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A Systematic Literature Review of Performance Hospital Supply Chain Management

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Abstract*—Over the last few decades, globalization has driven up the demand for hospital Supply Chain Management (SCM) with the goal of bio-medical development and improving performance. This review aims to offer both a qualitative and quantitative comprehension of the hospital SCM re-search field's overall developmental trend. By using the methodology science mapping approach are visualize the organization of academic knowledge, 87 significant papers, that were published between 2002 and 2023 in total due to their importance in recent years, were located, expanded upon, and summarized. Bibliographic analysis for under-standing the global research state and academic develop-ment was performed on visualized statistics can help identi-fy trends in data about co-occurring keywords, interna-tional cooperation, journal allocation/co-citation, and view clusters of study subjects based on this five categorization, 22 sub-branches in total of hospital SCM identification and topical discussion of knowledge were conducted, namely (i) technologies; (ii) planning; (iii) supply chain field in hospi-tals; (iv) logistics and (v) environmental. Lastly, suggestions for future study directions and current knowledge gaps were made due to constraints of international cooperation and insufficient platforms to quickly advance innovation technology research. The results contribute to a methodical intellectual representation of the current state of hospital SCM research. Furthermore, it offers heuristic ideas to practitioners and researchers to control the quality of de-veloped healthcare and logistics services.

Keywords*—*Hospital Logistics; Healthcare; Supply Chain Management; Artificial Intelligence.

I. INTRODUCTION

Toward the end of the twentieth century, information began to take center stage. It causes significant changes in today's social and economic spheres. In the medical field, managing all connected processes and related knowledge became difficult as a result of new technology, therapies and service kinds as well as developments in medical sciences and the specific challenges in hospitals SCM. Healthcare organizations must respond to these challenges if we view them as complicated bodies of knowledge [26]. It is necessary to create prediction models (a popular statistical methods for forecasting future actions), that could identify individuals who are more likely to require a lengthy hospital stay while undergoing treatment, regardless of the health sector in which h they arrive for therapy [81], supporting various clinical and managerial tasks [33] and the identification of illnesses, especially those with symptoms like asthma, is based on worldwide norms [82].

Demand spikes caused some emergency medical services in the UK to declare major events and issue warnings that care may be compromised due to excessive demand. Tools for risk assessment are necessary to manage and meet the demands on these services during such periods and to make the best use of the limited healthcare resources available [62]. Different hospital logistics modes for example, the coordinated planning, execution, and management of the flow of products and services, behaviors, and activities were suggested and progressively implemented through government regulations and technological advancements. For instance, artificial neural network model, intensive care medicine [2], biomedical informatics [8], hospital readmission [9], critical care [19,36], etc. Remarkable practical performance and significant academic outcomes were obtained over a broad spectrum of hospital supply chain management subjects. However, it is still in its infancy and is far from meeting the problems presented by a lack of cooperation across different research communities. As a result, an active and robust global collaborative atmosphere has yet to emerge. The damage increases exponentially as hospital logistical demand rises quickly, eventually having an irreversible effect on healthcare. Therefore, how can SCM performance be improved in hospitals? What is its effect on healthcare and the environment? and what is the role of AI in developing this?

Previous studies reviewed hospital SCM from different perspectives, A machine learning system (a type of computer system that is in charge of maintaining the programs and data needed to train and run the machine learning models that underpin an AI-powered service), created by Andrew Joseph Young and al [1] was able to forecast the inhospital death of patients who had experienced a catastrophic fall and were being assessed at a trauma center. Joon Myoung Kwon and al [87], created and verified an AI method for forecasting the mortality of acute heart failure (AHF) based on deep learning. kwon and al [65], suggested an early warning system based on deep learning that performs better at forecasting in-hospital cardiac arrest than the track-and-trigger systems now in use. Zihan Jiao and al [23], suggested electronic health is a computerized record of a patient's medical history that is kept up to date by the provider and medicine system called Tianxia120, an internet of medical things bioinformatics multi-modal system for proactive health management. Măruşter and Jorna [26], suggested a method for designing and modeling a business process from the standpoint of knowledge management, he used patient data from interdisciplinary hospitals as an example of his methodology. Mărușter and al [37], presented a methodology to provide a way to help individuals with peripheral vascular disorders be better coordinat-ed. Shaoren Wang and al [15], expedited the location of emergency medical facilities (EMFs), using the issue of the location-allocation model to determine the best place for facilities to meet a specific demand, which can assist EMFs in handling significant emergencies about public health, for assigning patients to these facilities during disasters.

Nevertheless, the studies that are currently available are out-of-date and inadequate, unable to offer a thorough examination of the burgeoning hospital SCM research over the last two years, given the publication date and the number of papers included. Additionally, integrating the several research directions to create a comprehensive knowledge framework for hospital SCM is more challenging. Consequently, it is crucial to conduct an unbiased, quantitative analysis of the overall development of the hospital SCM, both theoretically and practically.

The goal of this study is to create a hospital SCM knowledge classification system explore state-of-the-art research trends and hotspots and undertake an extensive evaluation of the international literature on SCM in hospitals. The first is a full description of the development of the hospital SCM research field, including an analysis of (i) publishing journals and years; (ii) regions, nations, and organizations; (iii) significant documents; and (iv) grouping of keywords and research themes. Secondly, based on the scientometric findings, creating the knowledge taxonomy. Third, determining the gaps in the field's knowledge and potential next research areas. We predict this study to give the best results for improving hospital SCM.

The research method's outline is presented with the help of science mapping, in Section 2. The outcomes of the gathering of data and the five sections within the scientometric evaluation are shown in Section 3. In Section 4, the knowledge branches are thoroughly discussed and a taxonomy of hospital SCM research based on keyword clustering is proposed. Additionally, the present research goals and shortcomings are noted. The main conclusions and restrictions are outlined in Section 5. A thorough inquiry into the subject of SCM hospital that incorporates valuable conference papers and publications is projected to provide a more thorough knowledge base for the next studies.

II. Research Approach

A. Review Protocol Overview

With the help of science mapping, this research based on a review carried out a methodical inquiry on the academic growth of hospital SCM globally. Science mapping is a quantitative analysis approach that studies bibliographic networks, such as those about journals, scholars, institutions, subjects, and keywords in a particular subject by using mathematical statistics and graphical tools [88]. This method may immediately synthesize important discoveries from the current knowledge system and has been widely used in various academic domains. Fig. 1 illustrates the three-phase, compre-hensive research approach.

