Managerial challenges in Digital Health: a bibliometric and network analysis

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Submitted to: Journal of Medical Internet Research
on: March 02, 2024

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Abstract

Background: Digital health has emerged as a transformative force in modern healthcare systems, witnessing a surge in technological innovations and solutions over the past two to three decades. Some studies gave an overview of the keywords and journals to decipher the visibility of digital health. Despite the increasing focus on digital health, a critical gap persists in quantifying the trends of peer-reviewed publications specifically within the management and organization literature.

Objective: To delineate the evolving landscape of digital health management literature from 1994 to 2022, this study aims to conduct a comprehensive bibliographic, bibliometric, and network analysis. By unveiling research trends and clusters, our objective is to contribute nuanced insights into the pivotal themes, influential works, and the structure of knowledge within this interdisciplinary domain. Additionally, we extend our investigation to identify and analyze literature clusters thanks to co-citation patterns, unraveling the intricate connections and themes that define the evolving landscape of digital health management research.

Methods: After a keyword analysis, all peer-reviewed, published before 2023, English-written articles or reviews on Scopus were considered in our analysis as soon as the main focus was digital health or closely related keywords. To unveil clusters and trends, a bibliographic-bibliometric or co-citations network analysis was conducted using Gephi to identify clusters.

Results: Out of 1186 papers about digital health or other highly-related keywords published between 1994 and 2022, 520 articles (43.8%) were included in the co-citation network and 468 papers were in significant clusters (>1% of the total number of nodes) and divided into 4 modularity classes. These 4 clusters were then interpreted using the highest centrality degree nodes of each cluster ("Adoption-engagement", "Behavior-trust-privacy", "Ecosystem transformations" and "Ethics-usage") with an analysis of the keywords and the most cited articles.

Conclusions: Our co-citation analysis unveils evolving themes in digital health management literature. Our study provides a snapshot from 1994 to 2022. While we refrain from extensive citation analysis, our thematic exploration suggests dynamic shifts in ethical considerations, global healthcare organization, and societal and professional acceptance. Encouraging further research in these nuanced clusters, our study prompts ongoing exploration into the intricate facets of the digital health management literature. With a more comprehensive understanding of the digital health management literature dynamic, we also hope that this study provides management researchers and health researchers insights on the principal fields to address further unidentified gaps.

(JMIR Preprints 02/03/2024:57980)
DOI: https://doi.org/10.2196/preprints.57980

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Keywords: Bibliometrics ; Co-citation ; Network Analysis ; Cluster analysis ; Digital Health ; Mhealth ; Telemedicine ; Management ; Adoption ; Ecosystems ; Privacy ; Literature Review

Introduction

Background

According to the Food & Drug Administration, digital health includes categories such as mobile health (mhealth), health information technology (HIT), wearable devices, telehealth and telemedicine, and personalized medicine [1]. Digital health can be explained as "the proper use of technology for improving the health and wellbeing of people at individual and population levels, as well as enhancing the care of patients through intelligent processing of clinical and genetic data" [2]. With an evolving paradigm for medicine, including prevention along with an aging population, digital health or e-health has become an inspiring shift or revolution for both researchers and governments [3,4]. However, the various challenges of digital health in management science have not yet been described in the literature.

Prior work

Worldwide, an expanding number of researchers is actively engaging in the exploration, application, evaluation, and leveraging of the advantages associated with digital health and its diverse technological counterparts in their investigations concerning individuals, populations, or healthcare organizations [5]. This heightened participation is discernible through the prevalent incorporation of the term "digital health" as a keyword in published peer-reviewed literature [6]. Over the past three decades, there has been a noticeable surge in both the quantity and diversity of research initiatives, study protocols, published works, and specialized journals, all playing pivotal roles within the realm of digital health. Based on the growth of the use of the keyword, various features have been identified as part of the ”digital health” with the 10 e’s: efficiency, enhancing quality, evidence based, empowerment, encouragement, education, enabling, extending, ethics and equity [7]. Since digital health is widely studied, especially in the medicine field or from a specific feature perspective such as mobile health apps [8], researchers in management are also studying the organization of digital health and its consequences for the health sector. However, this kind of research remains very niche in management or organizational science, with no real description of the principal communities of management researchers focusing on digital health.

