International Journal of Advances in Applied Sciences (IJAAS)
Vol. 13, No. 2, June 2024, pp. 411~418
ISSN: 2252-8814, DOI: 10.11591/ijaas.v13.i2.pp411-418

Electronic health records with decision support systems for sharper diagnoses: bibliometric analysis

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Article Info

Article history:

Received Feb 3, 2024
Revised Feb 25, 2024
Accepted Mar 7, 2024

Keywords:

Bibliometric analysis
Clinical decision support systems
Diagnosis
Electronic health records
Machine learning

ABSTRACT

Clinical decision support systems (CDSS) and electronic health records (EHRs) are computer systems designed to assist decision-makers in making optimal and streamlined judgments on disease diagnosis, treatment, patient care, and health institution management. This study conducted descriptive and bibliometric evaluations of CDSS integrated with EHRs studies published in journals included in the Scopus database from 2007 to 2024. During the initial phase, the publications were distributed based on their publication year, nation, institution, journal, and citation numbers, as part of a descriptive analysis. During the second stage, the articles were subjected to bibliometric analysis, which involved doing common keyword analyses. The research yielded 409 papers about CDSS and EHRs. The United States has been identified as the country with the highest number of studies on this issue. The journal with the highest number of citations observed was Studies in Health Technology and Informatics. Furthermore, the text showcases visual representations of co-citations and cooperation between authors from different institutions and countries. This study aims to present a systematic framework for examining CDSS with EHRs to improve diagnosis and offer a comprehensive viewpoint to researchers and specialists in the field.

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1. INTRODUCTION

Hospitals are extremely complex organizations with unique characteristics that include large departments and units that coordinate patient care. They rely heavily on hospital information systems (HIS) to support diagnosis, management, and education to improve services and practices. An electronic health record (EHR) is a digital rendition of official medical records or charts used in clinical environments [1]. EHR systems are computer systems specifically designed to handle EHRs. Understanding the extent of digitalization in medical charts and the functionality of EHR systems is crucial for optimizing their use in clinical settings. EHR systems offer a diverse range of capabilities that enable healthcare practitioners to handle many health issues in patients effectively [2], [3]. Instances of these functionalities include healthcare information exchange (HIE) and tools or functions of clinical decision support (CDS). EHR systems have been extensively implemented and utilized in most healthcare organizations [2], [4], [5]. An EHR system's level of sophistication is positively correlated with the quality of clinical care [6]. EHR systems are increasingly crucial, with most healthcare organizations currently employing them. It is anticipated that EHR systems will be swiftly implemented in the coming years [7].

Clinical decision support systems (CDSS) are computerized tools that assist clinicians in making complex decisions. CDS refers to a range of computer system solutions that improve the decision-making process of healthcare professionals within the clinical workflow. Some examples of services performed by CDS systems include issuing warnings, alerts, and reminders related to different aspects of medical decision-making [8]–[10]. CDSS can improve the quality of care, reduce healthcare expenditure, and minimize risks [11], [12]. They can provide intelligent suggestions and reminders based on clinical guidelines and nursing processes, shortening recording time and improving nursing diagnosis [13].

These systems are commonly integrated into EHRs and have evolved rapidly over the years [14]. Multiple research projects on the CDS features of EHR systems have found a strong correlation between CDS functions and the prevention of medical errors, adherence to best practices, improved diagnosis, and avoidance of improper prescriptions [15]–[17]. Multiple studies have been conducted on the features of CDS and the compilation of clinical items, including allergy lists and problem lists [4], [18], [19]. However, there are still unknowns regarding the impact of CDSS with EHR on providers, patient outcomes, and costs [1]. Bibliometric analysis is a useful method that provides a systematic review of research in a specific field or topic using a visual map, providing an in-depth perspective on the topic. Incorporating current research that makes use of bibliometric analysis methods, this article presents those methods. The first step was a comprehensive review of bibliometric studies on various subjects. by Merigó and Yang [20].