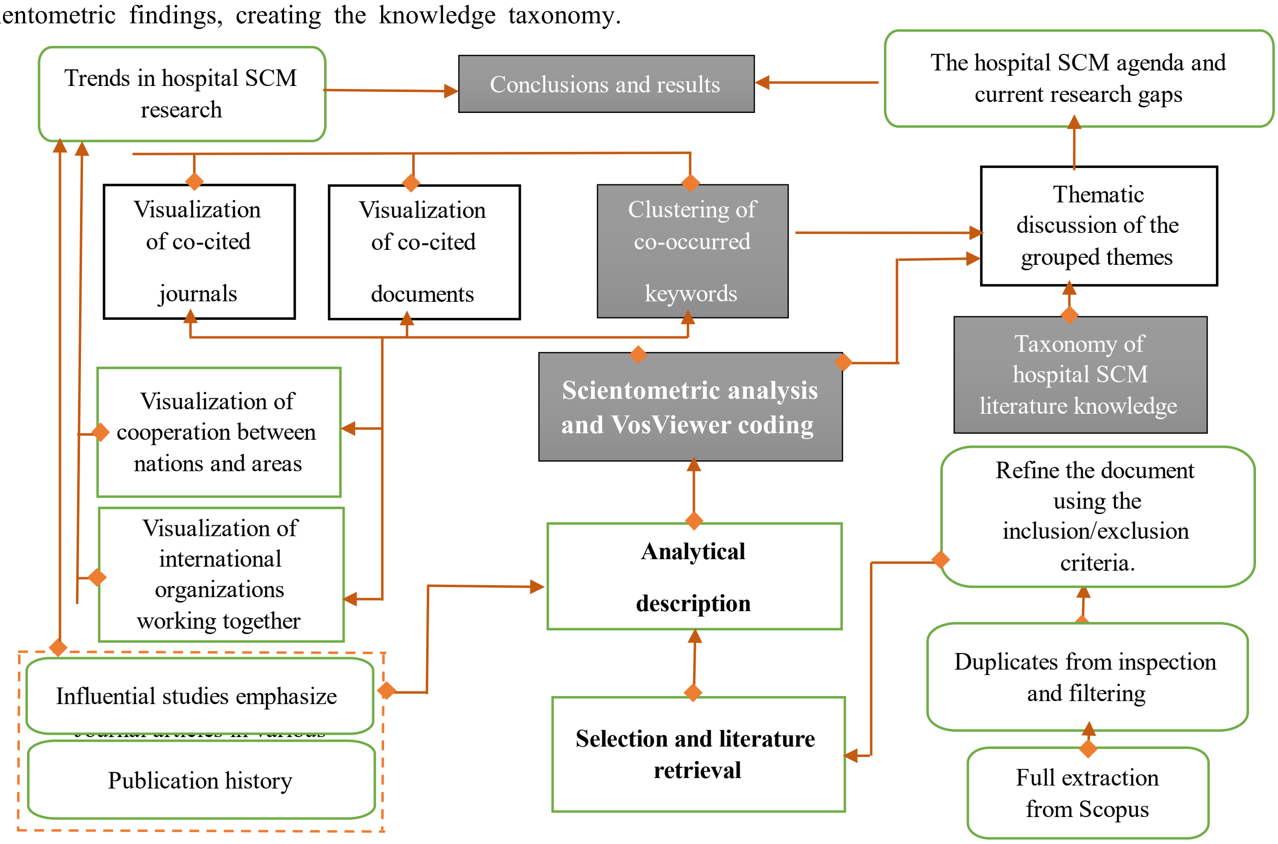

Fig. 1. The flowchart for evaluating SCM literature in hospitals

Step 1 involved obtaining the data through a comprehensive extraction from the digital database, Scopus it encourages the unplanned growth of innovative research projects and findings by enabling scientists to publish their work globally, ensuring a certain level of recognition and fostering professional advancement. The documents were then reevaluated, categorized, and encoded through two selection cycles, inclusion and exclusion criteria set the boundaries for the systematic review. They are established following the formulation of the research question and before the search, however, scoping searches can be necessary to establish suitable standards. In addition, there were descriptions of the most cited articles, journal allocation, and year publishing trend.

Step 2 accurate literature analysis greatly depends on the use of scientometric methods and scientometrics tools such as citation mapping, visualization, bibliographic coupling, co-authorship network, co-words mapping, etc. This review involved the execution of four scientometric tests: (i) Journal co-citation analysis, involves tracking pairs of papers that are cited together in the source articles, which aimed to determine the study topics related to the most cited journals. To discover popular journals in the hospital SCM sector, this analysis is beneficial to highlight the dissemination of publications in journals and referenced journals of the evaluated papers. (ii) Analysis of collaborations between countries and organizations can foster compassion, civic engagement abroad, and an awareness of diversity: to illustrate the global network of collaborative research on hospital supply chain management, allowing readers to rapidly comprehend the alliances between significant worldwide research institutions and communities. (iii) Document citation analysis is a method for determining an article's relative value or influence: to demonstrate the impact of hospital SCM publications and the related links between references. It is simpler to understand the growing trend of academics' interest in hospital SCM research by looking at the articles with a high citation count. (iv) Co-occurrence analysis of keywords is represented by the size of the nodes; larger nodes denote higher frequency: to map out the temporal zones in which the hotspots for hospital SCM keywords co-occurred and group them into many research themes. The knowledge structure of hospital supply chain management is elucidated by network analysis of co-occurring keywords, which also presents research hotspots and future research prospects.

The hospital SCM's hierarchical knowledge structure was proposed for a theme discussion in **step 3**. The text mining application VOSviewer was utilized in conjunction with science mapping to show the time perspective of the clustered keywords that were obtained from the same data. this software performs an analysis of the input file, creates a network map, and then offers options for map exploration and viewing developed by Van Eck and Waltman [90], is a comprehensive tool for bibliometric analysis based on Visualization of Similarities (VOS) technology. It offers distinct advantages in that it can be used to cluster disparate pieces of knowledge from other areas based on their relatability and similarity. A node in the networks that are visualized represents a specific bibliographic item, such as a country, organization, term, reference, etc. The node size indicates how many citations or occurrences were considered in the evaluation. A link indicates a relationship of co-citation, co-occurrence, or collabo-ration. Total link strength (TLS), a measure of the degree of correlation between any two nodes in the networks that are produced, is automatically output by the software. An item's relevance and centrality are higher when its TLS value is higher [89]. Nodes with low similarity should be kept as far apart as feasible, while those with high similarity were clustered together and identified by colors with other clusters [90].

B. *Selection and Retrieval of Literature*

The hospital SCM-related publications published between August 2002 and August 2023 were retrieved using Scopus's advanced retrieval capability. Only research papers were allowed as document types; book chapters, conference proceedings, letters, and editorial material were not allowed to guarantee the caliber of the literature. Additionally, those completely and partially irrelevant studies were removed despite the difficulty of the process. The next step in the selection process was to carefully study each document's abstract. This round's inclusion and exclusion criteria centered on whether the paper adhered to the study's focus on hospital SCM innovations in particular.

III. Analysis and Experiments with Scientometrics

A. *Trends in Chronological Publications*

The quantity of published papers in the portfolio each year between 2002 and 2023 is shown in Fig. 2. Evidently, until 2016, research on hospital SCM was essentially stationary; however, since 2017, annual growth in this area has been substantial. A startling 25 items could be searched by 2022. The vigorous growth of scholarly research points to the branch and extent of hospital SCM expansion. It is also clear from the publication count and the recently discussed themes that real-world applications of SCM in healthcare, public awareness, the rise in illnesses and associated complications, social demand, and development in technology are all important factors.

B. *Citation Analysis and Journal Allocation*

With a higher document availability of six papers, the worldwide journal of Medical Informatics placed first in Table I, which was sourced from published journals on the subject. The Journal of International Journal of Medical Informatics had 237 citations, making it the highest-ranked journal publication, offers a global platform for the sharing of novel findings and elucidating analyses related to the domain of medical informatics, and focuses on system assessment in healthcare environments. However, the source of published publications with citations revealed significant gaps. The Journal of Biomedical Informatics included approximately 138 citations. Surprisingly, a small publication in the field of clinical neuroscience with fifteen document citations was ranked ten in the sourced citations, indicating a negligible amount of appropriate citation references in the development of clinical neuroscience. In contrast, there were 213 citations for Artificial Intelligence in Medicine.

Every one of the 87 documents was located in 66 distinct publications. The top 10 journals contributed 33 papers, or 37.9% of the total, as indicated in Fig. 3. Based on the Journal Citation Reports (2022), the journal's influence and quality are determined by its readership, citation frequency, and reputation within the community. Impact Factor, SCImago Journal Rank, Article Influence, and H-Index are just a few of the many metrics and indicators of journal quality and impact that are employed [93]. International Journal of Medical Informatics (6.89%), followed by Journal of Biomedical Informatics (6.89%), Artificial Intelligence in Medicine (5.74%), Computers in Biology and Medicine (3.44%) and PLoS ONE (3.44%). Among the top 10 journals, four are from the USA, two from Ireland, and one each from the Netherlands, Germany, Canada, and the United Kingdom. The three academic domains of medicine are where the publications are primarily distributed, biomedical informatics, Biology in Medicine, and neurology. However, they undoubtedly make up a greater percentage in the biomedical informatics field, which is consistent with the idea of improving the performance of hospital SCM.