Goal of this study

This study employed a systematic bibliometric co-citation analysis of management publications centered on digital health. Utilizing modularity classes, we identified thematic clusters in research publications across all journals in the field of management science that addressed digital health. Our objective was to discern similarities in research trends, to facilitate scholars and managers in identifying key communities of researchers, and to answer: What are the main managerial challenges of digital health?

Methods

Data collection

Since Google Scholar is quite debated as to be a complete source for clinicians and not suited for citations, co-citations or author analysis [9,10], it was not suitable for this analysis. Even though PubMed is widely used by clinicians, it suffers from the same disadvantage of not being well-suited for this type of analysis. Web of Science and Scopus both offer a wide range of journal and visualization tools, including inclusion and exclusion criteria. However, Scopus has a substantially better coverage, especially in the field of social sciences from which encompasses management science [11]. For this reason, only Scopus was used in this study.

For data collection, all peer-reviewed journals were considered. The first research done was with “digital health” as a keyword, in the title or in the abstract (Textbox 1).

Textbox 1. Initial Scopus request.

TITLE-ABS-KEY ("digital health")

Since entries are still being added to the 2023 database approximately until March or April 2024, we excluded entries from 2023 or later to have more consistency or reproducibility (Textbox 2).

Textbox 2. Scopus request adding the time period.

TITLE-ABS-KEY ("digital health") AND (EXCLUDE (PUBYEAR , 2023))

For comparison purposes, other requests were tried with the same time range but with “ehealth” as keyword, in the title or in the abstract. After exclusion of entries that are not in English, not yet published or not articles or reviews, each request gave us 6000 to 8000 articles (Textbox 3).

Textbox 3. Scopus request adding the time period, the publication stage, the type of publication and the language.

TITLE-ABS-KEY ("digital health") AND (EXCLUDE (PUBYEAR, 2023)) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (LANGUAGE , "English"))

Textbox 4. Equivalent Scopus request with “ehealth” instead of “digital health”.

TITLE-ABS-KEY ("ehealth") AND (EXCLUDE (PUBYEAR, 2023)) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (LANGUAGE , "English"))