The previous studies focused on healthcare mobile technology. Research by Chen *et al*. [21] bibliometrically analyzed 1,405 2007–2016 natural language processing and medical research articles. The top 100 medical informatics publications were bibliometrically analyzed by Nadri *et al.* [22]. Clinical decision-making was the second most researched topic till 2016. Research by Jalali *et al*. [23] bibliometrically analyzed 472 cybersecurity-healthcare literature. In the past decade, the aforementioned articles have been published on PubMed and WoS. A bibliometric analysis was performed by Santos *et al*. [24] to examine scholarly articles that were published in the WoS, Scopus, and Science Direct databases between 2009 and 2018. They examined health issues using data mining and machine learning techniques to compile a collaborative map of 250 papers in the field. In their bibliometric analysis, Hu *et al*. [25] examined 1,575 studies obtained from the WoS database, with a particular emphasis on research about medical data mining. A bibliometric analysis was performed by Quach *et al*. [25] on a subset of research articles that examined the application of artificial intelligence in healthcare services. The scholarly community examined 5,235 surveys that were carried out in 2019. Diaby *et al*. [26] conducted a bibliometric study to review the literature on multi-criteria decision analysis in health services. The study focused on research conducted between 1960 and 2011. Adunlin *et al*. [27] performed a bibliometric analysis of research conducted in the same field between 1980 and 2013.

Through previous analysis of research on CDSS in EHRs, it is clear that there is a lack of studies that have conducted bibliometric analysis in this field. Within this domain, we explore bibliometric analysis studies conducted across several literary disciplines, with a particular emphasis on those about medical and healthcare domains. Bibliometric analysis can fill this gap by systematically analyzing publication trends, citation patterns, collaboration networks, and journal impact factors related to CDSS-EHR integration research. Through our research, we want to offer valuable insights on effective strategies, identify areas in need of more research, and provide recommendations for future research paths. Our objective is to enhance integrated CDSS-EHR systems to better assist clinical decision-making and enhance patient outcomes.

2. RESEARCH METHOD

This study analyzed global papers on clinical decision-support systems and EHRs in the diagnosis field from the Scopus database using bibliometric analysis. Scopus was chosen for its exceptional scientific papers, abstracts, and references, which are of high quality and significance, establishing it as a worldwide acknowledged data source [28]. To avoid redundancy of articles and authors from several sources, Scopus was selected as the data source due to its inclusion of journals from other databases. The investigation intended to access more prominent papers. To establish the search word, a general study was undertaken on CDS and EHRs. Given that the terms "CDS" and "clinical decision making" are commonly found in the titles and keywords of research publications, the search term "CDS" was selected along with "EHRs" and "diagnosis." The search results were refined based on the publication year, publishing language, publication type, and scanned index criteria.we limited the research to next words: Title-abs-ke ("Clinical Decision Support System" AND "Electronic Health Record" AND "Diagnosis") AND (Limit-To (exactkeyword, "Clinical Decision Support System") OR limit-to (exactkeyword, "Electronic Health Record") OR limit-to (exactkeyword, "Electronic Health Records") OR limit-to (exactkeyword, "Decision Support Systems, Clinical") OR limit-to (exactkeyword, "Diagnosis") OR limit-to (exactkeyword, "Decision Support Systems") OR limit-to (exactkeyword "Artificial Intelligence") OR limit-to (exactkeyword, "Machine Learning") OR limit-to (exactkeyword, "Clinical