TABLE I. TOP TEN NOTABLE SOURCES ACCORDING TO JOURNAL CITATIONS AND DOCUMENT RANKING

Rank	Source by Citation	Documents	Citations
1	International Journal of Medical Informatics	6	237
2	Journal of Biomedical Informatics	6	138
3	Artificial Intelligence in Medicine	5	213
4	Plos One	3	83
5	Computers in Biology and Medicine	3	25
6	Computer Methods and Programs in Biomedicine	2	72
7	Journal of Medical Internet Research	2	54
8	Medical and Biological Engineering and Computing	2	37
9	Journal of the American Medical Informatics Association	2	15
10	Journal of Clinical Neuroscience	2	15

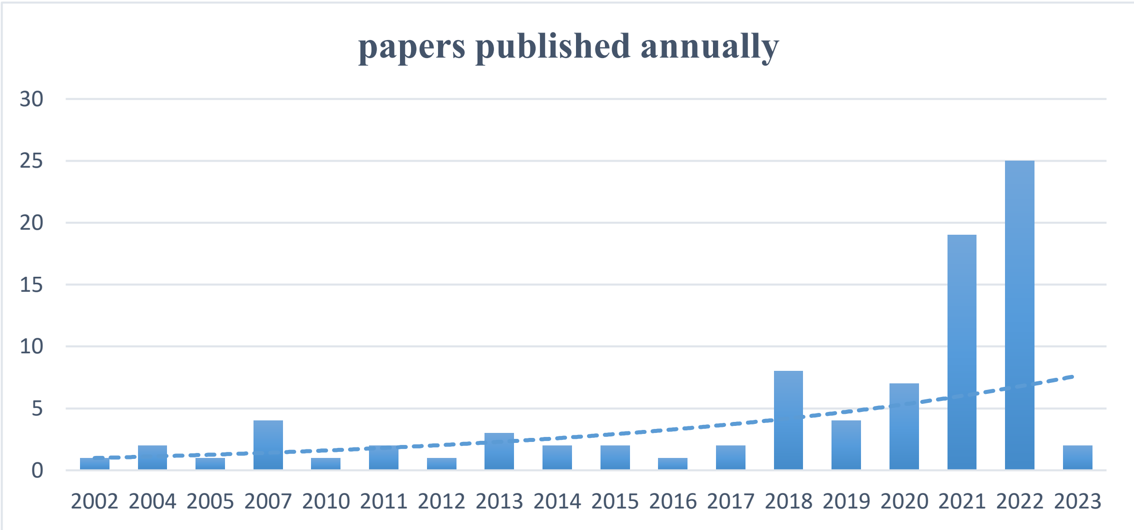

Fig. 2. Year profile of indexed documents

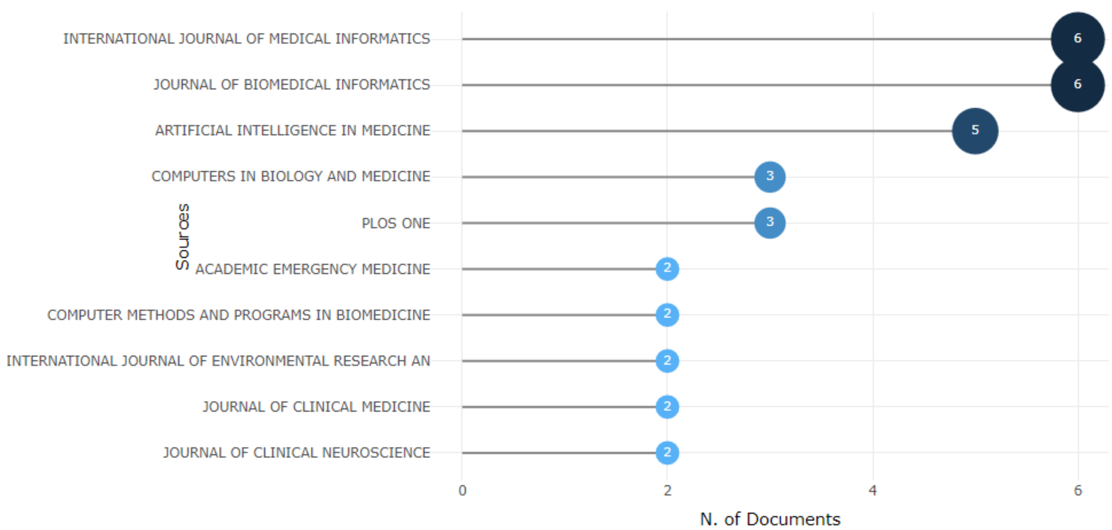

Fig. 3. Hospital SCM publication number rank of journals

C. Analysis of Collaboration Amongst Nations/Organizations

Table II, along with six indicators (total citations, average citations per nation or region, average normalized citation, average citation year, average citation count, and number of publications (NP)) lists the regions or countries that are actively researching hospital SCM. To get the average normalized citation, divide the total number of citations by the average number of citations published each year [91]. The network of collaboration between nations and regions is shown in Fig. 4. A nation was required to have a minimum of two documents and one citation, respectively. In the end, a map was created with 18 elements and 31 linkages.

In light of Table II, hospital SCM study is widely disseminated, particularly in Europe, North America, and Asia, indicating that it is a worldwide worry. The continental United States has the most publications and the most cumulative citations. Other countries/regions, such as Sweden, Belgium, Thailand, Japan, Austria, and Spain, have fewer publications; nonetheless, they maintain considerable average normalized citation statistics, indicating their great influence. Furthermore, these nations/regions are becoming increasingly active in promoting hospital SCM, as seen by the fact that the bulk of the publications they contributed were published within the last three years.

TABLE II. OVERVIEWS OF NATIONS AND AREAS ACTIVE IN SCM REAEARCH IN HOSPITALS

Region/Country	Continent	NP	TLS	Average year	Total Citations	Average Citation	Average Normalized Citation
United States	North America	29	6	2017	673	23.2	1.20
China	Asia	15	4	2021	113	7.53	1.03
Taiwan	Asia	9	5	2018	186	20.67	0.88
United Kingdom	Europa	8	7	2018	137	17.13	0.86
South Korea	Asia	7	1	2017	371	53	1.20
Netherlands	Europa	5	1	2008	107	53.5	0.79
Italy	Europa	5	8	2021	37	7.4	0.80
Australia	Asia	5	5	2020	47	9.4	0.75
Germany	Europa	4	5	2022	21	5.25	1.06
India	Asia	4	6	2016	84	21	1.18
French	Europa	3	4	2014	35	11.67	0.57
Switzerland	Europa	3	1	2021	11	3.67	0.28
Sweden	Europa	2	3	2021	22	11	1.31
Thailand	Asia	2	2	2021	4	2	0.25
Japan	Asia	2	1	2020	31	15.5	0.39
Austria	Europa	2	4	2020	31	15.5	1.67
Belgium	Europa	2	4	2011	37	18.5	1.00
Spain	Europa	2	1	2021	1	0.5	0.39