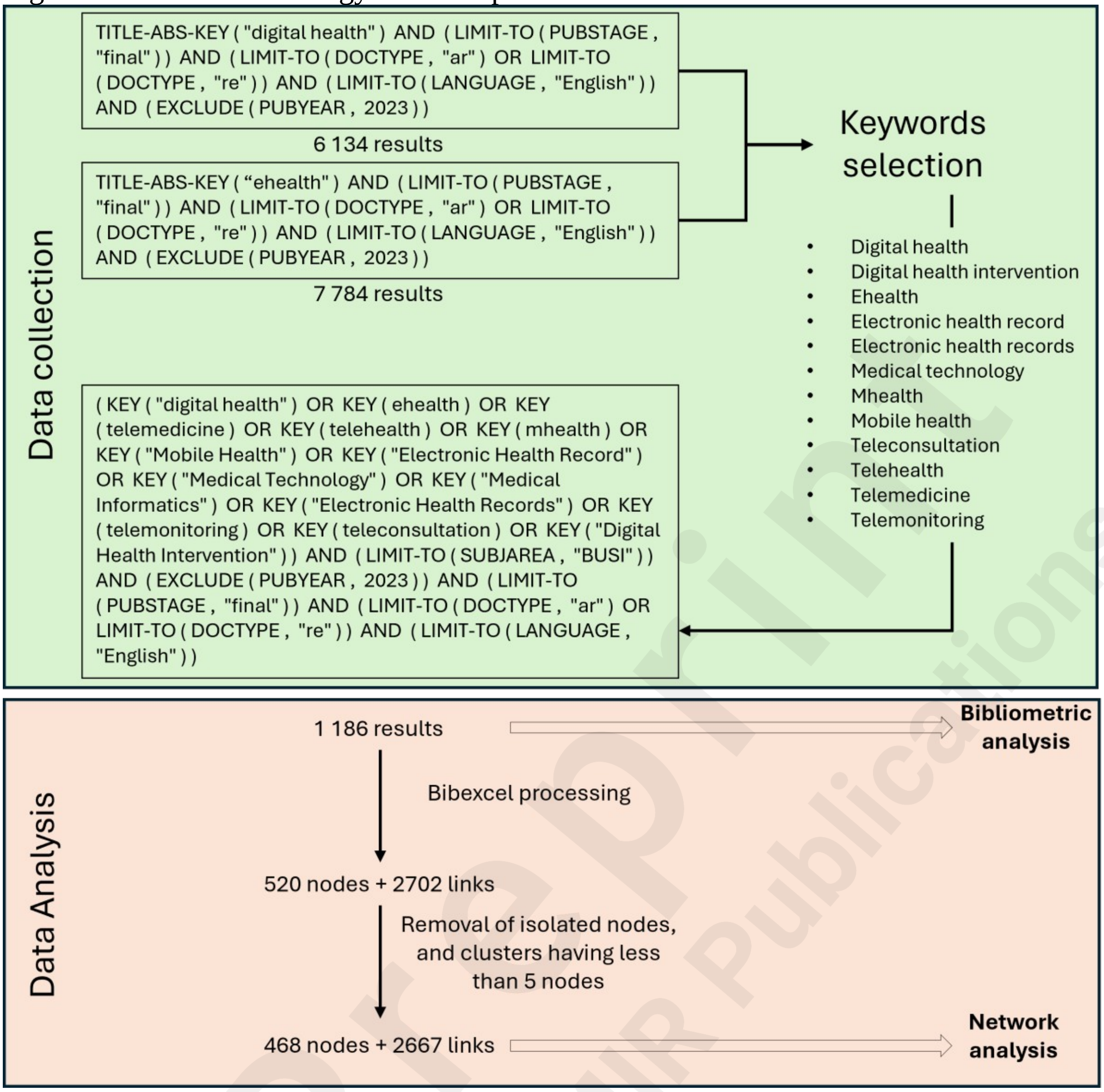
Among these articles, we conducted a basic keyword analysis: we looked at the most used keywords of all articles [6], and looked for all keywords that are “digital health”-related only. We selected the keywords that are in common in the keywords list from both the digital health request (Textbox 3) and the ehealth request (Textbox 4) to select our final keywords (Multimedia Appendix 1). According to this analysis, we were then left with the following keywords: digital health, ehealth, telemedicine, telehealth, mhealth, medical technology, telemonitoring, teleconsultation, and digital health intervention. A new request was then written to include all articles using these words, but only as keywords to make sure that it is not just said in an abstract with a non-digital-health-related article. For readability purposes, we only selected English-written articles. Since the object of this study is to analyze the trends and clusters in digital health management, we only included articles encompassed in the “Business, management and accounting” field to write our final request (Textbox 5).

Textbox 5. Final request for Scopus.

(KEY ("digital health") OR KEY (ehealth) OR KEY (telemedicine) OR KEY (telehealth) OR KEY (mhealth) OR KEY ("Mobile Health") OR KEY ("Electronic Health Record") OR KEY ("Medical Technology") OR KEY ("Medical Informatics") OR KEY ("Electronic Health Records") OR KEY (telemonitoring) OR KEY (teleconsultation) OR KEY ("Digital Health Intervention")) AND (LIMIT-TO (SUBJAREA , "BUSI")) AND (EXCLUDE (PUBYEAR , 2023)) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (LANGUAGE , "English"))

The 1186 articles metadata were exported from Scopus to Excel for the bibliometric analysis, and to Bibexcel for network generation (Figure 1).

Figure 1. Methodology description from data collection to data analysis



Data analysis

After extracting RIS format, CSV format and TXT format from Scopus, we conducted the first analysis: the bibliometric analysis.

The data were not yet shaped to conduct network analysis. BibExcel was used to create co-citations networks and extract the links and the nodes to be visualized [12]. Thanks to Excel, other fields of data (year, country, authors, citation count, source…) were added to the table to allow for further analysis.

Thereafter, all data were imported to Gephi to be visualized as a network. The created co-citation graph was not oriented. Force Atlas 2 algorithm was used to obtain a better visualization. A random color scale was generated to identify the clusters, and node sizes were given according to their degree centrality. No further treatment were added for visualization. The size of each node was given according to its degree centrality.