Decision Support Systems") OR limit-to (exactkeyword, "Algorithm") OR limit-to (exactkeyword, "Article") OR limit-to (exactkeyword, "Controlled Study") OR limit-to (exactkeyword, Clinical Decision Support") OR limit-to (exactkeyword, "Electronic Medical Record") OR limit-to (exactkeyword, "Algorithms") OR limit-to (exactkeyword, "Natural Language Processing") OR limit-to (exactkeyword, "Medical Informatics") OR limit-to (exactkeyword, "Data Mining") OR limit-to (exactkeyword, "Prediction") OR limit-to (exactkeyword, "Clinical Decision Making") OR limit-to (exactkeyword, "Patient Care") OR limit-to (exactkeyword, "Computer Assisted Diagnosis") OR limit-to (exactkeyword, "Diagnosis,Computer-Assisted") OR limit-to (exactkeyword, "Deep Learning") OR limit-to (exactkeyword, "Decision Making") OR limit-to (exactkeyword, "Health Care") OR limit-to (exactkeyword, "Early Diagnosis") OR limit-to (exactkeyword, "Learning Systems") OR limit-to (exactkeyword, "Health Care Delivery") OR limit-to (exactkeyword, "Diagnostic Accuracy") OR limit-to (exactkeyword, "Medical Computing") OR limit-to (exactkeyword, "Diseases") OR limit-to (exactkeyword, "Intensive Care Unit") OR limit-to (exactkeyword, "Treatment Outcome") OR limit-to (exactkeyword, "Information Processing") OR limit-to (exactkeyword, "Health Care Quality") OR limit-to (exactkeyword, "Learning Algorithm") OR limit-to (exactkeyword, "Systematic Review") OR limit-to (exactkeyword, "Quality Improvement") OR limit-to (exactkeyword, "Statistics And Numerical Data") OR limit-to (exactkeyword, "Hospitalization") OR limit-to (exactkeyword, "Diagnostic Test Accuracy Study") OR limit-to (exactkeyword, "Bioinformatics") OR limit-to (exactkeyword, "Patient Safety") OR limit-to (exactkeyword, "Knowledge Base") OR limit-to (exactkeyword, "Information Retrieval") OR limit-to (exactkeyword, "Precision Medicine") OR limit-to (exactkeyword, "Hospitals") OR limit-to (exactkeyword, "Hospital Admission") OR limit-to (exactkeyword, "Computer Interface") OR limit-to (exactkeyword, "Clinical Outcome") OR limit-to (exactkeyword, "Clinical Research") OR limit-to (exactkeyword, "Health") OR limit-to (exactkeyword, "Electronic Health") OR limit-to (exactkeyword, "Automation") OR limit-to (exactkeyword, "Natural Language Processing Systems") OR limit-to (exactkeyword, "Intensive Care Units") OR limit-to (exactkeyword, "Clinical Trial") OR limit-to (exactkeyword, "Artificial Neural Network") OR limit-to (exactkeyword, "Patient Treatment") OR limit-to (exactkeyword, "Patient Information") OR limit-to (exactkeyword, "Big Data") AND (Limit-to (LANGUAGE, "English"). The publication year for the study results considered was between 2007 and 2024 to encompass all recent studies. All research in various languages was categorized based on the language and type of publication we just included articles in the English language. By March 2024, 396 articles meeting these criteria were identified. The data for these articles were stored in 396 files retrieved via the Scopus interface, each containing distinct records.

This study will employ crucial procedures to achieve our research objectives. These include quantifying the occurrence rate of keywords, identifying keywords with high frequencies, constructing a co-occurrence matrix, grouping keywords into clusters, and analyzing the intellectual framework of topics through social network analysis. Before doing co-word analysis, it is important to establish the analysis unit. Researchers typically choose keywords taken from articles as fundamental units of analysis. For this study, we have used terms retrieved from projects in Scopus as our research data. The temporal duration is a decade, commencing in 2007 and concluding in 2024. We have obtained 396 research funds as shown in the flow diagram of the article in Figure 1. In conclusion, we obtained 433 keywords from the 396 research studies. Using visualization of similarities (VOS viewer) to analyze the data by inserting the data which were downloaded from Scopus and creating a map based on bibliographic data, then the data was chosen in according to analyze all co-occurrence keywords. We conclude all minimum keywords with 5 times co-occurrence, 443 keywords meet the threshold.