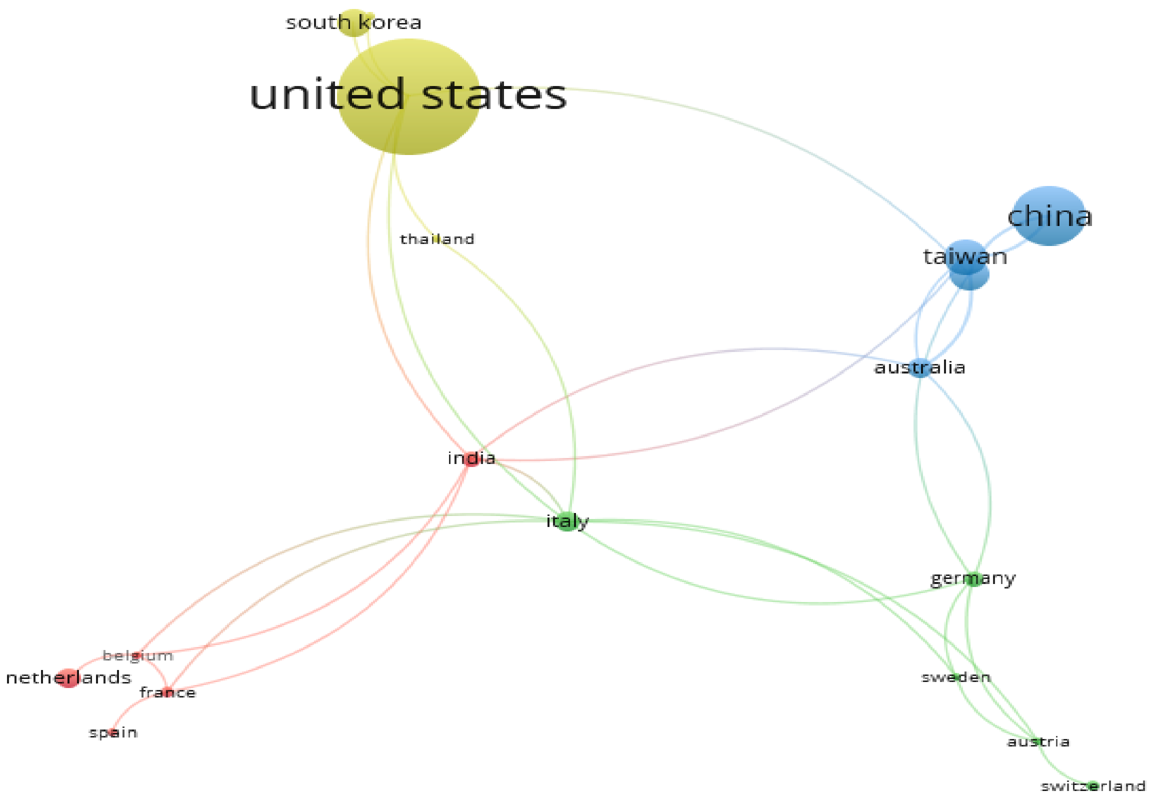

Fig. 4. Regional and national mapping aids in hospital SCM

Fig. 4 shows two examples of evidence. First, the worldwide hospital SCM research is separated into four communities based on collaboration. Two communities are led by European countries, such as Italy, Germany, Switzerland, and Sweden, while the other two communities are "China - Taiwan - Australia - United Kingdom" and "United States - South Korea - Thailand," which are dominated by China and the United States, respectively.

Second, international cooperation is insignificant. In the United States, for example, approximately 20% of 29 publications are finished wholly by domestic organizations. This phenomenon could be attributed to considerable disparities in the backdrop and paradigm of hospital SCM development between countries [86]. Furthermore, the knowledge gap generated by the broad scope of hospital SCM and the dispersed knowledge structure forces researchers to remain focused on their particular domains, such as medical informatics [59], biomedical engineering [42], and biology in medicine [46].

As a result, collaboration between hospitals from various backgrounds is not currently widespread. This has consequences and negatives for the development performance of healthcare and the environment in the world. To close this gap, must grow the dataset to include numerous time points for continuous analysis, as well as increase the size of the sample to investigate more potential predictors and their interactions.

Those organizations with more than two papers and more than a network with 6 items and 0 items were created from 30 citations among the 361 organizations that contributed to hospital SCM research, as shown in Fig. 5. As a result, it could be argued that hospital SCM research has not yet been successfully led by any organization. In addition, some Asian institutions have a better reputation in hospital SCM due to more citations, such as Mediplex Sejong Hospital (South Korea, 236 citations), Hanyang University of Seoul (South Korea, 129 citations), Royal Adelaide Hospital (Australia, 15 citations), South Australian Health and Medical Research Institute (Australia, 15 citations), University of Adelaide (Australia, 15 citations) and Zhongnan Hospital of Wuhan University (China, 1 citation). Additionally, Fig. 5 also reveals a lack of cross-organizational collaborative research in hospital SCM.

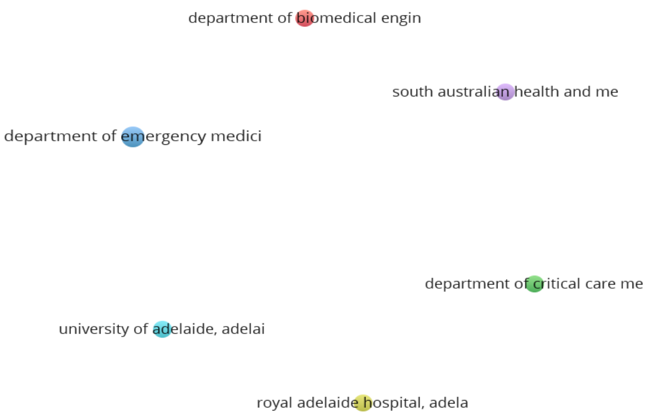

Fig. 5. Mapping the worldwide network of organizations that collaborate

D. Key Findings from Influential Research

The co-citation network was constructed and the most significant hospital SCM publications over the last 20 years were evaluated using the portfolio's document co-citation test. As illustrated in Fig. 6, a co-cited visual network map comprising 31 items and 87 was produced by setting the minimum number of citations in VOSviewer to 20. The documents identified by the first author's name are represented by the nodes on the map. The node and link colors represent the dates of publication and co-citation of the two works, respectively. The co-occurrence of ideas and outcomes in the literature indicates an evident kind of "local concentration and overall dispersion," demonstrating that some hospital SCM research was well acknowledged and produced some similar concepts and outcomes. The majority of high-citation publications were released around 2015, a watershed moment in hospital SCM research. According to the co-citation time series, hospital SCM information is spreading at an increasing rate.

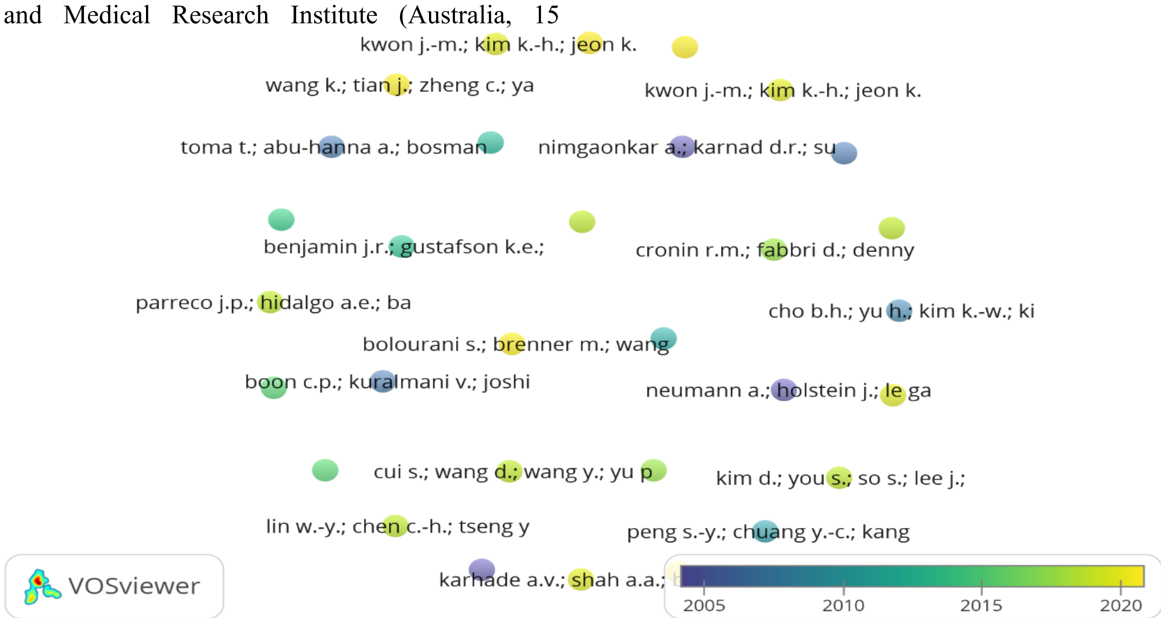

Fig. 6. A chart showing the relationship between co-citations and the important documents

Table III displays the top 16 most referenced publications, along with their authors, year of publication, title, total link strength (TLS), citation counts, and themes. We observe the most publications between 2015 and 2019, this demonstrates the importance of hospital SCM in recent years. The most referenced study was by Kwon and colleagues [65], who proposed an early warning system based on deep learning that predicts in-hospital cardiac arrest more accurately than traditional track-and-trigger systems. The second is Cho and al [49], who suggested a new method of providing information to clinicians for them to develop efficient and effective treatment plans. The third publication is followed by papers by Dai and colleagues [42], designed to use patient-specific medical data accurately and efficiently to forecast hospitalizations linked to cardiac conditions. Other highlighted documents' key subjects include (i) biomedical informatics [68][57][35][32]; (ii) medical informatics [58][59][76]; (iii) heart diseases [47,87]; (iv) intensive care medicine (COVID-19, neurology, mortality) [2][54][85] and (v) psychiatry [3][50]. However, these studies are insufficient, for development logistics in hospitals.

