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Knowledge Graph Modeling in Healthcare: A Bibliometric Analysis

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[1] Abstrak

Masalah kesehatan saat ini merupakan masalah yang paling banyak diteliti di seluruh dunia. Banyak peneliti kesehatan berkolaborasi dengan peneliti non-kesehatan untuk meningkatkan kualitas kesehatan. Graf pengetahuan adalah pendekatan ilmu komputer dan matematika yang banyak digunakan untuk memecahkan masalah kesehatan. Graf pengetahuan dapat memodelkan hubungan antar peristiwa untuk membangun pengetahuan baru. Oleh karena itu, studi komprehensif tentang pemodelan grafik pengetahuan dalam perawatan kesehatan dilakukan dalam penelitian ini. Metodologi penelitian dalam penelitian ini adalah: (1) pencarian artikel dan analisis bibliometrik umum; (2) visualisasi distribusi penelitian; dan (3) rekomendasi penelitian. Dalam tiga tahun terakhir, 867 artikel diambil dari tiga database. Analisis metrik kutipan juga dilakukan untuk mengetahui tingkat kualitas temu kembali artikel. Analisis dilakukan dengan menggunakan visualisasi jaringan dan kepadatan terkait hubungan antara topik penelitian dan tren. Hasil akhir dalam makalah ini adalah rekomendasi topik penelitian dan judul penelitian terkait pemodelan graf pengetahuan di bidang kesehatan.

Kata kunci: *analisis bibliometrik, graf pengetahuan, kesehatan*

[2] Abstract

Healthcare issues are currently the most researched issues worldwide. Many healthcare researchers collaborate with non-healthcare researchers to improve the quality of healthcare. The knowledge graph is a widely used computer science and mathematics approach to solving healthcare issues. It can model the relationship between events to build new knowledge. Hence, a comprehensive study on knowledge graph modeling in healthcare was conducted. The research methodologies in this study were: (1) article retrieval and general bibliometric analysis; (2) visualization of research distribution; and (3) research recommendations. In the last three years, 867 articles were retrieved from three databases. The citation metrics analysis was also conducted to determine the quality level of article retrieval. An analysis was conducted using network and density visualization related to the relationship between research topics and trends. The final results in this paper are recommendations for research topics and research titles related to knowledge graph modeling in healthcare.

Keywords: *bibliometric analysis, knowledge graph, healthcare.*

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1. Introduction

The utilization of information technology produces many big data with various data types such as photos, videos, and text. [1]. The relationship between these data can be described in a graph. Knowledge and ontologies can be represented in graphs [2], suitable for exploring large-scale data relationships [1]. Graph theory modeling on a large scale can impact various scientific fields, including sociology, physics, computer science, and another field [2].

The problems in the healthcare domain are increasing sharply, especially in the case of the Covid-19 pandemic [3]. The research development in the healthcare field is currently overgrowing. Those research problems were the Covid-19 pandemic and many other research topics in the healthcare domain. One of the research topics in the healthcare domain is predicting heart failure factors such as patient information, symptoms, and ECG [4]. The development of health research from year to year can undoubtedly provide new knowledge for researchers related to world problems and trends in topics and health issues. Graph modeling is one of the tools that can predict epidemic situations in society [3].

The research data published in journal sources is undoubtedly increasing. The research data can be categorized based on the year of publication, research institution, country, emerging trends, number of citations, and indexing [5]. The collected research introduces knowledge such as trends in research topics measured quantitatively and qualitatively [6]. Research topic prediction using quantitative methods will be more objective than qualitative methods [7]. There were methods for predicting trends in research topics such as bibliometrics, scientometrics, and informetrics [6]. The results of these quantitative measurements can be expressed using graphs. Understanding a data set can be easier if a depiction such as a graph [8].

A comprehensive study of bibliometric analysis on knowledge graphs was conducted. The research purpose is to map the study of knowledge graphs in modeling healthcare. The study limited the Knowledge Graph modeling in healthcare by limiting the search terms to achieve the purpose. The contributions of this study were: (1) to conduct a comprehensive bibliometric analysis; and (2) to provide research recommendations on knowledge graph modeling in healthcare.