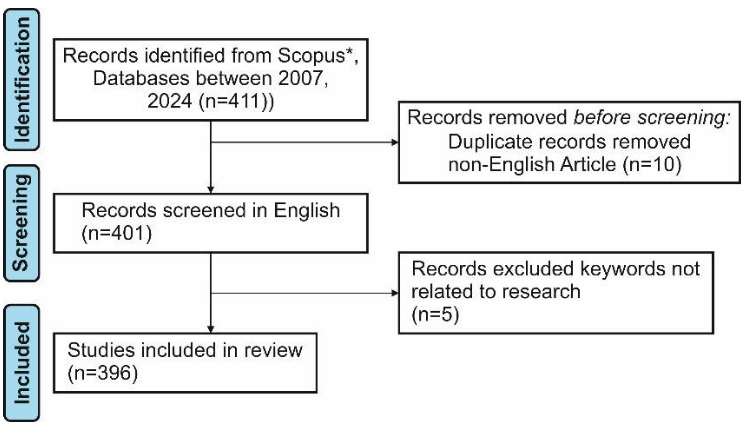

Figure 1. Flow diagram of the article selection process Scopus

3. RESULTS AND DISCUSSION

In Figure 2 a total of 396 publications that met the criteria were chosen for inclusion in the study. of these, 253 (62.8%) were original articles, 57 (14.4%) were reviews, 73 (18.5%) were conference papers, and the remaining articles were included in other categories. It is important to point out that the year 2023 saw the publication of a significant number of papers (14.3%). In the end, there were 396 research articles authored in English that were incorporated into the bibliometric study.

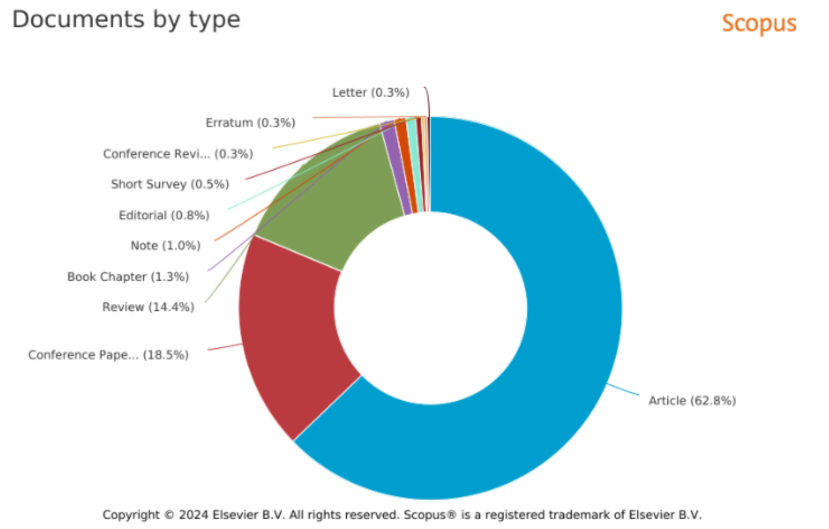

Figure 2. Documents types of published articles

This study looked into the effects of the implementation of both EHRs and CDSS together in hospitals and clinics to improve the diagnosis and early detection of disease While previous studies investigated the impact of CDSS only, they did not explicitly address its influence on personalizing the diagnosis with EHRs. We found that the integration between the two systems correlates with the potential to revolutionize healthcare by providing doctors with the information they need to make more accurate and timely diagnoses. The proposed method in this study tended to have an inordinately higher proportion of specific findings as relevant for diagnosis.

The essential substance of an article can be represented by its keyword, and the frequency of occurrence and co-occurrence might somewhat indicate the topics emphasized in a specific field. [29] Our findings indicate that higher complexity is not associated with poor performance in diagnosis accuracy. The proposed method may benefit from increased complexity without negatively affecting diagnosis accuracy. An analysis of the keywords utilized in the research revealed a total of 3818 keywords. When a term was repeated at least five times, 443 keywords were classified as such. As the number of repetitions grows, the number of keywords that may be classified inevitably decreases. Figure 3 indicates the published research on the role of CDSS with HER to improve diagnosis as the world's attention has increased from 2007 and gradually until 2024 and it’s expected to increase in the next years.