We then used Gephi to calculate degree centrality and modularity classes. Degree centrality measure

the number of links for each node, closeness centrality measures the communication efficacy in a network, betweenness centrality measures the number of time a node is in the shortest path, closeness centrality measures the efficacy to communicate with other nodes in a specific area and Katz or Eigenvector centrality measures the indirect influence of neighbors for each node. Given the aim of the study, we decided to use degree centrality among the other types of centrality thanks to its unique ability to characterize the number of shared citations. Even if co-citation PageRank can be used in co-citation analysis [13], the most relevant value to quantify the representativeness of a node inside a cluster is the degree centrality.
All these data were then exported to be further analyzed with Excel for sorting, filtering, keyword analysis and basic graph generation.

Statistical Analysis

Power

Citation analysis assesses the number of citations and is employed to rank journals and researchers, indicating their impact on scientific research [14]. Despite its criticisms [15], it continues to be utilized for literature analysis, identifying influential authors, journals, or articles within specific research domains. We used the citation count for the bibliometric analysis.

For network analysis, the degree centrality was used instead of the total number of citations in order to classify the papers intra-cluster. The intra-cluster ranking on degree centrality is used to find papers that are representatives of the cluster. The extra-cluster representations are used to show the relative density of each cluster.

To identify clusters, we used the Louvain algorithm from Gephi based on their modularity class [16]. This algorithm is built on the idea of searching high local density inside the network [17].

Data Exclusion

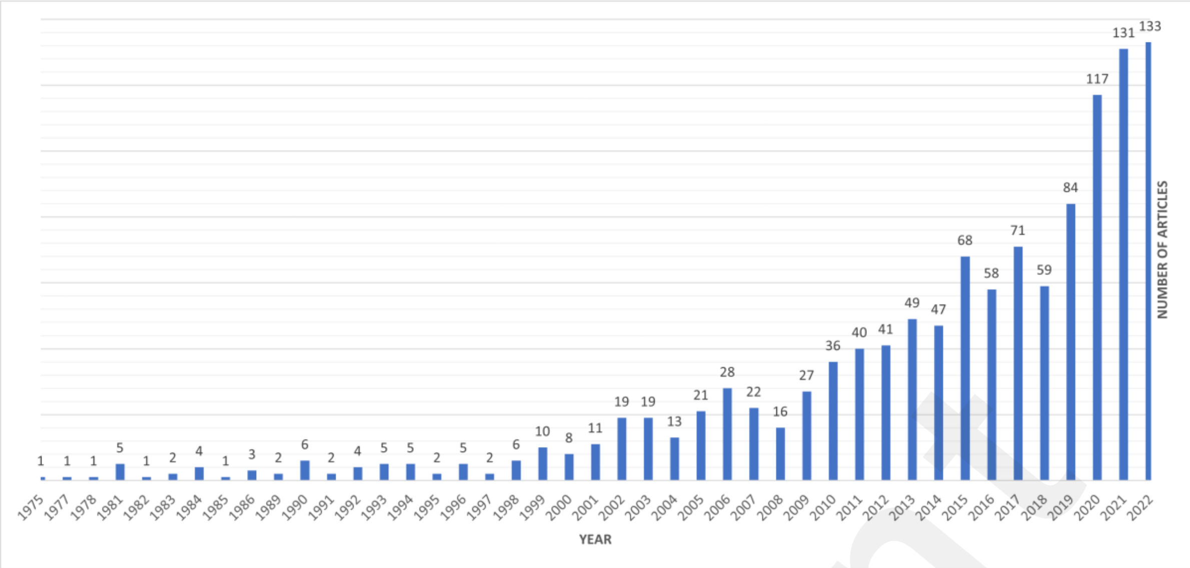
For data visualization, after having processed all papers (1186) to create the co-citation network, we were left with 520 papers (nodes) and 2667 links. Some of the papers had no co-citation links with each other, meaning that they did not share any bibliography. Articles with no links to other articles (isolated nodes) were removed along with nodes that were not in clusters representing at least 1% (12/1186) of the total number of nodes. All the following data from the network analysis are then based on the 468 remaining articles (Multimedia Appendix 2). No more nodes exclusion occurred after this step (Figure 1).

