicine.

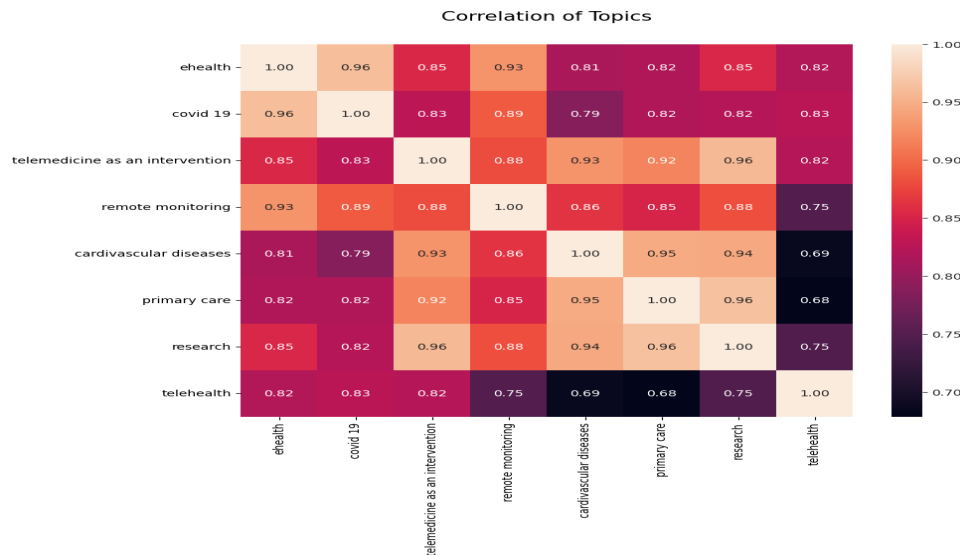


Fig. 4. Correlation of topics.

In order to obtain the correlation between the telemedicine topical clusters, the BOW approach was used. The BOW method utilized the author's keywords from each article, and vectors were developed for the top 1000 most frequent words in each topic. As demonstrated in Figure 4, the "eHealth" and "COVID-19" topics have the highest correlation value of 0.96. Following them, "Research" correlates with "Primary Care" and "Intervention" with a correlation value of 0.96.

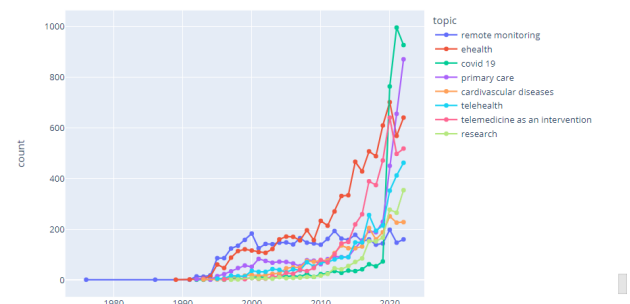


Fig. 5. Publication trend of articles on each of the topics in the field of telemedicine.

Figure 5 indicates the publication trends in the eight topical clusters. The findings show that the "COVID-19" topic has the highest publication rate, followed by the "Primary Care" topic. The year 2020 marks the beginning of the growth in the "COVID-19" topic, while the "Primary Care" topic started gaining momentum in 2018.

4. Discussion

The eHealth, due to its effectiveness, accuracy, safety, low cost, and high accessibility, has attracted the attention of researchers in the medical field. On the other hand, telemedicine is recognized as an electronic intervention in healthcare, which can be utilized for various purposes such as surgery, primary care, telemonitoring, and even prevention, treatment, and follow-up, especially in remote, deprived, and high-risk areas. Considering the demographic trends and significant global progress towards an aging population, reduction in the healthcare workforce, increased life demands compared to the past, and the fact that healthier individuals

spend more time outside their homes and at their workplaces, telemedicine has become a significant concern for many people. One of the potential advantages of telemedicine is the reduction in the burden of visiting healthcare facilities [34-36]. Therefore, it is not surprising that eHealth has the highest percentage of published articles compared to other topical clusters in the field of telemedicine (Figure 1).