2. Methods

Bibliometrics analysis has become an essential tool to comprehensively analyze the relationships and outcomes of research. There are several tools and software that have been developed to perform bibliometric analysis, namely: (1) bibliometric databases (PubMed, Scopus, Crossref, and Google Scholar); (2) general bibliometric and performance analysis (Publish or Perish, CRExplorer, and ScientoPyUI); (3) Science Mapping Analysis (VOSviewer, Bibexcel, BiblioShiny, BiblioMaps, and CiteSpace); and (4) Python and R libraries (Bibliometrix, BiblioTools, scientoText, and ScientoPy) [9]. This article conducted a bibliometric analysis of graph modeling using several tools: (1) publish or perish; and (2) VOS viewer.

The research stages conducted in this Bibliometric Analysis study were: (1) article retrieval and general bibliometric analysis; (2) visualization of research distribution; and (3) research recommendations. The article retrieval was conducted using Publish or Perish software to retrieve the bibliometric databases. The bibliometric databases that were used in this study were: (1) Google Scholar, (2) Scopus, and (3) PubMed. At this stage, the articles were filtered by the year of publication. The retrieved article should have been published in the last three years (2018-2021).

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The results of the paper retrieval using Publish or Perish can be saved in the form of Bibtex. The Bibtex file was then imported into Mendeley to update the article metadata. The article metadata included several components, i.e., title, authors, journal name, year of publication, and other information. The next step was to export all articles in *.ris format for data analysis. The data analysis stage included data visualization and trend analysis using a bibliometric map using the VOSviewer. VOSviewer is a tool that can be used to create publication maps based on shared networks that can be used to assess and analyze the output of research worldwide [10]. In addition, it can be used to conduct data mining, mapping, and grouping of the articles. The last stage in this study was to analyze the articles that have been retrieved from the bibliometric analysis process and provide the research recommendations.

3. Results and Discussions

Based on the method that has been described, this study conducted three stages of research, namely: (1) article retrieval and general bibliometric analysis; (2) visualization of research distribution; and (3) Research recommendations.

3.1 Article Retrieval and General Bibliometric Analysis

The article retrieval process was conducted using Publish or Perish. In article retrieval, there were three keywords used as the search terms, namely: (1) health graph database; (2) healthcare graph database; and (3) medical graph database. Publish or Perish calculated the following citation metrics, namely: (1) total number of papers; (2) total number of citations; (3) average number of citations per year; (4) average number of citations per paper; (5) average number of authors per paper; (6) Hirsch's h-index and related parameter, shown as h-index; (7) Egghe's g-index, shown as g-index. The results of the articles retrieved and citation metrics are shown in Table 1.

TABLE I. ARTICLES RETRIEVED AND CITATION METRICS USING PUBLISH OR PERISH

Search Terms	Source	Papers	Citations	Cites/ year	Cites/ paper	Authors/ paper	h-index	g-index
health knowledge graph	Google Scholar	119	268	38.29	2.25	3.63	9	12
	Scopus	200	675	225	3.38	0.97	14	18
	PubMed	42	0	0	0	5.76	0	0
healthcare knowledge graph	Google Scholar	42	69	23	1.64	3.36	5	7
	Scopus	74	180	60	2.43	0.86	7	11
	PubMed	12	0	0	0	5.42	0	0
Medical knowledge graph	Google Scholar	140	310	103.33	2.21	3.69	8	13
	Scopus	200	1081	360.33	5.41	0.96	14	28
	PubMed	38	0	0	0	4.66	0	0

Based on the results of article retrieval, 867 articles were retrieved. The articles retrieved on Google Scholar were found in 119 articles, Scopus articles were found in 200 articles, and PubMed was found in 42 articles using the search term of health knowledge graph from the last three years. For the healthcare knowledge graph, 42 articles were found on Google Scholar, 74 articles on Scopus, and 12 articles on PubMed. As for the medical knowledge graph search term, 140 articles were found on Google Scholar, 200 articles on Scopus, and 38 articles on PubMed.

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The citation data was very diverse in these three search terms. In the health knowledge graph, there were 268 citations in Google Scholar with an average of 38.29 citations/year and 2.25 citations/paper with a nine h-index. In Scopus journal sources, there were 675 citations with an average of 225 citations/year and 3.38 citations/paper with a 14 h-index. Meanwhile, at PubMed, there was no citation data at all. There were 69 citations in Google Scholar for the healthcare knowledge graph and an average of 23 citations/year and 1.64 citations/paper with a five h-index. In Scopus journal sources, there were 180 citations with an average citation of 60 citations/year and 2.43 citations/paper with a seven h-index. While in PubMed, there was no citation data. There were 310 citations in Google Scholar for the medical knowledge graph search term with an average of 103.3 citations/year and 2.21 citations/paper with an 8.0 h-index. In Scopus journal sources, there were 1081 citations with an average citation of 360.33 citations/year and 5.41 citations/paper with a 14 h-index. While in PubMed, there was no citation data.