Results

Bibliometric analysis

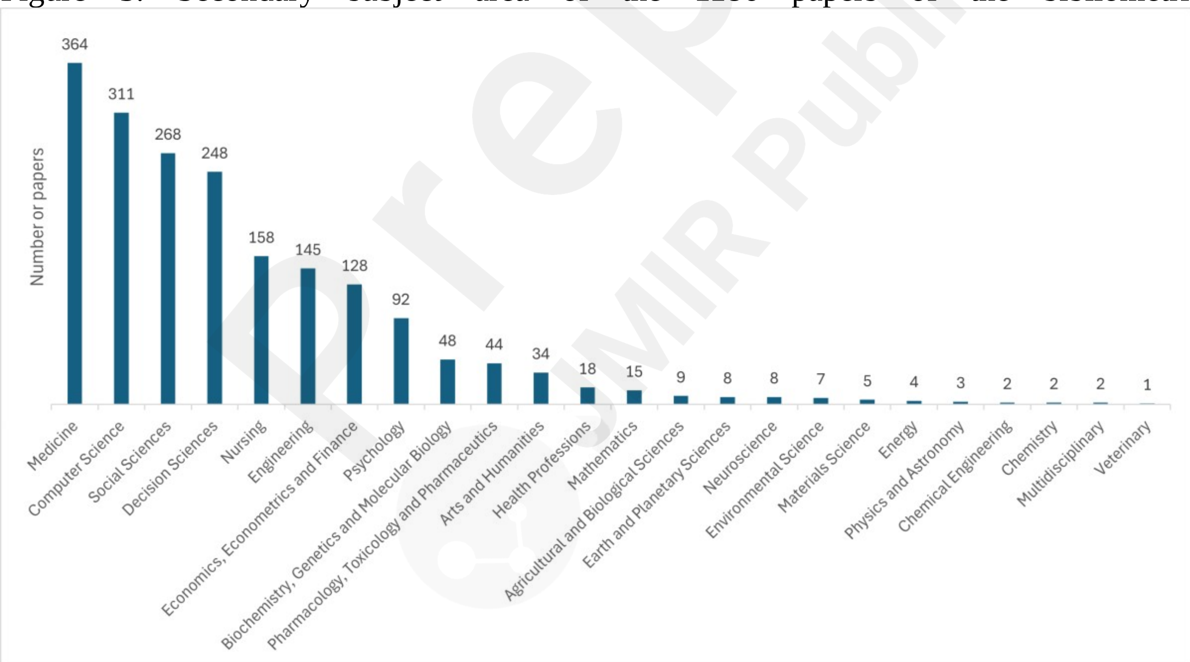
Until 2022, the final request (Textbox 5) gave 1186 English-written papers and reviews that are all in the final publication stage (published). The oldest article is from 1975 and the most recent are 133 articles from 2022 (Figure 2).

Figure 2. Year of publication of the 1186 papers of the bibliometric analysis



All 1186 articles are published with the subject area “Business, Management and Accounting. A total of 25 other subject areas can be found with a maximum for Medicine with 364 articles followed by Computer Sciences with 311 articles (Figure 3, Multimedia Appendix 3). Other subject areas are highly represented (more than 10% of the articles) like Social Sciences (268 articles), Decision Sciences (248 articles), Nursing (158 articles), Engineering (145 articles), and Economics, Econometrics and Finance (128 articles).

