

# Analyzing and Visualizing Knowledge Structures of Health Informatics from 1974 to 2018: A Bibliometric and Social Network Analysis

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**Objectives:** This paper aims to provide a theoretical clarification of the health informatics field by conducting a quantitative review analysis of the health informatics literature. And this paper aims to map scientific networks; to uncover the explicit and hidden patterns, knowledge structures, and sub-structures in scientific networks; to track the flow and burst of scientific topics; and to discover what effects they have on the scientific growth of health informatics. **Methods:** This study was a quantitative literature review of the health informatics field, employing text mining and bibliometric research methods. This paper reviews 30,115 articles with health informatics as their topic, which are indexed in the Web of Science Core Collection Database from 1974 to 2018. This study analyzed and mapped four networks: author co-citation network, co-occurring author keywords and keywords plus, co-occurring subject categories, and country co-citation network. We used CiteSpace 5.3 and VOSviewer to analyze data, and we used Gephi 0.9.2 and VOSviewer to visualize the networks. **Results:** This study found that the three major themes of the literature from 1974 to 2018 were the utilization of computer science in healthcare, the impact of health informatics on patient safety and the quality of healthcare, and decision support systems. The study found that, since 2016, health informatics has entered a new era to provide predictive, preventative, personalized, and participatory healthcare systems. **Conclusions:** This study found that the future strands of research may be patient-generated health data, deep learning algorithms, quantified self and self-tracking tools, and Internet of Things based decision support systems.

**Keywords:** Medical Informatics, Data Mining, Algorithms, Machine Learning, Publications

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## 1. Introduction

The emergence of health informatics dates back to the time when computers were developed that had the ability to store and process a large amount of data. As a result, in the 1960s, a new field of study called 'the health informatics' was established [1]. The next trend was the creation of Electronic Medical Records (EMRs). Then bioinformatics was expanded in the late 1990s to study biological data, such as DNA [2]. During the decades of the 80s and 90s, scientific communities studied and developed novel EMR frameworks to transfer from paper records, to share data widely, and to reduce the cost and time of processing data. The first EMR

implementation was started in the 1990s, but they become truly clinically viable after 2000 [3]. Health informatics is also known as healthcare informatics, medical informatics, nursing informatics, or biohealth informatics [4]. Recent advances in healthcare IT, health data standards, Electronic Health Records (EHRs), and health information exchange (HIE) have increased the growth of this scientific field [5], which has attracted interests in both academic and professional contexts.

The health informatics field has grown over the past quarter century, and many efforts have been made to define it in a scientific and formal language [6]. As health informatics has been practically implemented across medical settings [7], it has also become a major focus of scientific research. All of the technological innovations within the domain of health have been made possible through scientific knowledge. However, the healthcare sector is a field in which the development of new scientific knowledge is 'hectic' and technological expansion is profoundly 'rapid' [8]. Health informatics is also a new discipline [9] whose development is linked with technological trends.

Despite its increasing growth and interest among scholars and practitioners, currently, there is no comprehensive characterization of the knowledge structure of this field, and studies on its evolution are scarce. This understanding is necessary to facilitate the relevant technology growth and academic endeavors. Most existing works have evaluated health informatics research by conducting qualitative research methods, such as systematic literature review [10,11], and most have focused on a period of time limited to the last 10 to 20 years. These studies do not offer a complete and objective overview of the current state of research. A systematic literature review answers a specific question and is more focused and narrow in its approach with having a hypothesis to support or reject [12]. Qualitative reviews can be accompanied by several biases, such as publication bias, search bias, and selection bias [13]; such biases threaten objectivity since qualitative analysis requires personal judgment and the expertise of researchers [14]. On the other hand, the stream of publications on health informatics history suggests that this scientific field is multidisciplinary, and "one of the common challenges of multidisciplinary research is a lack of common language" [15].

This paper is intended to address these challenges and provide a theoretical clarification of the health informatics field. A comprehensive quantitative and more objective review of scientific articles can provide academia with valuable information without the intervention of a researcher's bias

about the knowledge structures, hidden trends, information flow, and future research orientation [16]. Moreover, it can help the multidisciplinary scientific fields to find their 'common language'. The findings of this research will supplement previous studies that have attempted to portray the thematic evolution of the field. In this study, we reviewed the literature on health informatics by conducting text mining methods, scientometric analysis, and social network visualization to find "the communities embedded in the social network datasets, and moreover, (to analyze) the evolutions of the communities in dynamic networks" [17]. Text mining in social networks enables the discovery of new patterns as well as existing relations and trends among various unstructured documents [18] by methods, such as keyword mapping or clustering of networks with similar content [19]. Keyword co-occurrence networks as part of bibliometric networks based on the context of citations [20] also enable the identification of differences and similarities of knowledge structures and sub-structures in health informatics. These findings will enable researchers to better understand the current state of health informatics, prevailing subjects, and future lines of research. This work is ultimately intended to extend the theoretical development and clarify the conceptual background of health informatics.

This research mapped the scientific networks, uncovered the prominent and hidden patterns in scientific networks, tracked the flow and burst of scientific subjects, and discovered what effects they have had on the scientific growth of health informatics. The originality of this study is related to its methodology and the timeframe used. We studied the evolution of health informatics during the past 44 years from 1974 to 2018 by applying three research methods: text mining, scientometric analysis, and social network analysis. These methods have not been previously used in studying the knowledge evolution of health informatics field. The scope of our timeframe (44 years) helped us analyze bursts and interactions between keywords, between countries, between authors, and between scientific subject categories since the first works were published in 1974 to provide a broader mapping than those used in previous qualitative studies.

This study aimed to illuminate the knowledge structure of health informatics by (1) reviewing a large number of publications (more than 30 thousand documents); (2) identifying hidden patterns during the last 44 years and visualizing them; (3) identifying the emerging scientific and technological trends since 1974, identifying the relations of keywords, authors, countries and scientific subject categories and their

bursts; (4) identifying key studies and visualizing their relations; and (5) suggesting future lines of research.