In the present study, an analysis and investigation of the research in the field of telemedicine were conducted to obtain an overview of the subject. In order to achieve this objective, text mining techniques, especially topic modeling, and the LDA algorithm were employed to identify the research topics in the field of telemedicine. The topic modeling of the telemedicine field (Figure 1) revealed eight topical clusters: eHealth, intervention, primary care, remote monitoring, COVID-19, telehealth, cardiovascular disease, and research. In a study conducted by Sikandar et al. on telemedicine and e-health research in the Scopus database, e-health, telehealth, intervention, teleconsultation, and primary health care were also mentioned in the results of the co-occurrence analysis of keywords [12]. Since the present study did not impose a time constraint on searching for telemedicine articles and utilized text mining techniques, it identified more topics.

The main objectives of the present research included the application of state-of-the-art topic modeling methods, interpretation of documents based on topics, and ultimately, organizing and categorizing the obtained texts. Accordingly, this study employed topic modeling methods for topical analysis of telemedicine studies using LDA and TF-IDF algorithms.

In terms of TF-IDF weights, the words "information," "image," "visit," "healthcare," and "technology" had the highest weights in the body of the conducted studies. According to Figure 1, the topic of "care" is among the most frequent and heavily weighted terms, indicating its importance in the field of telemedicine. Accordingly, telemedicine is claimed to be the application of remote communication technologies for providing medical, diagnostic, therapeutic, and care services. Care is one of the primary services delivered to different individuals through telemedicine. Telephone calls, mobile applications, video conferences, emails, and text messages are among the most common communication tools used in telemedicine for purposes such as prevention, triage, diagnosis, screening, treatment, follow-up, and care, with follow-up and care being among the most common services provided by telemedicine [37].

One of the applications of telemedicine is remote monitoring and managing chronic diseases, where the treatment and control of these diseases will incur costs for both the patient and the healthcare center. In these conditions, one of the best solutions is to utilize the capabilities of telemedicine. According to Figure 1 and the analysis of studies (32 and 31), one common application of telemedicine is in the management and control of cardiovascular diseases as a prevalent type of chronic disease. In this regard, Farabi et al. [31] considered telemedicine effective in improving clinical outcomes of cardiovascular diseases. Moreover, Kruse et al. (2017) regarded the use of telemedicine in managing cardiovascular diseases as a factor in reducing hospitalization time and readmission; however, based on their findings, telemedicine still faces challenges in achieving customer satisfaction [32].

Since the onset of the COVID-19 pandemic, attention to telemedicine has steadily increased. The emergency nature of

the pandemic, the rapid spread of the disease, the World Health Organization's emphasis on controlling this disease, and the recommendation for quarantine and social distancing have led healthcare providers to adopt telemedicine as an effective and efficient approach due to the lack of direct contact with patients [38]. Accordingly, as observed in Figure 1, COVID-19 has emerged as a research trend in the field of telemedicine from late 2020 until now (34-36).

The main limitation of the present study is the restriction of the search to the PubMed database as a specialized database for medical research. It is recommended to conduct further research focusing on published resources from other information databases to ensure comprehensive coverage of relevant studies.

5. Conclusion

The present study identified topical clusters in telemedicine using text mining techniques and topic modeling tools, with the largest and smallest clusters belonging to "eHealth" and "research," respectively. Text clustering requires the extraction and preservation of semantic information, and one of the features of this extraction is the use of some features obtained from this technique. Therefore, this study employed the LDA model as a semantic analysis method for feature extraction. The classification of topics in this field indicated the satisfactory performance of the LDA algorithm. The extracted topic classes exhibited sufficient capacity and robust topical relationships. Although the words within each topic cluster may not be identical, they are undoubtedly relevant. Unlike traditional clustering, a topic model allows researchers to receive data from multiple clusters rather than a single cluster. These features are beneficial in the realm of telemedicine.

In general, the results of the present study provide a better foundation for developing policies and research programs, as well as increasing awareness and utilization of emphasized topics. The intellectual structure of the telemedicine field can be inferred from the indexed outputs in global databases, and by identifying prominent topics that represent the main research trends in a subject area, not only can future research topics and trends be predicted, but existing gaps in the literature can also be identified. As we mentioned in the methodology, PubMed was the only database which was reviewed in this study, so it is the limitation of this work. However the researchers can consider other databases for future studies. Also, Modeling the topics of global telemedicine articles and comparing different algorithms with the current one is recommended for future research. Further studies in this field can lead to improved effectiveness, quality, and accuracy of telemedicine services.

Acknowledgment

The authors thank the Research & Technology department at Shahid Sadoughi University of Medical Sciences. This study was approved by the Ethics Committee of the university (Code: IR.SSU.SPH.REC.1402.136)

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