3.2 Visualization of Research Distribution

Based on the general bibliometric analysis results described in the previous section, the distribution of Google Scholar, Scopus, and PubMed publications can be analyzed using VOSviewer. In this study, the visualization of research distribution was classified based on the search terms that have been determined. Each article metadata retrieved from the previous section analyzes the relationship between the terms. By clustering the terms in the research distribution analysis, the relationship between one research topic and another can be shown. In addition, VOSviewer can also map the bibliometric analysis using three types of visualization: (1) network visualization, (2) overlay visualization, and (3) density visualization.

As previously mentioned, the VOSviewer analysis was classified based on the search terms. However, based on the findings when conducting metadata analysis, the results of the first and second search terms had high similarities to the article's retrieval results. Hence, the results of the first and second search terms were used as one bibliometric mapping. All search terms were mapped using VOSviewer. Therefore the relationship between these terms can be analyzed. Figure 1 and 2 represents the visualization of terms and relationships using network and density visualization, respectively.

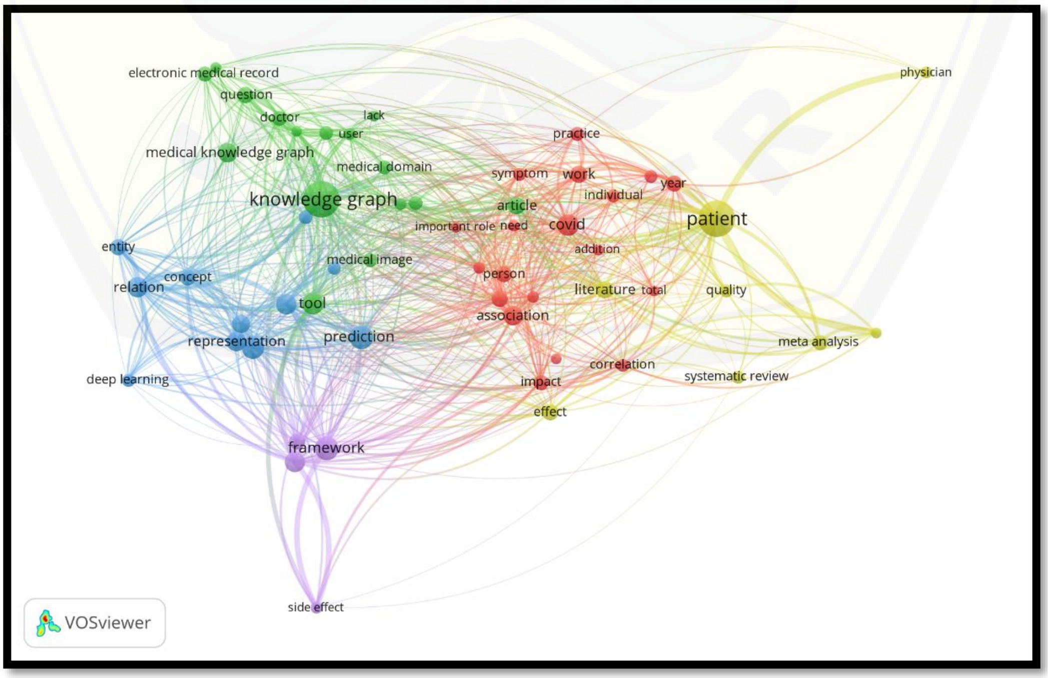

Figure 1. Network Visualization on Terms and Relationships

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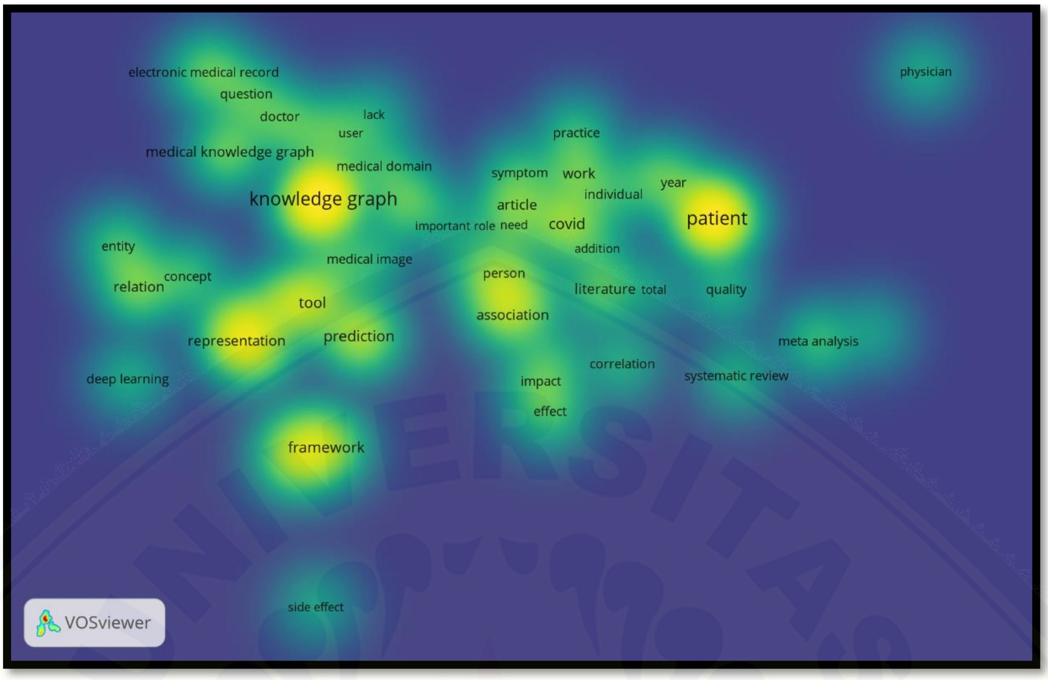

Figure 2. Density Visualization on Terms and Relationships

Five clusters were obtained after being analyzed using network visualization (red, blue, green, yellow, and purple), which showed the relationship between the research topic. In Figure 1, the keywords were labeled with colored circles depending on the cluster. The size of the circle was correlated to the number of terms occurrences on article metadata (more specifically, the title and abstract of the article). The more often a term occurred in article metadata, the greater size of the circles. Thus, it can be concluded that the size of the circle depended on the frequency of terms occurrence. As shown in Figure 2, the density