## II. Methods

### 1. Data Set Extraction and Filtration

This work was a quantitative study of health informatics science based on text mining and scientometric analysis of articles. This study analyzed and mapped four networks: co-occurrence of keywords, country co-citation network, co-occurrence of subject categories, and author co-citation network.

As the first step, we collected data from the Web of Science database by searching papers that included ‘health informatics’ in their subject. We limited our search to this keyword only and did not include other keywords, such as medical informatics or nursing informatics. The result of this search in August 2018 was 30,115 articles published during the period from 1974 to 2018. Regarding our inclusion and exclusion criteria, we included all papers from all disciplines and subjects and did not apply any specific exclusion criteria regarding time and discipline. Our inclusion criteria were to include all papers from all of the Web of Science subject categories and all document types. This enabled us to collect all relevant information of all documents on health informatics. However, we excluded non-English papers. Indexes of the search were SCI-Expanded, SSCI, A&HCI, CPCI-S, CPCI-

SSH, ESCI, CCR-Expanded, and IC. Contents of records that were saved were full record and cited references. In sum, the population of this research was all scientific documents that included ‘health informatics’ as their subject and were indexed from 1974 until the end of August 2018 in the Web of Science Core Collection. To increase the quality of the data, we applied some pre-processing. Some examples of pre-processing steps were the removal of duplicates (126 duplicates were deleted), and stop words, tokening, and stemming. Stop words included the most common words like ‘and’, ‘if’, and so forth. Tokenization included converting a sequence of characters into a sequence of tokens, and stemming was conducted to reduce inflected words to their root form. For instance, the words ‘treatment’, ‘treats’, and ‘treated’ were reduced to ‘treat’.

### 2. Analytical Tools

We used multiple types of software for analysis and visualization as shown in Table 1. We used CiteSpace 5.3 and VOSviewer as analysis tools, and we used Gephi 0.9.2 and VOSviewer to visualize the networks.

#### 1) Overlay visualization of keywords by VOSviewer

To conduct this analysis, 60,926 keywords were identified. We set the minimum number of occurrences to 40. Around 698 keywords met the threshold.

Table 1. Methods, goals, and tools of the research

Method	Goal	Analysis tool	Visualization tool
Text mining			
Word co-occurrence analysis	To analyze the co-occurrence of keywords and to identify relationships and interactions between the subjects and emerging research trends	CiteSpace	Gephi & VOSviewer
Burst analysis	To identify the burst interval of words for detecting subjects in a particular period and to capture the relation between burst intervals. Kleinberg’s burst detection algorithm was used to identify sudden increases or ‘bursts’ in the frequency of words used over time.	CiteSpace	CiteSpace
Scientometric analysis			
Co-citation analysis	To measure the semantic similarity of documents by using citation analysis and citation relationships	CiteSpace	Gephi
Country co-citation analysis	To analyze the co-citation activities of countries	VOSviewer	VOSviewer
Author co-citation analysis	To measure the co-citation activities of authors	CiteSpace	Gephi
Co-occurring subject category	To measure the co-occurrence of the most popular subject categories	CiteSpace	Gephi

## 2) Word co-occurrence analysis and burst analysis by CiteSpace and visualization by Gephi

To analyze word co-occurrence in CiteSpace, we set the number of years per slice to 5. We then selected the top 30% of most frequently occurring items from each slice. The common practice among previous studies was to select between the top 50% to 20% of the items. As a result, the CiteSpace software chose the 30 most cited or most

frequently occurring items from each slice to construct the networks. We used the same criteria for all our analysis on CiteSpace (i.e., co-occurring subject categories, co-author citation network, word co-occurrence analysis).

We used the Gephi software to visualize the network. The Gephi software identified 131 nodes and 466 edges. Our partitioning parameter was modularity. Modularity is used to identify clusters. Modularity results in grouping of nodes

**Table 2. Clusters of keyword co-occurrence**

Cluster	Items identified by the software	Identified by the author	
		Scientific field	Research themes
Cluster 1 (red), 25.19%	Electronic medical record, health information technology, adoption, care, hospital information systems, clinical decision support, ontology, health, safety, standardization, error, patient safety, nurse, impact, database, prevention, electronic health record, adverse drug event, healthcare, implementation, physician order entry, association, diabetes mellitus, usability, system, decision making, risk, mortality, information technology, quality assurance technology, informatics, network	Health informatics	Utilization of computer science in healthcare Impact of health informatics on patient safety and quality of healthcare
Cluster 2 (pink), 12.21%	Representation, decision support system, computer-based patient record, work station, record, language, decision support, knowledge, outcome, standard, patient education, knowledge representation, model, expert system, terminology, service	Management and information science	Decision support, knowledge representation, and management in medicine
Cluster 3 (light blue), 9.16%	Behavior, trial, support, reminder, intervention, physician, computer, guideline, medicine, practice guideline, cost, performance	Behavioral science	Professional behavior change Computer-based guideline implementation systems
Cluster 4 (dark blue), 9.16%	Internet, quality, communication, breast cancer, information, medical information, worldwide web, future, research, health information, public health, surveillance	Health information management and dissemination	Quality of health information on the internet
Clusters 5 (green), 8.40%	Student, developing country, nursing informatics, technology assessment, PAC, evaluation, United States, health information systems, program, telematics, management, health informatics application, epilepsy, clinical trial, medical history taking, seizure, neuropsychology, quality of life, seizure severity scale, adult, psychometrics, qualitative approach	Health informatics	Health informatics education Nursing informatics Clinical history taking
Clusters 6 (yellow), 5.34%	Health informatics, curriculum, training, education, artificial intelligence, telemedicine	Engineering	Telehealth innovations

that are far more strongly connected and it gives insights into the strength of networks [21]. To calculate the modularity score, we chose the randomization option to produce a better decomposition, and we marked the ‘use edge weights’ option as well. We set the resolution to 0.7. The goal was to get more but smaller communities. The modularity result was 0.526, which is relatively average, and indicates reasonable relationships within the same clusters and reasonable relationships across the clusters. The number of detected clusters was 24. The graph layout was Force Atlas.