E. *Co-Occurrence Analysis of Keywords*

Co-occurrence analysis of terms was used to highlight the boundaries and provide an explanation of the internal makeup and structure of hospital SCM [89]. To acquire a comprehensive intellectual landscape of hospital SCM research, the options "All Keywords" and "Full Counting" were examined in VOSviewer analysis. Fig. 7 depicts a network of 34 nodes representing keywords (307 keywords in total papers) and 426 linkages. The core keywords and co-occurrence correlations for hospital SCM research are shown in Fig. 7. We sorted these terms into seven groups and used different colors to distinguish between them. These clusters contribute, to evaluating the risk of future outcomes, to creating individualized treatment plans and predictive modeling is essential to managing healthcare. In that Cluster #1 has 8 items, concentrating on prognostic models are used to evaluate the risk of future outcomes in persons with a certain disease or health condition by combining various prognostic indicators, Cluster #2 has 6 things that are focused application the techniques of artificial intelligence in critical care (sepsis, risk stratification etc), Cluster #3 has 5 items, focusing on applying predictive analytics in hospital, Cluster #4 has 5 items emphasizes on predictive modeling is essential to managing population health, Cluster #5 has 4 items, focusing on applying techniques of artificial intelligence in clinical neuroscience (length of stay, rehospitalization etc), Cluster #6 has 4 items emphasize on AI can be used to create individualized treatment plans, identify illnesses, and support medical professionals in making decisions etc, and Cluster #7 (two items) focuses on AI assist emergency medical services in classifying patients more rapidly and precisely than they can using their present procedures, etc. However, these keywords are insufficient, for studying the performance of SCM in hospitals. Fig. 7 displays the size of cluster 6 is larger than others this explains the role and importance technics of AI for improving the supply chain in hospitals.

TABLE III. TOP PUBLICATIONS INFLUENCING HOSPITAL SCM

Author	Year	Title	TLS	Citation	Subject Concerning Hospital SCM
Kwon et al [65]	2018	An algorithm based on deep learning for predicting in-hospital cardiac arrest.	0	131	Heart association
Cho et al [49]	2008	Application of irregular and unbalanced data to predict diabetic nephropathy using visualization and feature selection methods.	0	102	Artificial intelligence in medicine
Dai et al [42]	2015	Prediction of hospitalization due to heart diseases by supervised learning methods.	0	99	Medical informatics
Cui et al [68]	2018	An improved support vector machine-based diabetic readmission prediction.	0	71	Computer Methods and Programs in Biomedicine
López Pineda et al [57]	2015	Comparison of machine learning classifiers for influenza detection from emergency department free-text reports.	0	57	Biomedical informatics
Kwon and Kim et al [87]	2019	Artificial intelligence algorithm for predicting mortality of patients with acute heart failure.	0	56	Heart association
Lin et al [58]	2018	Predicting post-stroke activities of daily living through a machine learning-based approach on initiating rehabilitation.	0	51	Medical informatics
Kwon et al [47]	2019	Deep learning for predicting in-hospital mortality among heart disease patients based on echocardiography.	0	49	Echocardiography
Boon et al [35]	2007	Hybrid outcome prediction model for severe traumatic brain injury.	0	48	Biology and medicine
Bolourani et al [54]	2021	A machine learning prediction model of respiratory failure within 48 hours of patient admission for COVID-19: Model development and validation.	0	48	Medical internet research
Saxe et al [3]	2017	Machine learning methods to predict child posttraumatic stress: A proof of concept study.	0	42	Bmc psychiatry
Cronin et al [59]	2017	A comparison of rule-based and machine learning approaches for classifying patient portal messages.	0	40	Medical informatics
Nimgaonkar et al [2]	2004	Prediction of mortality in an Indian intensive care unit: Comparison between APACHE II and artificial neural networks.	0	41	Intensive care medicine
Regnier-Coudert et al [76]	2012	Machine learning for improved pathological staging of prostate cancer: A performance comparison on a range of classifiers.	0	37	Artificial intelligence in medicine
Peng et al [85]	2010	Random forest can predict 30-day mortality of spontaneous intracerebral hemorrhage with remarkable discrimination.	0	37	Neurology
Liu et al [32]	2014	Development and validation of a machine learning algorithm and hybrid system to predict the need for life-saving interventions in trauma patients.	0	37	Medical and biological engineering

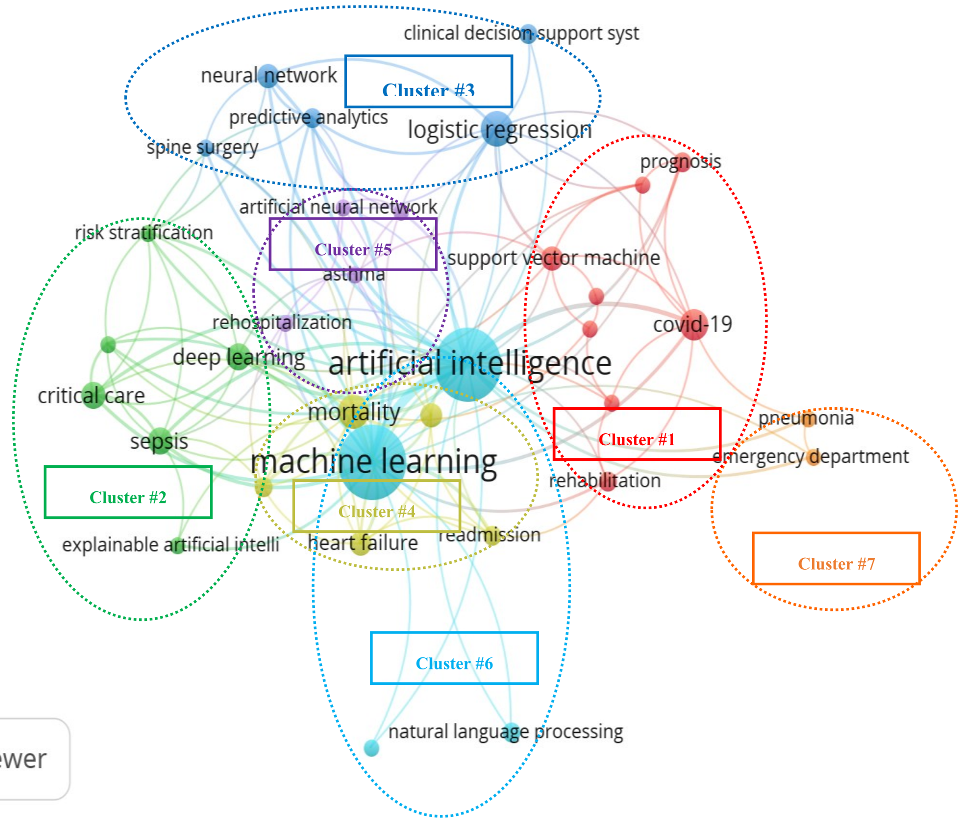

Fig. 7. Co-occurring keyword mapping

TABLE IV. KEY TERMS AND THEME CLUSTER SUMMAIRIES FROM HOSPITAL SCM RESEARCH

Cluster ID	Keywords	Occurrence	TLS	Average Citation	Average Norm. Citation	Period
Cluster #1 (red) Size = 25	Covid-19	7	15	7.57	1.40	2021-2023
	Support vector machine	4	9	26.25	0.83	2020-2023
	Prognosis	3	6	12.67	0.58	2017-2023
	Rehabilitation	3	6	21.67	0.47	2019-2023
	Extreme gradient boosting	2	6	1.00	0.77	2022-2023
	Feature selection	2	2	56.50	1.27	2013-2023
	Hospital readmission	2	4	46.50	1.12	2011-2023
	Prognostic models	2	5	11.00	0.35	2013-2023
Cluster #2 (green) Size = 21	Deep learning	5	14	47.20	1.59	2019-2023
	Critical care	5	13	9.20	1.14	2021-2023
	Sepsis	5	15	6.60	0.98	2021-2023
	Risk stratification	2	11	15.00	1.86	2021-2023
	Intensive care unit	2	10	12.00	1.49	2021-2023
	Explainable artificial intelligence	2	4	0.5	0.39	2022-2023
Cluster #3 (blue) Size = 21	Logistic regression	9	17	20.22	0.83	2014-2023
	Neural network	4	12	18.00	0.90	2017-2023
	Clinical decision support system	3	2	5.67	0.35	2016-2023
	Predictive analytics	3	13	8.33	1.03	2021-2023
	Spine surgery	2	8	17.50	0.93	2020-2023
Cluster #4 (yellow) Size =22	Mortality	8	21	12.12	0.57	2017-2023
	Heart failure	4	10	19.75	1.40	2020-2023
	Predictive modeling	4	10	12.25	1.27	2019-2023
	Readmission	3	8	11.00	0.89	2022-2023
	Acute kidney injury	3	9	1.33	1.03	2022-2023
Cluster #5 (purple) Size =27	Length of stay	2	7	1.50	0.51	2021-2023
	Artificial neural network	2	7	2.50	1.93	2022-2023
	Rehospitalization	2	7	3.00	2.31	2022-2023
	Asthma	2	6	17.50	1.93	2020-2023
Cluster #6 (Sky blue) Size =81	Machine learning	39	76	18.49	1.22	2020-2023
	Artificial intelligence	37	81	13.86	1.06	2020-2023
	Natural language processing	3	2	24.00	1.06	2019-2023
	Predictive models	2	2	50.00	1.02	2018-2023
Cluster #7 (orange) Size =4	Emergency department	2	4	3.00	0.25	2021-2023
	Pneumonia	2	4	2.00	0.37	2021-2023