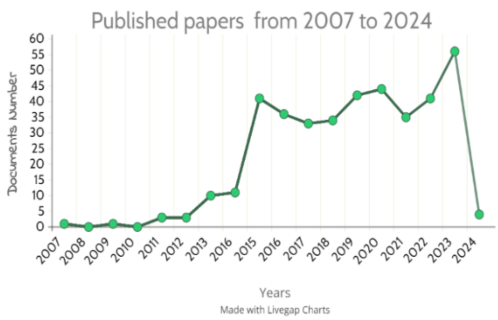

Figure 3. Published papers on CDSS and EHRs from 2007 to 2024

In Figure 4, it’s obvious that the published articles on CDSS with HER of them have well-established and robust economies. Upon examining the nations, the low ranking of emerging and underdeveloped countries in this list can be attributed to various difficulties faced by researchers, including limited proficiency in foreign languages, overwhelming academic workload, and inadequate support for project grants. Figure 5 shows that the most commonly used terms are "clinical decision support" (319 times), " EHRs" (220 times), and "diagnosis" (132 times). Because the research spans multiple domains, including medical, informatics, pharmacy, and engineering, this condition is mirrored in common word analysis. Figure 5 depicts a diverse range of study topics, disease and medicine names, and scientific procedures within these domains. Word groupings are represented by clusters of various color codes, such as green, yellow, red, and blue. The amount of times colors and words are used together and the number of repetitions determines their association.