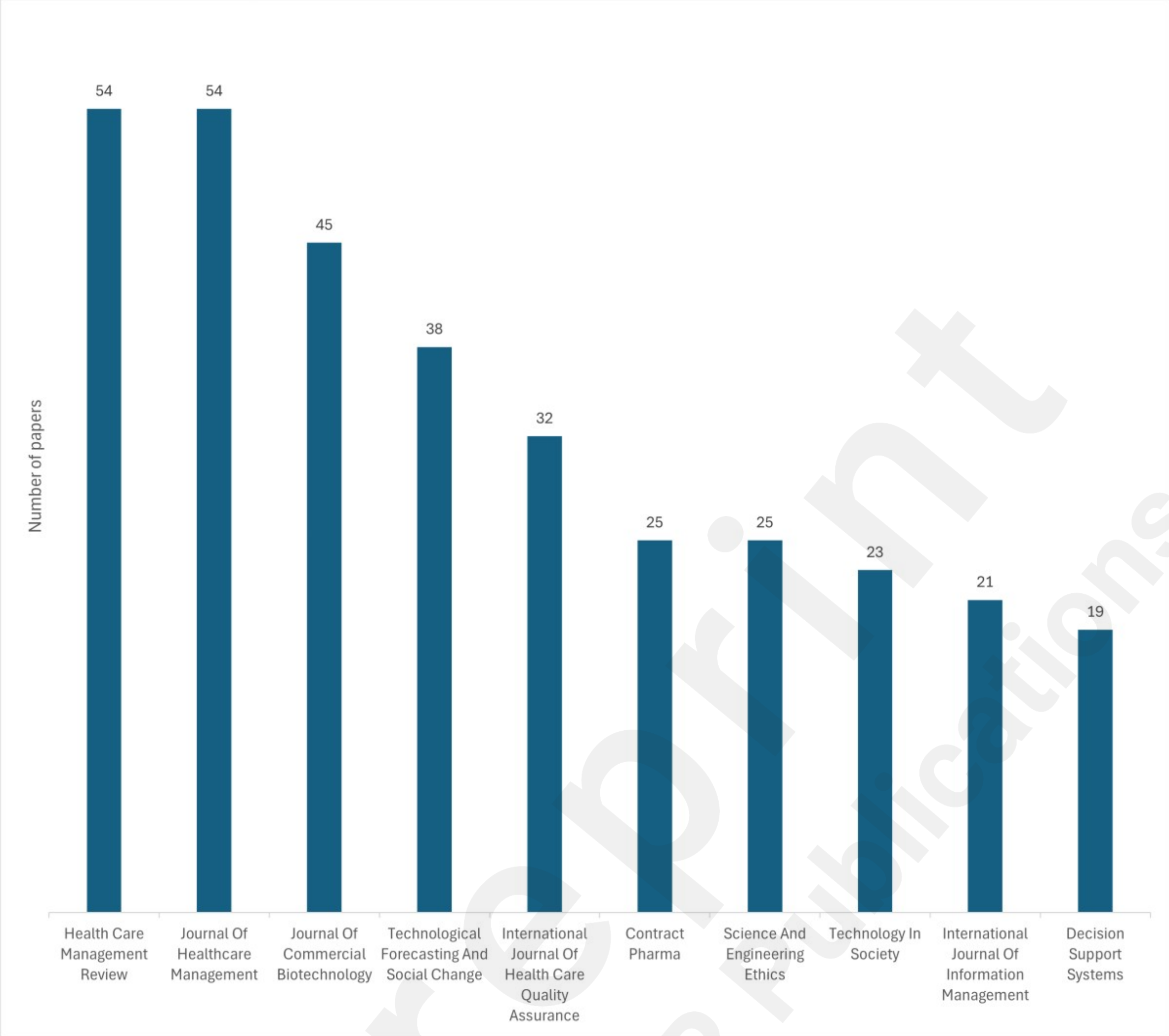
Figure 3. Secondary subject area of the 1186 papers of the bibliometric analysis



Among these articles, 101 are considered as reviews, meaning that the research is not based on primary data but on secondary published data.

More than 160 different sources having published from 1 to 54 articles (Figure 4, Multimedia Appendix 4). The top 3 most represented sources are Health Care Management Review (54 articles), Journal Of Healthcare Management (54 articles), and Journal Of Commercial Biotechnology (45 articles).