Table IV contains thorough information about the important keywords. The table displays frequently used terms over the last three years, they might turn into the focal points of upcoming studies. The ten most often studied and closely related concepts are machine learning (Feq. = 39, TSL = 76), artificial intelligence (Feq. = 37, TSL = 81), logistic regression (Feq. = 9, TSL = 17), mortality (Feq. = 8, TSL = 21), Covid-19 (Feq. = 7, TSL = 15), sepsis (Feq. = 5, TSL = 15), deep learning (Feq. = 5, TSL = 14), critical care (Feq. = 5, TSL = 13), neural network (Feq. = 4, TSL = 12) and heart failure (Feq. = 4, TSL = 10). These terms are crucial for creating hospital supply chain management research topics and tying together important areas of study. As stated by the average citation metric, as following keywords received a lot of attention: biomedical informatics, artificial intelligence, critical care, surgery medical, clinical neuroscience, and emergency. Artificial intelligence and big data contribute include improving logistics in healthcare, environmental sustainability, and hospital SCM. For example, measuring performance in health care [31], creating new mortality models [39], prediction of cardiac arrest by deep learning [43], etc. Its importance is to reduce mortality, treat patients, and facilitate access to hospitals, etc. These clusters strongly relate, where using machine learning, deep learning, and predictive modeling to improve and develop many domains, for instance, surgery, emergency department, critical care, risk stratification, etc. A static depiction of a certain domain, the keyword co-occurrence network ignores variations in the terms' usage over time [92].

IV. Discussion

A. Taxonomy of Current Research Knowledge

The previously mentioned analysis sheds light on the state of research, evolutionary trends, and contentious issues in global hospital supply SCM, and the text mining application VOSviewer was utilized to show the time perspective of the clustered keywords that were obtained from the same data. However, general scientometric conclusions cannot accurately reflect the precise division of a domain's varied knowledge [89]. In addition, taxonomy can be elitist and exclusionary. A full taxonomy of hospital SCM knowledge from 2002 to 2023 was proposed based on clustering analysis of high-frequency keywords, and each separated branch was then thematically analyzed in depth. This section looks at various approaches in each of the suggested taxonomy's dimensions and discusses them. The approaches take into account these relationships and are based on the features of the problem being tackled. To make the taxonomy more concise and easy to grasp, topics with comparable qualities were incorporated into different categories of themes and manually renamed. The mind mapping of the hospital SCM research themes is shown in Fig. 8, where 22 sub-branches and 5 alignments are produced. There was also a list of the number of articles that each theme featured.

1) New technologies suggested for the development of hospital SCM

Developing cutting-edge infrastructure and technologies is a long-term, forward-thinking way to address the healthcare issue.

Many innovative ways to address the difficulty of hospital SCM are to develop new technologies such as medical Artificial Intelligence [18][25][24][53][79][86][87] and big data [1][23][49][64][83]. In the meantime, several new technologies have been proposed in recent years, for example, Acute Physiology and Chronic Health Evaluation (APACHE II) [2], Target-Selective Gradient Backprop (TSGB) approach [12], Location-Allocation Problem (LAP) model [15], SHapley Additive exPlanations (SHAP) [27], Clinical Decision Support Systems (CDSS) [41] and Tianxia120 [23].

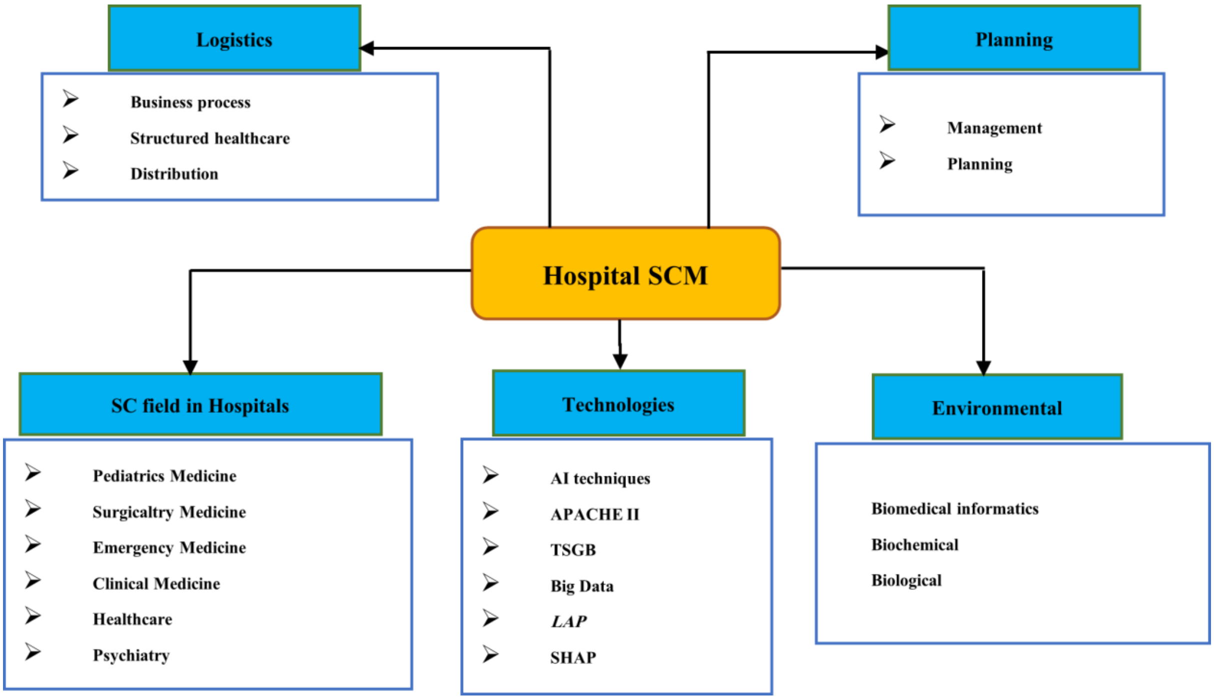

Fig. 8. The SCM themes' knowledge taxonomy

In medicine, artificial intelligence refers to the application of many methods such as machine learning models [3]-[7], [10]-[14], [22], [30], [36], [50], [54], [73], [76], [79], deep learning models [47][61][62][66][82], artificial neural networks [2][24][55], Natural Language Processing [8][53][75] etc. Furthermore, Artificial Intelligence (AI) technology is commonly used in hospital SCM, development and validation of a deep-learning-based artificial intelligence algorithm for predicting mortality of patients with acute heart failure (DAHF) by using large data [79][87], and unfavorable results in adult emergency department pneumonia patients [86], forecasting death in the surgical critical care unit [53], as well as forecasting death in COVID-19 patients [24]. Other aspects of the CUHAS-ROBUST application's development and performance of pulmonary tuberculosis screening in Indonesia that is resistant to rifampicin [18], and the development of a survival classification model that can quickly and automatically triage in the prehospital environment [25] etc.

Artificial intelligence (AI) has the potential to drastically change a variety of industries, including healthcare and security is now sitting atop the hype curve. AI is expected to improve workflow, therapy planning and monitoring, and diagnostics in healthcare, especially radiology. Even though radiologists are apprehensive about how AI may affect the need for and training of the present and future workforce, most of us are excited about the prospect of using AI to significantly enhance our capacity to diagnose illness earlier and with greater accuracy [94].