### 3) Country co-citation network by VOSviewer

To analyze and map the country co-citation network, we set the minimum number of documents of a country to 5. Out of the 157 countries, 103 countries met the threshold.

### 4) Co-occurring subject category by CiteSpace and Gephi

After analyzing the network on the CiteSpace based on the criteria mentioned above, we used Gephi to visualize this network. We used the modularity parameter; the score was 0.622, and 11 clusters were identified. We used the Force Atlas as our layout.

### 5) Author co-citation network by CiteSpace and Gephi

We followed the same procedure on the CiteSpace software to analyze the network. The modularity score of the network was 0.754, and 81 clusters were identified. We used the Force Atlas layout for this as well.

## III. Results

### 1. Word Co-occurrence Analysis

From the analysis of co-occurring keywords, six clusters and nine research themes were derived, which are depicted in Table 2 and Figure 1. The research themes were identified by the authors.

Cluster 1 (red color) is associated with studies on the utilization of computer science in the healthcare industry as well as the impact of health informatics on patient safety and the quality of healthcare. These studies claim that health information technology improves patient safety by reducing medication errors, reducing adverse drug reactions, and improving compliance with practice guideline (e.g., [22,23]). HIE also improves patient safety by measures such as improving medication information processing or improving laboratory information processing (e.g., [24]).

Cluster 2 (pink color) is associated with decision support, knowledge representation, and management in medicine. Studies claim that using these systems will improve clinical practice (e.g., [25]), improve the practice of evidence-based medicine (e.g., [26]), and reduce errors in medicine (e.g., [27]).

Cluster 3 (light blue color) is associated with the professional behavior change (e.g., [28]) and computer-based guideline implementation systems (e.g., [29]).

Cluster 4 (dark blue color) is associated with the quality of health information on the internet (e.g., [30,31]).

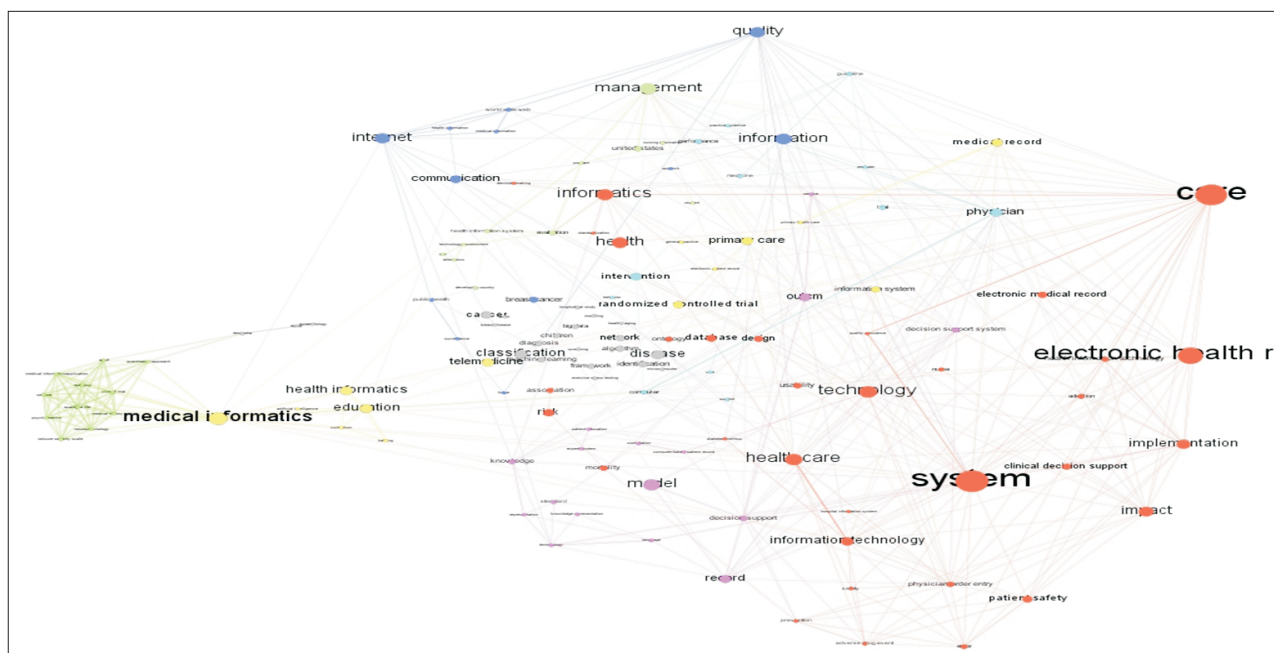


Figure 1. Map of co-occurring keywords visualized by the Gephi software (top 30% per 5-year slice).



Cluster 5 (green color) is associated with health informatics education, nursing informatics [32,33], and clinical history taking [34]. The studies on health informatics education deal with the impact of health informatics on curriculum, education, and training of health care professionals as well as healthcare information systems research and development (e.g., [32,33]).

Cluster 6 (yellow color) is associated with the telehealth innovations in health education and healthcare.

## 2. Burst Analysis

The analysis of subject categories with the strongest citation bursts (Table 3) by using Kleinberg's burst detection algorithm shows the emergent research front concepts. Before 1991, no burst terms were identified. This analysis shows that in 1991, hospital information system and health informatics were burst terms, while in 1992, health information system, telematics, and primary healthcare were burst terms. Three years after Berners-Lee posted a short summary of the World Wide Web (WWW) project on the alt.hypertext newsgroup in 1991, the WWW became one of the burst terms of health informatics in 1994. In 1994, other terms, such as health informatics, computer-based patient record, and expert systems, became burst subjects. In 1995, some of the burst subjects were patient education and public health. In 1997, electronic patient record became a popular keyword. In 1999, subjects such as information retrieval, recommendation, medical information, health information, medical records system, security, confidentiality, patient record, and preventive care were burst terms. In 2002, bioinformatics and information system became burst subjects. In 2004, biohealth informatics received a burst. In 2007, the concept of e-health and in 2009, clinical decision support system became burst terms. No burst terms were identified between 2010 and 2015. In 2015, mobile health, big data, telehealth, prediction, machine learning, algorithm, social media, and mobile health became popular.