visualization had the same way of displaying the terms as in the network visualization. Each point in the density visualization had a different color indicating the term density. The more significant number of terms occurrences, the red color will indicate the density. Contrary, the smaller number of terms occurrences will be indicated by the blue color.

3.3 Research Recommendations

Based on a network and density visualization shown in Figures 1 and 2, the relationship between terms can be analyzed and used as research topics. According to the visualization analysis, one of the dominant topics is knowledge graphs. A knowledge graph is a form of graph used to mine, organize and manage knowledge from large-scale data to improve the quality of knowledge [11]. The knowledge graphs had some relationships with other topics such as electronic medical records (EMR), deep learning, prediction, and other topics based on network visualization. It showed research correlations between the knowledge graph and these topics, indicated by the yellow indicator in the density visualization. That indicator showed that the frequency of occurrence of knowledge graph topics was relatively high. Thus, the density visualization indicates a yellow indicator. If compared to deep learning on the network and density visualization, it can be implied that deep learning research topics related to graphs were pretty minimal. It indicates that the research opportunity on that topic was considerable.

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In addition to using the analysis of terms from the network and density visualization, a more detailed analysis was also carried out related to the article. All articles analyzed in this study were mainly retrieved from the Scopus databases, which had high citation rates, h-index, and g-index, according to Table 1. Scopus is one of the peer-reviewed journal databases that provide good scientific articles [12]. The articles were ranked based on the number of citations based on the article retrieval. The higher the number of citations indicates that the article had better quality because many researchers had referred to the article. Based on Table 2, we recommend 24 research titles ranked by the number of citations.