Other technologies, such as the APACHE II, are frequently employed and regarded as the standard grading system when comparing hospital outcome prediction using an artificial neural network model constructed using data, whereby the system compares the predicted and actual outcomes for each patient based on memory and prior experience [2]. Furthermore, an innovative approach to the evaluation of Venous thromboembolism (VTE) risk presents the state-of-the-art multi-task tree-based technique (TSGB) algorithm to address the cross-departmental multi-task prediction problem [12]. A location-allocation problem (LAP) model that can assist emergency medical facilities (EMFs) in handling significant public health emergencies was presented to speed up the locations and the assignment of patients to these facilities during disasters. Considering the impact of the COVID-19 infection rate on the market for EMFs [15]. Additionally, for patients with heart failure brought on by coronary heart disease, the proposition of a model SHAP determines the 3-year risk of all-cause death to produce detailed justifications for each option and give physicians an intuitive understanding of the influence of key features. [27]. In addition, Tianxia120 is an electronic medical healthcare system that comprises a physician terminal and a patient terminal. They can conduct digital prescriptions, multiparameter self-diagnostic, logistics for cold-chain, drug distribution, and online inquiry (via graphic, audio, video, telephone, etc.). Comprehensive medical and health data, exploring medical tools, and processing a large data aggregation for healthcare are all capabilities of the system [23].

2) *Hospital SCM planning research*

This field focuses on planning, implementing, development, management, and information on hospital SCM sub-jects.

For, Duy Van Le and al [8], selected the dictionary and period that best predicted risk evaluation scores on tested tools by analyzing the frequency and presence of words in a forensic Electronic Health Records (EHR) dataset, contrasting four reference dictionaries, a total of seven machine learning algorithms, and separate distinct EHR analysis periods. Kristina Fuest and al [19], demonstrated that AI-informed clustering of a sizable intensive care unit (ICU) cohort can offer tailored mobilization suggestions that increase the chance of being released home. Măruşter and Jorna [26], suggested a way to model and restructure a business process from the perspective of knowledge management. Using hospital data of interdisciplinary patient groups as an example of methodology, they demonstrated how knowledge supporting the reorganization of care for multidisciplinary patients should be provided to improve the efficiency of treatment. Boon and al [35], created an integrated prognostication model that combines various outcome classes and prognostic indicators for significant brain damage from trauma several prediction models were created utilizing data that was prospectively gathered from 513 patients with severe closed head injuries who were hospitalized to the neurocritical unit at Singapore. Bacchi and al [52], validated models that forecasted the destination of discharge planning, duration of stay, survival to discharge, and discharge modified Rankin Scale (mRS), all of which had previously been obtained using external and projected datasets. Haoyu Yang et al. [64], suggested the strategies for creating reliable prediction models with data that wasn't available at the time of prediction, which can be applied to enhance the effectiveness of risk models as such end of surgery. Niederwanger and al [71], found the most appropriate score in pediatric sepsis patients in terms of disease survey timing and insensitivity to missing data, researchers compared and assessed the prognostic ability of several widely used systems of scoring for children (PRISM, PRISM III, PRISM IV, PIM, PIM2, PIM3, PELOD, PELOD 2). Tarumi and al [75], investigated a variety of predictive techniques and variables for physiological stage forecasts and evaluated them according to the validity of their predictions using data from the United Kingdom.

3) *Hospital practices and application areas*

Numerous different studies on hospital SCM practices have been carried out in the past ten years as such emergency medicine [4][30][74][86], healthcare [28][84], clinical medicine [6][34][52][55][69][78], pediatrics medicine [5][9], surgical medicine [1][56] and psychiatry [3][50].

Real-world applications can provide a wealth of relevant experience and teaching. For example, A machine learning method developed utilizing state-level registry information at a class 1 trauma center could accurately predict surgical outcomes [1], and identify factors that predict the neural-cognitive result of pediatric surgical patients with early schoolage CDH (congenital diaphragmatic hernias) [56]. In addition, the applicability of a diagnosis approach based on ML techniques for individuals with disorders encompassing autism spectrum who also have intellectual incapacity [50], and using data accessible at the moment of trauma, precise methods of prediction for PTSD (posttraumatic stress disorder) would greatly improve the management of traumatized children [3]. While application in emergency medicine, creating a ML model that forecasts unexpected fatalities within 30 days of emergency department discharge [4], enhancing the performance, promoting the adoption, and studying the impact of ML within emergency medicine [30]. Additionally for patients with pneumonia in the emergency room, artificial intelligence of things (AIoT) can hold the key to forecasting unfavorable outcomes [86].

For pediatric medicine, using a machine learning-assisted prediction model, artificial neural network modelling, and conventional methods (logistic regression, etc), risk variables for six-month readmissions of children with asthma are identified [9], and the therapy outcome of orthokeratology in children [5]. Additionally, for healthcare developing and validating a machine learning model to forecast hospital mortality in patients with sepsis who need to be readmitted to the intensive care unit [28], and determining those who have a greater risk of readmission [84]. Whereas for clinical medicine, artificial intelligence has become a useful tool in the field of cardiovascular medicine by extending improved standards for patients enhancing the efficacy of cardiologists [34], and estimating death in patients with lactic acidosis who are acknowledged to the critical care unit [6]. In clinical neuroscience, verification of previously developed models for the prediction of discharge mRS (modified Rankin scale), survival to discharge, length of stay (LoS), and discharge destination using external and upcoming databases [52], as well as for projecting the expected LoS for stroke patients who are admitted, together with the discharge location, hospital death rates, and mRS prediction [69].

4) *Logistical of hospital*

Over the last years, hospital logistics management has been the process of planning and controlling the flow of a business process as such goods, services [26][64], structured healthcare [37], cold chain logistics and medicine distribution [23] etc.

For example, The COVID-19 pandemic and the virus's quick propagation have caused an enormous increase in the need for emergency medical facilities (EMFs), using a location-allocation problem (LAP) model, Shaoren Wang et al. [15] accelerated the identification of EMFs and the distribu-tion of patients to these facilities during disasters. This model can assist EMFs in managing significant public health catastrophes. Liuzzi [16] developed a deep learning model that uses data from hospital admission to estimate the length of the COVID-19 infection, this approach might be effective in addressing the heavy workload and intricate logistical requirements of medical facilities between pandemic outbreaks. Tianxia120, a multimodal medical data collection, and bioinformatic system proposed by Zihan Jiao et al. [23] that may offer "one-step service" to hospitals and patients, is made up of a physician terminal and a patient terminal. They can do online research (by voice, text, picture, etc.), multiparameter self-diagnosis, electronic prescriptions, distribution of medications, cold chain logistics, and so forth. A knowledge management viewpoint was put up by Laura Marusan and colleagues [26] as a method for business process modeling and redesign, using hospital data of multidisciplinary patients as an example of a strategy, information that supports the restructuring of care for patients with multiple specialties could be provided, as well as the creation of new interdisciplinary units, to increase the efficiency of treatment. A logistic-based patient grouping approach for multidisciplinary treatment and the establishment of a new inventory where various disciplines collaborate for particular patient groups was developed by Laura Marus and colleagues [37]. The clinical decision support system (CDSS), developed based on physiology, illness variables, therapy factors, and details of the demonstration, was used by Hsu et al. [41] to maintain spontaneous breathing, prevent needless ventilator use prolongation, and lower medical care costs.

5) *Evaluation of the environmental impact of hospital SCM initiatives*

These studies' subjects primarily came from four back-grounds: Biological [16][22][27][32][39][62], Biomedical informatics [8][12][33][41][57][75][84], and Biochemical [34].

For example, Piergiuseppe Liuzzi and al [16], suggested the technique of a deep learning model that can forecast the length of the infection based on data available at the time of hospital admission; predictors include COVID-19 symptoms and signs, hematochemical analysis findings, anamnestic and analytic data, and previous treatments given to patients. Minyue Yin and al [22], examined many machine learning (ML) models for the early identification of acute, severe pancreatitis in patients receiving acute pancreatitis hospitalization. Wang [27] developed an explainable machine learning model that accurately predicted the three-year total cause death rate for patients suffering from illness of heart-related related heart failure (HF). Nehemiah Liu and al [32], created and verified various parameters of ML systems and algorithms that can forecast whether trauma patients would require life-saving measures (LSIs).