Overlay visualization of keywords (Figure 2) with a minimum occurrence of 40 shows that since 2016, scholarly subjects that are of great interest in the health informatics field are precision medicine, big data, deep learning, machine learning, patient engagement, patient portals, engagement, m-health, social media, mobile applications, and the Internet of Things.

## 3. Countries with the Highest Numbers of Citations and Citation Link Strength

Visualization of countries with the highest numbers of cita-

**Table 3. Top subject categories with the strongest citation bursts**

Subject category	Strength	Year	
		Begin	End
Hospital information system	34.3351	1991	2008
Computer	61.7229	1991	2010
Education	24.2662	1991	1999
Quality assurance	10.0207	1991	2003
Health informatics	74.4232	1991	2007
Primary healthcare	11.9073	1992	2003
Training	13.4332	1992	1998
Health information system	33.5982	1992	2010
Telematics	4.7011	1992	1998
Patient care	19.8744	1994	2008
Reminder	10.6895	1994	2003
Health informatics	11.1652	1994	1998
Integration	14.0980	1994	2008
Computer-based patient record	4.7161	1994	1998
Standardization	4.0422	1994	1998
Knowledge	5.5249	1994	1996
Curriculum	8.7599	1994	1998
World Wide Web	44.9786	1994	2008
Standard	38.6422	1994	2012
Decision making	7.0478	1994	1999
Knowledge representation	10.2669	1994	2002
Cost	4.0422	1994	1998
Expert system	13.8354	1994	2003
Surveillance	28.4454	1994	2013
Practice guideline	10.7626	1995	2003
Patient education	4.0680	1995	1998
Public health	34.7156	1995	2013
Electronic patient record	27.6224	1997	2008
Internet	41.3069	1998	2010
Evidence-based medicine	10.2709	1998	2007
Evaluation	42.0204	1998	2003
Computerized	19.5069	1999	2008
Academic medical center	7.1308	1999	2003
Hospitalized patient	7.7793	1999	2003
Confidentiality	7.7793	1999	2003
Clinical practice guideline	6.4823	1999	2003
Recommendation	17.3375	1999	2008
General practice	23.8740	1999	2008
Controlled trial	6.4823	1999	2003
Medical information	11.0222	1999	2003

Continued on the next page.

Table 3. Continued 1

Subject category	Strength	Year	
		Begin	End
Patient record	19.5069	1999	2008
Adverse drug event	7.1308	1999	2012
Accuracy	5.8339	1999	2003
Time	5.8339	1999	2003
Security	27.1035	1999	2008
Information retrieval	6.4823	1998	2003
Preventive care	37.7792	1999	2003
Nursing	5.8339	1999	2008
Medical records system	19.5069	1999	2003
Health information	31.8890	1999	2012
Randomized trial	20.3110	2000	2008
Physical order entry	61.9673	2000	2013
Decision support system	3.9671	2001	2003
Prevention	6.5087	2001	2005
Bioinformatics	31.8800	2002	2012
Information systems	11.5413	2003	2010
Intensive care unit	12.9089	2004	2008
Quality	4.9971	2004	2007
Access	12.9089	2004	2008
Biohealth informatics	18.7819	2004	2008
Medication error	32.6035	2004	2013
Attitude	14.6705	2004	2008
Satisfaction	17.6070	2004	2008
Evaluation study	15.8450	2004	2008
Strategy	13.4961	2004	2008
Privacy	33.4763	2006	2013
Interoperability	44.2374	2007	2013
e-Health	37.9751	2007	2013
Simulation	38.7056	2007	2012
Ontology	18.0995	2008	2012
Clinical decision support system	31.6027	2009	2013
Gene expression	30.8302	2009	2013
Documentation	30.8302	2009	2013
Protein	28.5133	2009	2013
Workflow	28.8994	2009	2013
EHR	32.3753	2009	2013
Identification	4.6764	2014	2015
Clinical trial	21.9374	2014	2018
Heart failure	23.4808	2014	2018
Segmentation	26.3161	2014	2018

Table 3. Continued 2

Subject category	Strength	Year	
		Begin	End
Validation	35.3688	2014	2018
Risk factor	28.2667	2014	2018
Physical activity	23.1266	2014	2018
Therapy	19.0135	2014	2018
Mobile health	24.6842	2015	2018
Big data	43.1307	2015	2018
Telehealth	24.0326	2015	2018
Prediction	35.8917	2015	2018
Emergency department	23.4547	2015	2018
Machine learning	55.4519	2015	2018
Algorithmw	35.8708	2016	2018
Social media	43.4226	2016	2018

tions (Figure 3) shows that the United States has the highest number of citations and the highest citation link strength compared with the rest of the world (with 12,567 documents, 234,522 citations, and total link citation strength of 34,414) in the field of health informatics. The United Kingdom (2,290 documents, 52,466 citations, and total link strength of 11,788), Canada (1,987 documents, 36,831 citations, and total link strength of 9,538), Germany (1,622 documents, 30,831 citations, and total link strength of 9,135), and the Netherlands (941 documents, 20,967 citations, and total link strength of 8,578) have the highest global contribution and network interaction in the field of health informatics.

#### 4. Co-occurring Subject Category

The analysis of co-occurring subject categories (based on the Web of Science category) resulted in the clusters depicted in Figure 4. The figure shows that, in general, some of the categories of the blue cluster, including health informatics, healthcare science services, computer science, interdisciplinary applications, and information systems, have the highest contribution and interaction in the field of health informatics. Some of the categories of the purple cluster that have more interaction with the blue cluster are engineering, computer science, electrical engineering, biomedical engineering, and artificial intelligence. At the top of the network, there is a green cluster that has some interaction with the category of interdisciplinary applications in the blue cluster. Some of the categories of the green clusters are neurosciences, cell biology, biochemical research methods, biochemistry, and genetics.