TABLE II. ARTICLE RECOMMENDATIONS BASED ON CITATIONS RANK

No	Titles	Cites
1	NiftyNet: a deep-learning platform for medical imaging [13]	233
2	EGBMMDA: Extreme gradient boosting machine for MiRNA-disease association prediction [14]	126
3	Disease prediction using graph convolutional networks: Application to Autism Spectrum Disorder and Alzheimer's Disease [15]	89
4	Electronic systems for patients to report and manage side effects of cancer treatment: Systematic review [16].	32
5	Deep learning intervention for health care challenges: Some biomedical domain considerations [17].	28
6	Accelerating health data sharing: A solution based on the internet and distributed ledger technologies [18].	25
7	Retinal artery and vein classification via dominant sets clustering-based vascular topology estimation [19].	23
8	Impact of isolation precautions on quality of life: a meta-analysis [20].	23
9	Linking Bisphenol S to Adverse Outcome Pathways Using a Combined Text Mining and Systems Biology Approach [21].	21
10	Building the national database of health-centered on the individual: Administrative and epidemiological record linkage - Brazil, 2000-2015 [22].	20
11	Exploiting semantic patterns over biomedical knowledge graphs for predicting treatment and causative relations [23].	19
12	Applications of network analysis to routinely collected health care data: A systematic review [24].	19
13	Distributed learning on 20 000+ lung cancer patients – The Personal Health Train [25].	18
14	N-of-1 randomized intervention trials in health psychology: A systematic review and methodology critique [26].	17
15	Integration of multi-objective PSO-based feature selection and node centrality for medical datasets [27].	16
16	Efficacy and safety of photodynamic therapy for cervical intraepithelial neoplasia and human papillomavirus infection: A systematic review and meta-analysis of randomized clinical trials [28].	16
17	A Novel Software to Improve Healthcare Base on Predictive Analytics and Mobile Services for Cloud Data Centers [29].	16
18	Automatic superpixel-based segmentation method for breast ultrasound images [30].	15
19	Real-world data medical knowledge graph: construction and applications [31].	13
20	Using shape expressions (ShEx) to share RDF data models and guide curation with rigorous validation [32].	11
21	One size does not fit all: Querying web polystores [33].	9
22	A Scalable Smartwatch-Based Medication Intake Detection System Using Distributed Machine Learning [34].	7
23	Information management in healthcare and environment: Towards an automatic system for fake news detection [35].	5
24	Real-Time Intelligent Healthcare Monitoring and Diagnosis System Through Deep Learning and Segmented Analysis [36].	5

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Based on the extraction of article retrieval as shown in Table 2, we recommend articles about knowledge graphs in the health domain. Currently, biological and medical devices, treatments, and applications can generate large volumes of data in the form of images, sounds, text, graphs, and signals creating the concept of big data. Big health data contain great value and can benefit all the healthcare ecosystem stakeholders [18]. The use of knowledge graphs and deep learning to analyze and diagnose the healthcare domain has received unprecedented attention in the last decade [17]. Graph knowledge-based electronic systems also have the potential to manage the side effects of cancer treatment [16].

A study conducted by Parisot et al. [15] models a disease prediction using a convolutional graph network. Nodes in a graph can represent individuals within a large population of patients or health records dataset. Graph-based approaches for supervised or unsupervised learning in disease prediction focused solely on pairwise similarities between subjects. Gibson et al. [13] developed a Nifty Net framework, a deep learning platform used for medical imaging. The framework is built using TensorFlow to construct an abstract computation graph. Zhao et al. [19] classified the retinal vascular tree into arteries and veins using dominant sets clustering, a graph-theoretic approach proven to work well in data clustering.

Based on the article's recommendation, it can be interpreted that the opportunity for graph knowledge research in the health domain is still very likely. Some studies combine knowledge graphs and deep learning to forecast disease. In addition, some studies combine graphs with data mining to classify health domain data. So that in the future, it is hoped that there will be more related studies that model graphs for the healthcare domain.

4. Conclusions

A knowledge graph is an approach that can model problems in the healthcare domain. Currently, many researchers use this approach to solve research problems. It is indicated by the growth of research numbers related to the knowledge graph in the last three years. A comprehensive study using bibliometric analysis was conducted on the growth of knowledge graph research in the last three years (2019-2021). There were 867 articles retrieved from three bibliometric databases. Several terms and relationships can be analyzed further by using network and density visualization. Thus, the analysis can obtain research topics, such as knowledge graph, EMR, deep learning, and prediction. In addition, several research titles obtained from the Scopus database are also recommended to other researchers to conduct further research.

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