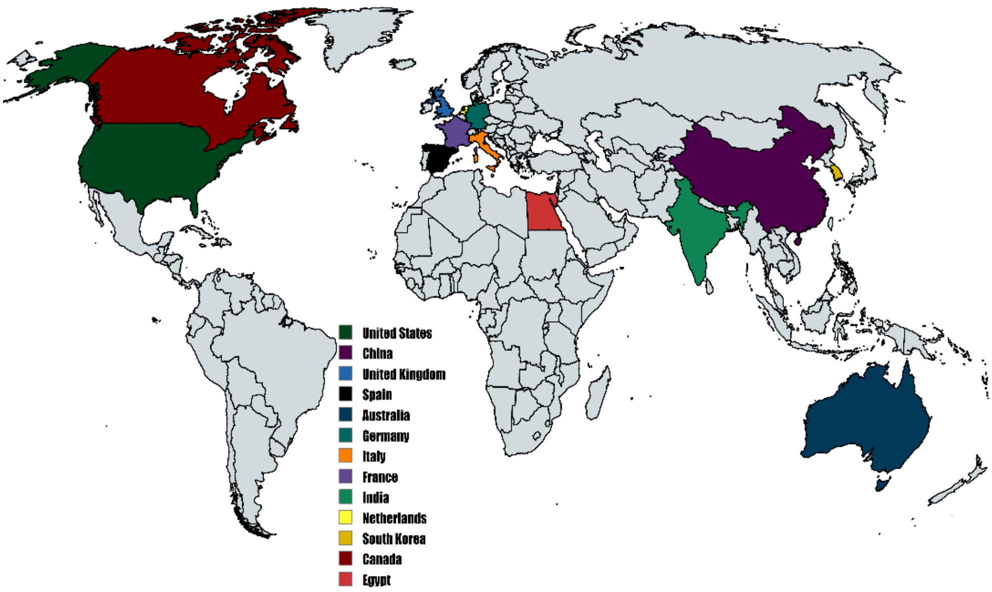

Figure 4. Most countries that have publications in CDSS and EHR

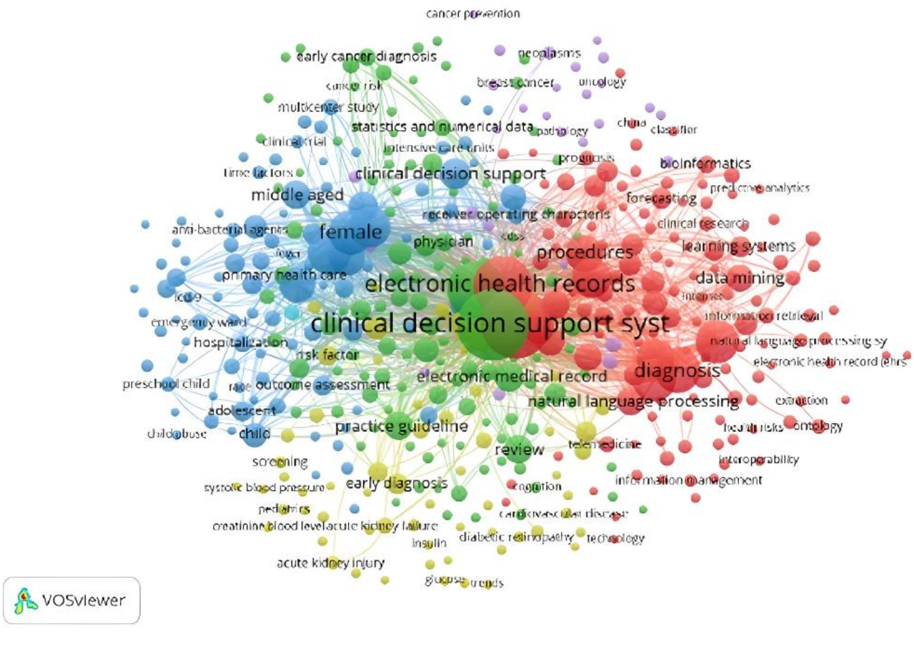

Figure 5. Visual map of common words

In addition, VOS viewer offers an overlay visualization map that can be used to examine the adoption of keywords over several years to evaluate the progression of the study title. Based on the overlay visualization map shown in Figure 6, the yellow node suggests that the keyword is now something that researchers are interested in. The current research trends in CDSS using EHRs, for instance, are centered on natural language processing, early diagnosis, pathology, and prognosis. This is done to improve diagnosis. Based on these terms, it is possible to predict that the early diagnosis of pathology through natural language processing will be the focus of future publications in EHRs integrated with CDSS. In addition, researchers are engaged in the process of ensuring that meaningful and important information may be quantified while simultaneously protecting the privacy and security of users and the system.

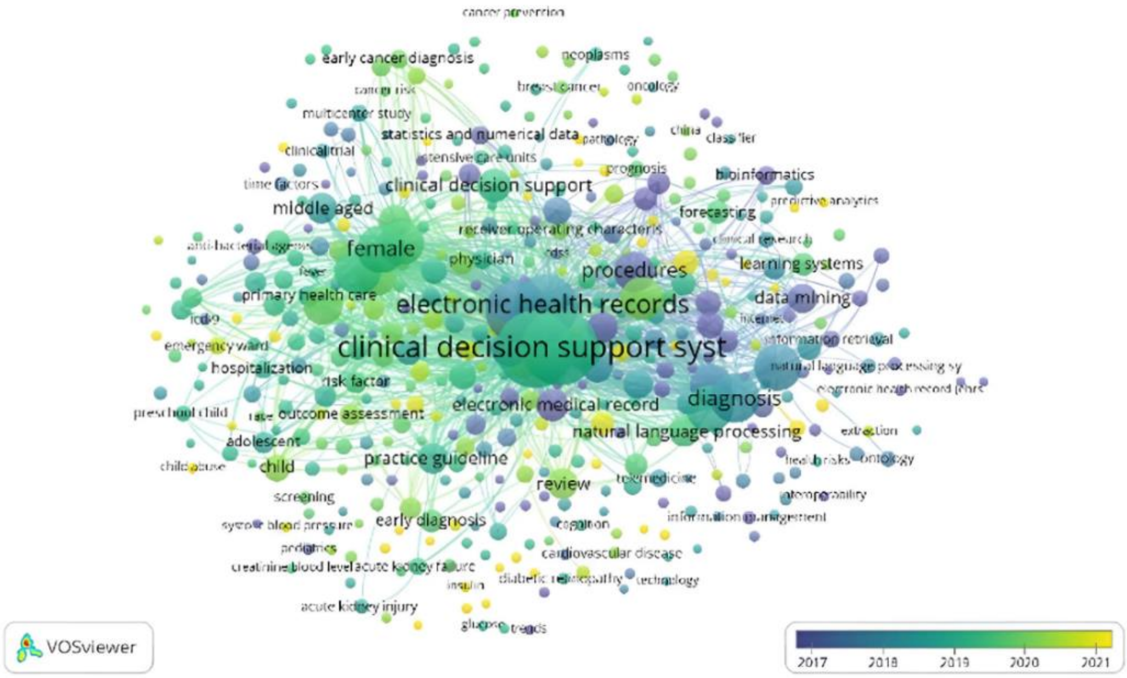

Figure 6. The overlay visualization map of the keywords by using VOS viewer software