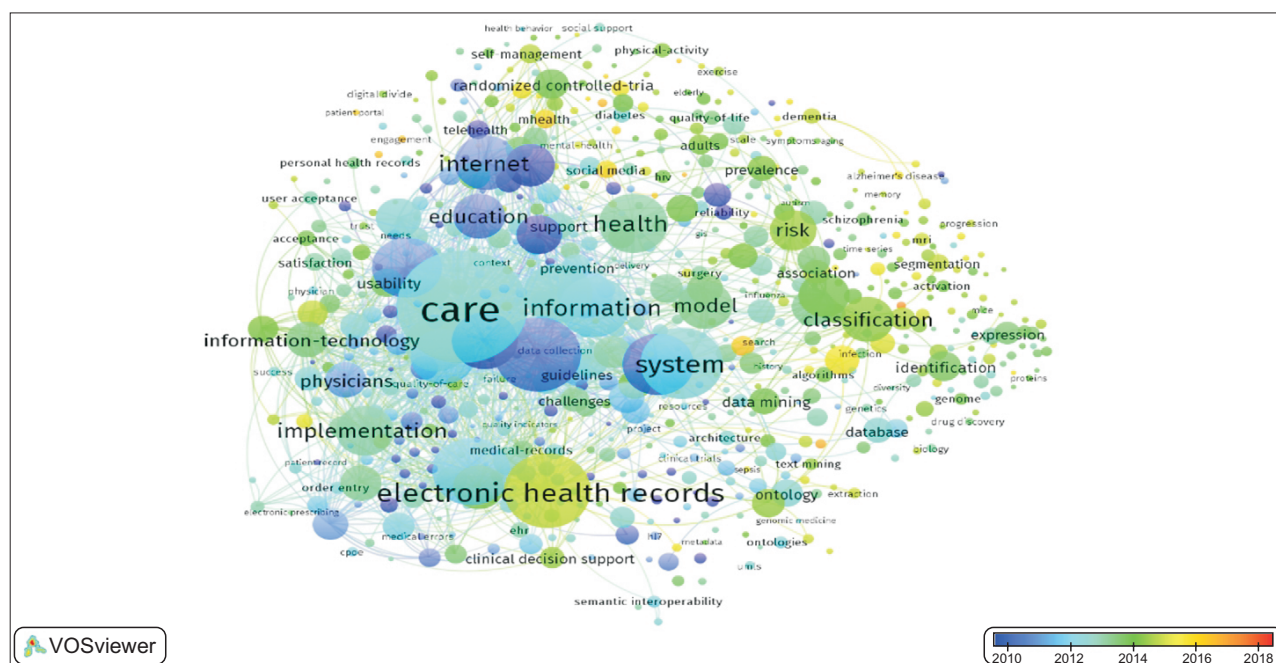


Figure 2. Overlay visualization of keywords from 2010 to 2018.