Moreover, Toma and colleagues [33], found that anticipating the state of survival of critical care patients after their hospital stay is helpful for several clinical and administrative activities. Tarumi [75] evaluated three approaches to utilizing digital health (biomedical informatics) record data from various sources to forecast pharmacotherapy results for type two diabetes. The most predictive period for risk assessment scores on tested instruments developed by Le and colleagues [8] was investigated through the use of seven ML algorithms and varying EHR analysis periods. Xue and colleagues [84] prove that independent functioning metrics may be evaluated utilizing ML algorithms to forecast acute care readmissions, enhancing the efficacy of preventive healthcare.

According to Damien Grusona et al [34], another use of biochemicals could enhance the precision and speed of diagnosis, support clinical decision-making, and result in better health results by integrating technology utilizing artificial intelligence with laboratory medical practice into cardiovascular care.

B. Agenda and Lacking Research

The scientometric already stated study and topical debate revealed, the thorough study tendency, popular academic issues, and taxonomy of knowledge of the hospital SCM area. Although academics and practitioners have made great advances in developing hospital SCM theory and practice, there are still several limits that must be addressed later on in research. Such as constraints on international cooperation and the absence of innovative technologies.

1) Constraints of international cooperation and the comprehensive assessment system

There is still insufficient international cooperation in the model of research. More discussion is warranted regarding the general application of most hospital SCM expertise based on local situations, for example, the Artificial Intelligence of Things (AIoT) model, not applicable to other hospitals or countries [86]. In addition, artificial intelligence-based risk evaluations of thirty-day published are predictors of unexpected readmission after carotid artery stenting.; however, they have not undergone independent evaluation and are currently limited to the United States population, there is no external validation for the risk scores that are displayed [63].

To close this gap, more research is required to gather and combine unstructured data on all pertinent indications of clinical risk, factors affecting, the environment, imaging biomarkers, lifestyle choices, and other factors to enhance predictions. This will be done even though the research will be expanded to include patients in different regions and hospitals and we will use data from various countries for external validation. and future objectives for our study include growing the dataset to include numerous time points for continuous analysis, as well as increasing the size of the sample to investigate more potential predictors and their interactions.

2) Supplementary studies from an international and comprehensive angle

It is acknowledged that a complete or comprehensive study is still necessary to develop the hospital SCM knowledge system, even though the knowledge branch of research is flourishing. Further studies are necessary to provide a more thorough explanation of the hospital length of stay, the patient's discharge process, the cause of death [29], and the main grievance detailed for all, unexpected, and predictable deaths within each category.

The decision-making process and operation of hospital SCM involve numerous parties, including medical center officials, asphysicians, patients, and medicines transportation officials, etc. Hospital SCM should have both long-haul and dynamic effects. As a result, the entire picture takes into account a variety of viewpoints, including the dynamic assessment of the entire life-cycle of hospital logistics operations and the interaction of decision-makers from various back-grounds, and future research testing generalizability will be very intriguing.

3) Insufficient platform to quickly advance innovation technology research

The impact of implementing hospital SCM from a management standpoint is minimal in the absence of innovative technologies. Some novel technologies, however, require a long time to transition from laboratory to implementation before they can significantly ameliorate the negative consequences of logistics. Such as applications of the XGBoost algorithm were studied in a single medical facility and were shown to be an accurate prediction method for patients with subarachnoid hemorrhage caused by aneurysm, however, the program was not made easily accessible [45], additionally is unable to accurately extract past medical histories, including those of respiratory conditions and cancers, which may also have an impact on extended mortality. A prospective study is being planned to validate the AI algorithm and verify the association between health history and cardiac problems [87].

A lengthy period of proof is required for the introduction of a new object, such as the technology's dependability and the uncertainty surrounding the true benefits. The issue, though, is frequently a lag or gap in the study on the validation of the AI algorithm and test generalizability in other hospitals. As a result, developing efficient platforms and cuttingedge technologies based on interdisciplinary, cross-organizational collaboration is crucial for hospital supply chain management practices. Examples of these technologies of artificial intelligence include machine learning, natural language processing, artificial neural networks, deep learning, and the XGBoost algorithm, etc.

V. CONCLUSION

The notion of hospital supply chain management has gained increased interest and contemplation from government sectors, academia, practitioners, medical center officials, and global organizations. Both in the technology and medical domains, a great deal of tangible advancement was made. For example, using the technology of AI and big data for developing healthcare, emergency departments environmentally sustainable, etc. Using a three-step evaluation program, this study examined 87 valuable contributions to hospital SCM over the last two decades. They were classified according to the publishing year, the journal to which they were assigned, and the number of citations. Next, the bibliographic networks of nations, organizations, co-citations in documents and journals, and study subjects' keyword co-occurrence were then shown to aid in understanding the global research state and academic development. A comprehensive knowledge taxonomy of the hospital SCM area was developed, based on a scientific analysis, with there are 22 sub-branches and five main alignments.

The findings show a considerable rise in the chronological publication of SCM from hospitals. International Journal of Medical Informatics, Journal of

Biomedical Informatics, Artificial Intelligence in Medicine, Computers in Biology and Medicine, and PLoS ONE. Since 2002, it has provided more than a quarter of all hospital SCM papers. Current research is most important based on the maps of journal allocation and co-cited journals to biomedical informatics, biology in medicine, and neurology. The key nations for hospital SCM research are the United States, China, Taiwan, and the United Kingdom. The network of co-authored organizations and countries demonstrated a lack of collaboration among various research communities.

The most regularly cited hospital SCM challenges in each cluster are indicated by the co-occurring term map where concentrating on prognostic models are used to evaluate the risk of future outcomes in persons with a certain disease or health condition by combining various prognostic indicators (cluster #1), application the techniques of artificial intelligence in critical care (sepsis, risk stratification, etc) (cluster #2), applying predictive analytics in hospital (cluster #3), predictive modeling is essential to managing population health (cluster #4), applying techniques of artificial intelligence in clinical neuroscience (length of stay, rehospitalization, etc) (cluster #5), AI used to create individualized treatment plans, identify illnesses, and support medical professionals in making decisions, etc (cluster #6), and AI assist emergency medical services in classifying patients more rapidly and precisely than they can use their present procedures, etc (cluster #7). On this premise, the hospital SCM knowledge taxonomy was manually synthesized from five aspects: (i) technologies, (ii) planning, (iii) supply chain field in hospitals, (iv) logistics, and (v) environmental.

Finally, a prospective roadmap was proposed, which was separated separate 3 streams: (i) the collaboration between hospitals from various backgrounds is not currently widespread. To close this gap, the dataset to include numerous time points for continuous analysis, as well as increasing the size of the sample to investigate more potential predictors and their interactions; (ii) the complete or comprehensive study is still necessary to develop the hospital SCM knowledge system. Further studies are necessary to provide a more thorough explanation of the hospital length of stay, the patient's discharge process, the cause of death, and the main grievance detailed for all, etc; (iii) an insufficient platform to quickly advance innovation technology Research, require a long time to transition from laboratory to implementation. Developing efficient platforms and cuttingedge technologies based on interdisciplinary, cross-organizational collaboration is crucial for hospital supply chain management practices.

It should be highlighted, although that the data used in this study was limited to research and review papers that were published in peer-reviewed journals, and that they were only obtained from the mainstream database while taking software applicability into account. While the majority of the persuasive points of view in hospital SCM research may be represented by the indexed papers, certain important articles that were published in alternative formats may inevitably be missed. A thorough inquiry into the subject of SCM hospital that incorporates valuable conference papers and publications is projected to provide a more thorough knowledge base for the next studies. Thus, we have unanswered questions in this domain for example, how might ongoing technological advancements, regulatory changes, or global events (e.g., pandemics) shape the future of hospital SCM research and practice? Lastly, we call stakeholders at the hospitals to heed the recommendations and actively contribute to advancing knowledge and practice in hospital SCM.

COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this review.

CONTRIBUTION STATEMENT

Conception or design of the work: Soulaiman Louah. Data collection: Soulaiman Louah. Data analysis and interpretation: Soulaiman Louah. Drafting the review: Soulaiman Louah. Critical revision of the review: Soulaiman Louah, Hicham Sarir and Mohamed kriouich. Final approval of the version to be published: Soulaiman Louah, Hicham Sarir and Mohamed kriouich.

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