To acquire further information regarding these phrases, we procured a graph that illustrates density visualization, as depicted in Figure 7. In the item density visualization, items are represented by their label in a way similar to the network visualization. Every location on a map is allocated a color according to the density of things found at that point. This hue is inherently a shade that is between the colors yellow and blue. As the quantity of objects in the area of a specific location grows and their magnitudes increase, the hue of the location shifts towards yellow. Conversely, if there are a smaller number of things around a point and those objects have lower weights, the color of the point will be more similar to blue. By examining the density picture, we can readily determine that CDSS, and EHRs, have a high density representing these keywords and have a strong relationship with other keywords. The user's text is empty. It is a legitimate inference that a higher density of research indicates a greater level of maturity and development in the study of the issue. Nevertheless, we cannot disregard the fact that there are fewer terms in the yellow area, with the majority of keywords being located around the blue area. It is evident that there are fewer key research disciplines, and a significant number of these fields are still in their early stages of development.

This study investigated a comprehensive analysis of EHR data and the development of a machine-learning model for early disease diagnosis. However, additional and in-depth research may be required to confirm its generalizability and applicability to different clinical settings, particularly regarding potential biases in the data and variations in healthcare practices across different populations. Our research shows that the proposed machine learning model is more resilient than traditional diagnostic methods in identifying early signs of disease. Future research may look into further refining the model and developing practical tools for integrating it into clinical workflows, such as decision support systems for healthcare professionals. Recent observations indicate that the increased availability of EHRs has opened up new opportunities for utilizing data-driven approaches in healthcare. Our findings offer definitive proof that early disease diagnosis can be significantly improved through machine learning analysis of EHR data, rather than solely relying on traditional methods that may be limited by human subjectivity and lack of comprehensive data analysis.

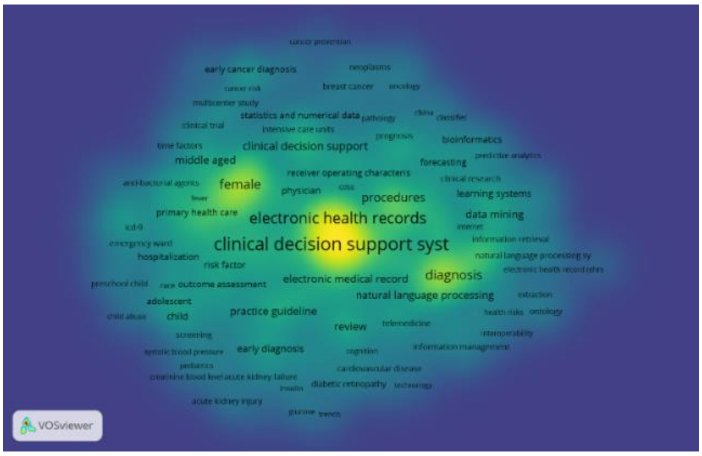

Figure 7. A density visualization map was performed with a VOS viewer

4. CONCLUSION

The bibliometric analysis of the integration of CDSS and EHR for diagnosis has revealed a growing interest in this topic. The research is globally distributed, with key institutions and influential writers providing valuable insights. The study emphasizes the importance of features such as clinical guideline implementation, drug interaction alerts, and real-time decision support. However, it also highlights challenges related to data quality, usability, and ethical concerns. The findings can guide researchers toward future research directions, promoting the exploration of AI-powered CDSS and standardized data exchange protocols. The findings can be used by healthcare practitioners to understand the advantages and constraints of integrating CDSS-EHR to improve diagnostic accuracy and efficiency. Policymakers can use the findings to make informed decisions on healthcare data standardization, interoperability, and ethical considerations related to CDSS implementation. Technology developers can use the findings to create more efficient and user-friendly CDSS-EHR integration solutions. Further research is needed to explore the practical effects of integrating CDSS with EHR on diagnosis results and user viewpoints.

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