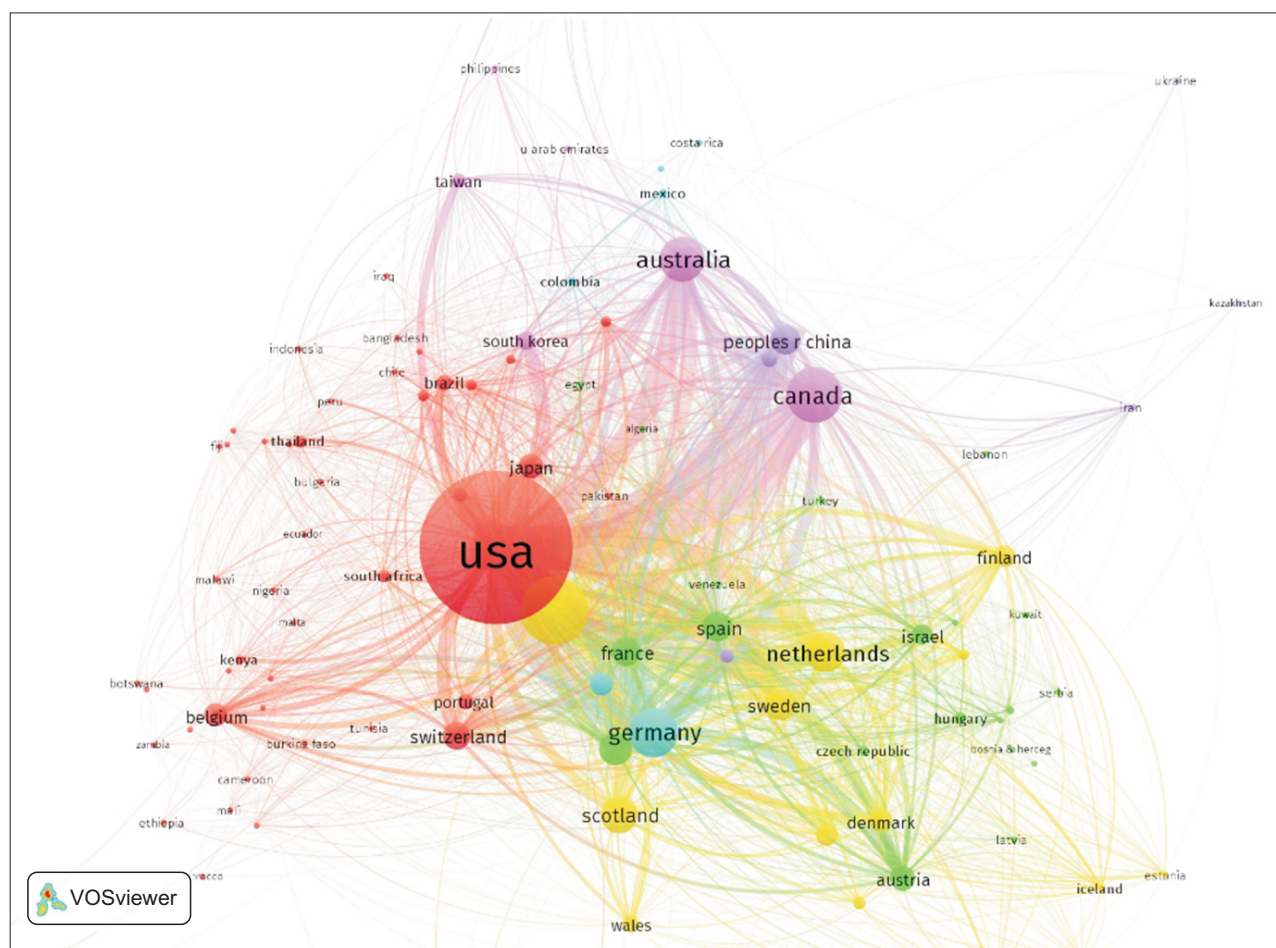


Figure 3. Visualization of countries' citation numbers and citation links with the other countries (top 30% per 5-year slice).



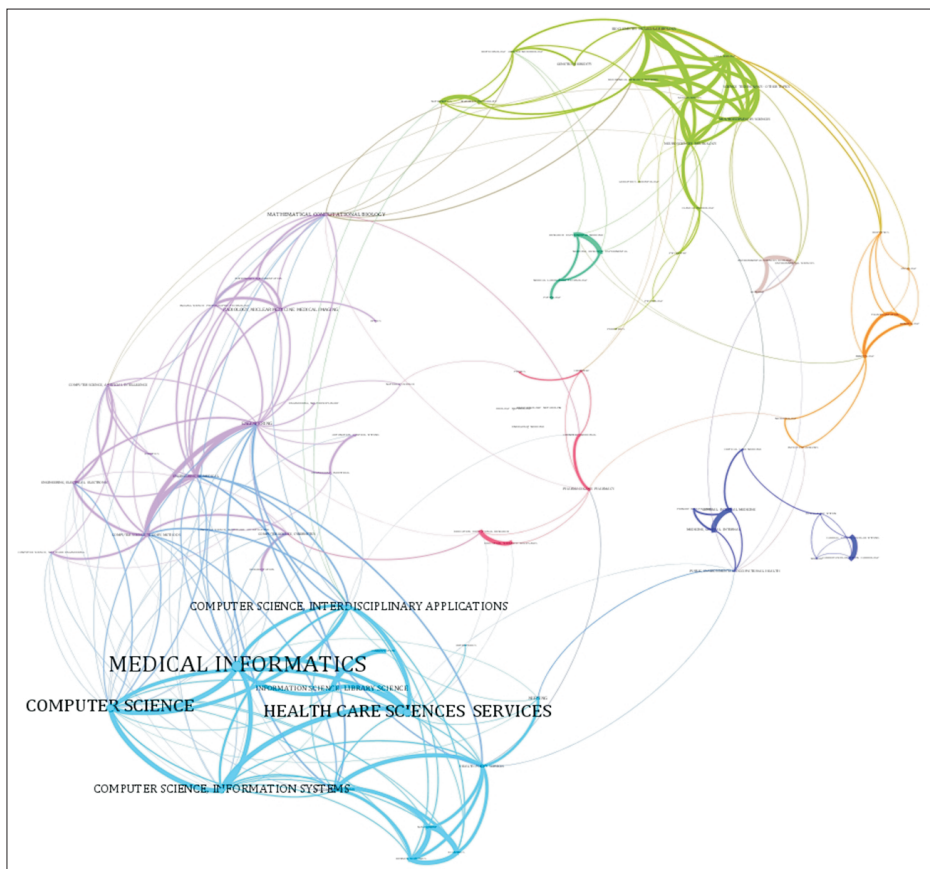


Figure 4. Co-occurring subject categories (top 30% per 5-year slice).

### 5. Author Co-citation Network

The author co-citation analysis is visualized in Figure 5. Some of the key research strands of the highly cited authors are the following:

- Marsden S. Blois, MD, FACMI was a visionary in health informatics to bring together medicine and information science. He passed away in 1988.
- Dr. Elske Ammenwerth, Professor for Health Informatics. Some of her research strands are the systematic evaluation of health information systems, evaluation methodologies and evaluation guidelines, and evidence-based health informatics.
- G. Octo Barnett, MD, Professor of Medicine, and head of Laboratory of Computer Science. Some of the key concepts of his research are ambulatory care information systems, intraoperative care, medical record systems, and artificial intelligence.
- David Westfall Bates, MD, Professor of Medicine. Some of the key concepts of his research are adverse drug reaction reporting systems and ambulatory care information systems.
- Clem J. McDonald, MD, Professor of biomedical communications. In 1972, Dr. McDonald developed one of the

nation's first EMR systems, the Regenstrief Medical Record System (RMRS), and directed its use in clinical trials.

## IV. Discussion

Based on the papers included in the WoS database service, it was clarified that health informatics is an information engineering field that is applied to healthcare [35]. The study showed that health informatics is applied to various subject categories, such as nursing, public health, biomedical research, and occupational therapy. The co-occurrence of the keywords showed that the overall goal is to improve the effectiveness of care delivery to patients [36]. This study shows that research on health informatics is not only concerned with engineering aspects but also with non-engineering sides of the health informatics. Issues such as the adoption of medical professionals of health informatics and behavioral changes are also key research themes [37].

Moreover, on the human side, as the burst analysis table (Table 3) shows, concerns such as safety, security, surveillance, and privacy have been of great importance since the early stages of the development of health informatics [38]. The study showed that, since 2016, health informatics have

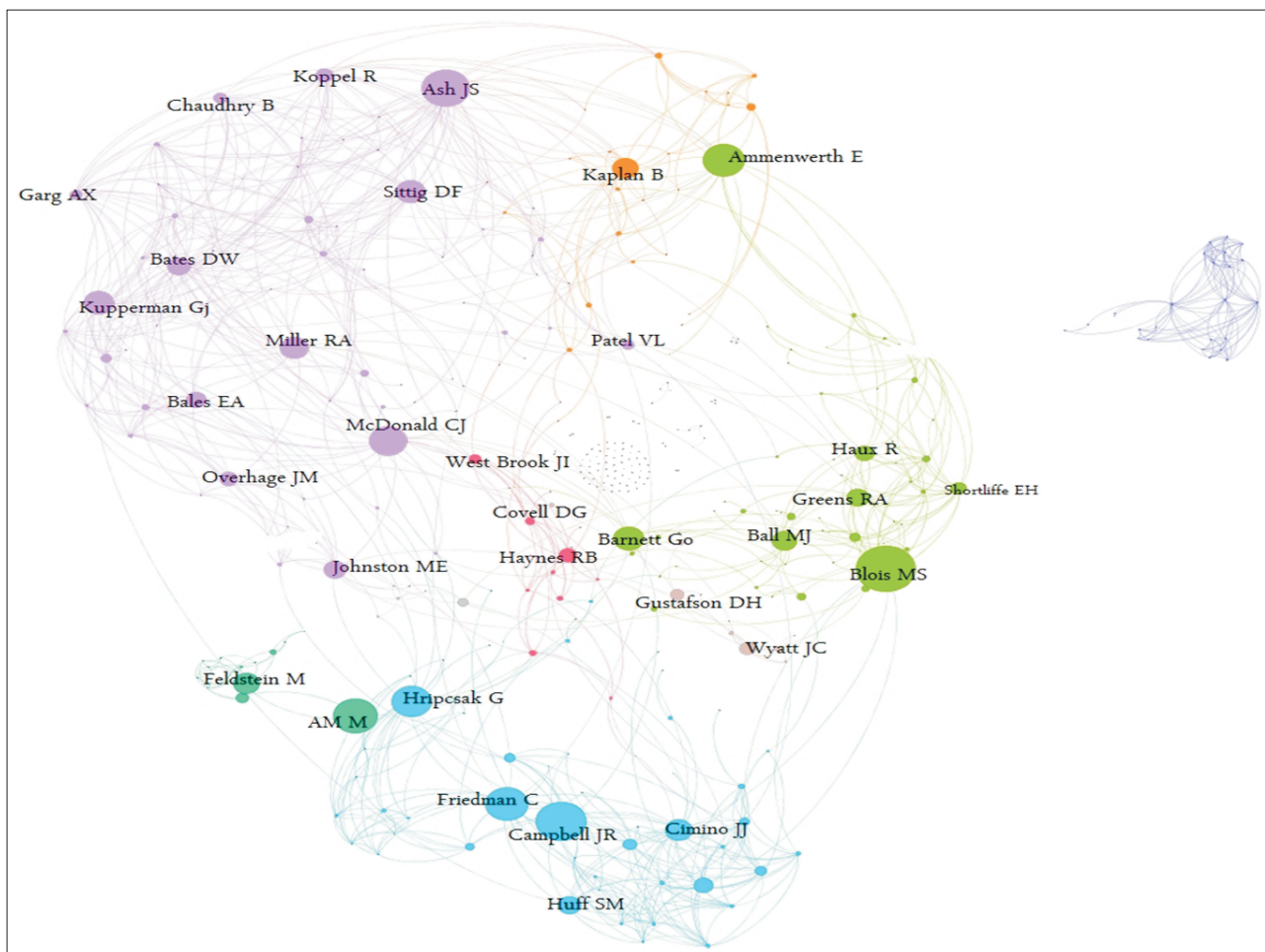


Figure 5. Visualization of author co-citation analysis based on modularity score.

entered a new era, which is predictive, preventative, personalized, and participatory. Health informatics has entered an era in which greater patient engagement with the support of information technologies is incorporated to improve health outcomes [39]. The connection of providers with patients is facilitated by the emerging health technologies, such as patient portals, social media, social health communities, wearables, self-tracking sensors and so forth [40]. On the other hand, patients will have access to consolidated medication management. With the emergence of ‘quantified self’ and patients’ awareness of their genetic profile, one possible strand of research can be on the changes on electronic health records and new forms of patient’s engagement [41].

One other possible future research strand is related to patient-generated health data, increasing the literacy of patients on social and self-tracking tools, and on top of that the ethical issues of biometric and patient generated data. Another important strand of research is precision or personalized medicine to understand how a person’s genetics, environment, and lifestyle can assist physicians to best treat

and prevent diseases. One future strand of research could be the role of deep learning, new machine learning algorithms, and advanced big data analytics on precision medicine. On the other hand, with the advent of cutting-edge technologies, it is also necessary to conduct new studies on technology adoption and behavioral changes to improve healthcare management. While e-learning is studied highly in the literature, it is also necessary to study the effectiveness of mobile learning and peer-to-peer learning on patient outcomes.

This study also showed that the research strands of highly cited authors are medicine and information science; and the United States has the highest number of citations and the highest citation link strength compared to the rest of the world. The study also showed that diagnosis systems and preventive care were early scholarly subjects. However, most of the diagnosis systems have been for recognition; future studies could focus on early and preventive diagnosis systems with the aid of big data and machine learning methods. Other important subjects that have not been studied enough and could be of future research interest are open-source soft-

ware, crowdsourcing, blockchain technology, cloud and fog computing, and image analysis.

This research had its own limitations because we included only papers in English. Moreover, we only studied papers on health informatics since we did not include terms like medical informatics in our search for papers.

## Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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## References

1. Carter CE, Veale BL. Digital radiography and PACS. St. Louis (MO): Mosby; 2008.
2. Fitzgerald-Hayes M, Reichsman F. DNA and biotechnology. Boston (MA): Elsevier; 2010.
3. Smallwood RF. Managing electronic records: Methods, best practices, and technologies. Hoboken (NJ): John Wiley & Sons; 2013.
4. Ballweg R, Brown D, Vetrosky DT, Ritsema TS. Physician assistant: a guide to clinical practice. Philadelphia (PA): Elsevier; 2017.
5. O'Carroll PW, Ripp LH, Yasnoff WA, Ward ME, Martin EL. Public health informatics and information systems. New York (NY): Springer; 2003.
6. Masic I. The history and new trends of medical informatics. Donald School J Ultrasound Obstet Gynecol 2013;7(3):301-2.
7. Bronzino JD. Medical devices and systems. Boca Raton (FL): CRC Press; 2006.
8. Scaletti A. Evaluating investments in health care systems: health technology assessment. Heidelberg: Springer; 2014.
9. Hayes BM, Aspray W. Health informatics: a patient-centered approach to diabetes. Cambridge (MA): MIT Press; 2010.
10. Deng H, Wang J, Liu X, Liu B, Lei J. Evaluating the outcomes of medical informatics development as a discipline in China: a publication perspective. Comput Methods Programs Biomed 2018;164:75-85.
11. Kruse CS, Stein A, Thomas H, Kaur H. The use of electronic health records to support population health: a systematic review of the literature. J Med Syst 2018;42(11):214.
12. Ross T. A survival guide for health research methods. Maidenhead, UK: McGraw-Hill Education; 2012.
13. Walker E, Hernandez AV, Kattan MW. Meta-analysis: its strengths and limitations. Cleve Clin J Med 2008;75(6):431-9.
14. Stegenga J. Is meta-analysis the platinum standard of evidence? Stud Hist Philos Biol Biomed Sci 2011;42(4):497-507.
15. Watanabe M. Going multidisciplinary. Nature 2003;425(6957):542-3.
16. Chen C. Mapping scientific frontiers: the quest for knowledge visualization. London: Springer; 2013.
17. Xu G, Zhang Y, Li L. Web mining and social networking: techniques and applications. New York (NY): Springer; 2011.
18. Gonzalez GH, Tahsin T, Goodale BC, Greene AC, Greene CS. Recent advances and emerging applications in text and data mining for biomedical discovery. Brief Bioinform 2016;17(1):33-42.
19. Aggarwal CC, Wang H. Text mining in social networks. In: Aggarwal CC, editor. Social network data analytics. Boston (MA): Springer; 2011. p. 353-78.
20. Bornmann L, Haunschild R, Hug SE. Visualizing the context of citations referencing papers published by Eugene Garfield: a new type of keyword co-occurrence analysis. Scientometrics 2018;114(2):427-37.
21. Khokhar D. Gephi cookbook. Birmingham, UK: Packt Publishing Ltd.; 2015.
22. Parente ST, McCullough JS. Health information technology and patient safety: evidence from panel data. Health Aff (Millwood) 2009;28(2):357-60.
23. Alotaibi YK, Federico F. The impact of health information technology on patient safety. Saudi Med J 2017;38(12):1173-80.
24. Kaelber DC, Bates DW. Health information exchange and patient safety. J Biomed Inform 2007;40(6 Suppl):S40-5.
25. Kawamoto K, Houlihan CA, Balas EA, Lobach DF. Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success. BMJ 2005;330(7494):765.
26. Sim I, Gorman P, Greenes RA, Haynes RB, Kaplan B, Lehmann H, et al. Clinical decision support systems for the practice of evidence-based medicine. J Am Med Inform Assoc 2001;8(6):527-34.
27. Bates DW, Cohen M, Leape LL, Overhage JM, Shabot

- MM, Sheridan T. Reducing the frequency of errors in medicine using information technology. *J Am Med Inform Assoc* 2001;8(4):299-308.
28. Bauchner H, Simpson L, Chessare J. Changing physician behaviour. *Arch Dis Child* 2001;84(6):459-62.
  29. Shiffman RN, Liaw Y, Brandt CA, Corb GJ. Computer-based guideline implementation systems: a systematic review of functionality and effectiveness. *J Am Med Inform Assoc* 1999;6(2):104-14.
  30. Purcell GP, Wilson P, Delamothe T. The quality of health information on the internet. *BMJ* 2002;324(7337):557-8.
  31. Gagliardi A, Jadad AR. Examination of instruments used to rate quality of health information on the internet: chronicle of a voyage with an unclear destination. *BMJ* 2002;324(7337):569-73.
  32. Skiba DJ. Informatics competencies for nurses revisited. *Nurs Educ Perspect* 2016;37(6):365-7.
  33. Graves JR, Corcoran S. The study of nursing informatics. *Image J Nurs Sch* 1989;21(4):227-31.
  34. Bickley L, Szilagyi PG. Bates' guide to physical examination and history-taking. Philadelphia (PA): Lippincott Williams & Wilkins; 2012.
  35. Hersh W. Medical informatics education: an alternative pathway for training informationists. *J Med Libr Assoc* 2002;90(1):76-9.
  36. Norris AC. Current trends and challenges in health informatics. *Health Informatics J* 2002;8(4):205-13.
  37. Gagnon MP, Ngangue P, Payne-Gagnon J, Desmartis M. m-Health adoption by healthcare professionals: a systematic review. *J Am Med Inform Assoc* 2016;23(1):212-20.
  38. Wilkowska W, Ziefle M. Privacy and data security in e-health: requirements from the user's perspective. *Health Informatics J* 2012;18(3):191-201.
  39. Pilemalm S, Timpka T. Third generation participatory design in health informatics: making user participation applicable to large-scale information system projects. *J Biomed Inform* 2008;41(2):327-39.
  40. Kvedar J, Coye MJ, Everett W. Connected health: a review of technologies and strategies to improve patient care with telemedicine and telehealth. *Health Aff (Millwood)* 2014;33(2):194-9.
  41. Swan M. Health 2050: the realization of personalized medicine through crowdsourcing, the quantified self, and the participatory biocitizen. *J Pers Med* 2012;2(3):93-118.