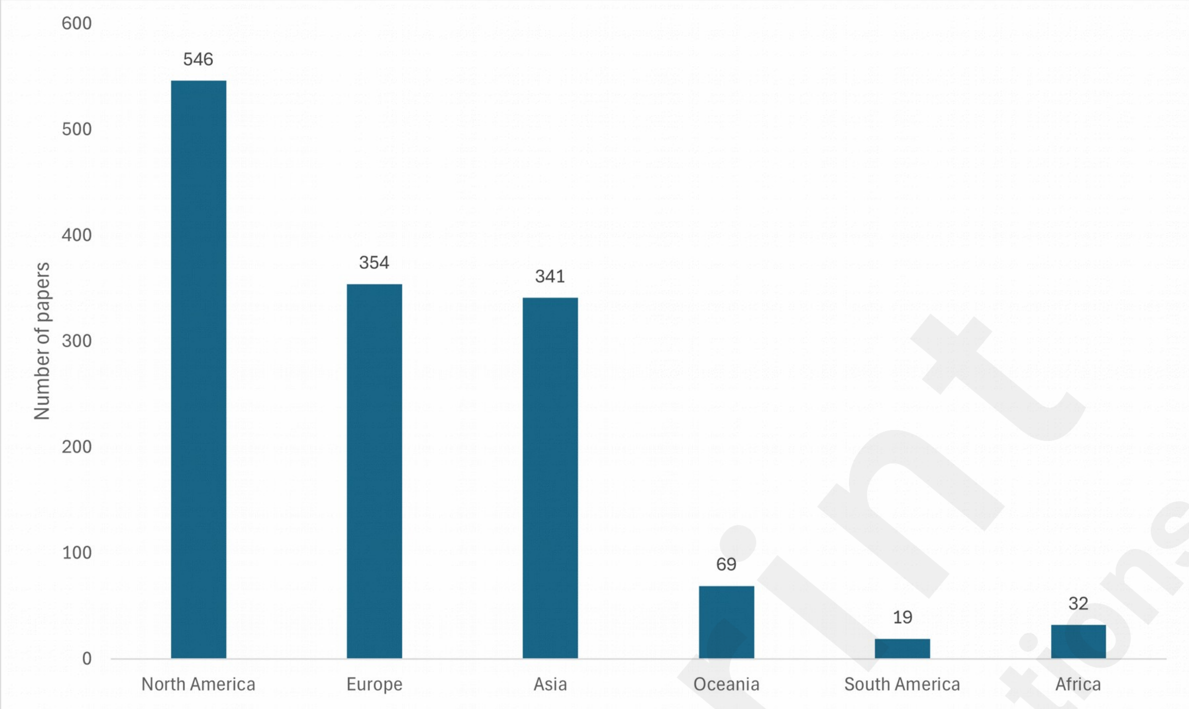
Figure 4. Sources of the 1186 papers of the bibliometric analysis



The analysis of keywords with no cluster-focus approach is biased since the request is keyword-based. Hundreds of various keywords appeared and the top 5 most represented were “Human”, “Article”, “Humans”, “Medical Technology” and “Telemedicine” (Multimedia Appendix 5). For this reason, a cluster-focus keyword analysis was conducted. The keywords being humanly attributed to research papers, one cannot expect them to be homogeneous among research teams, universities, laboratories, and a fortiori countries. We conducted a grammatical, semantic, and conceptual analysis to standardize terminology and consolidate related terms into cohesive categories. This involved identifying variations in spelling, language, and word usage across different contexts, and subsequently grouping synonymous terms and phrases to ensure consistency and accuracy in our analysis (Multimedia appendix 6).

Every paper had to be affiliated to the countries of the authors, which means that one article can have two countries of affiliation depending on the authors and partnerships. In total, 77 countries are represented (Multimedia Appendix 7) over 6 geographical zones : North America, Europe, Asia, Oceania, Africa, and South America (Figure 5). The top 5 countries are United States (with 492 articles affiliated), United Kingdom (with 85 articles affiliated), China (with 79 articles affiliated), Australia (with 63 articles affiliated), and India (with 59 articles affiliated). 112 articles were not automatically affiliated to a country. All articles are written in English. 2 articles are also written either in Spanish or in Portuguese.

Figure 5. Affiliation zone of the 1186 papers of the bibliometric analysis



It is important to notice that top cited articles or top degree centrality articles, papers were all from the 4 clusters of 468 papers and not in the excluded 52 papers. For readability, every "global ranking" is then based on the 468 articles and not the 520 papers.

Thanks to Gephi, 4 clusters were identified (Figure 6). We named them from 1 to 4 (Table 1) and explained them hereafter.

Figure 6. Cluster representation of the 468 papers using Gephi

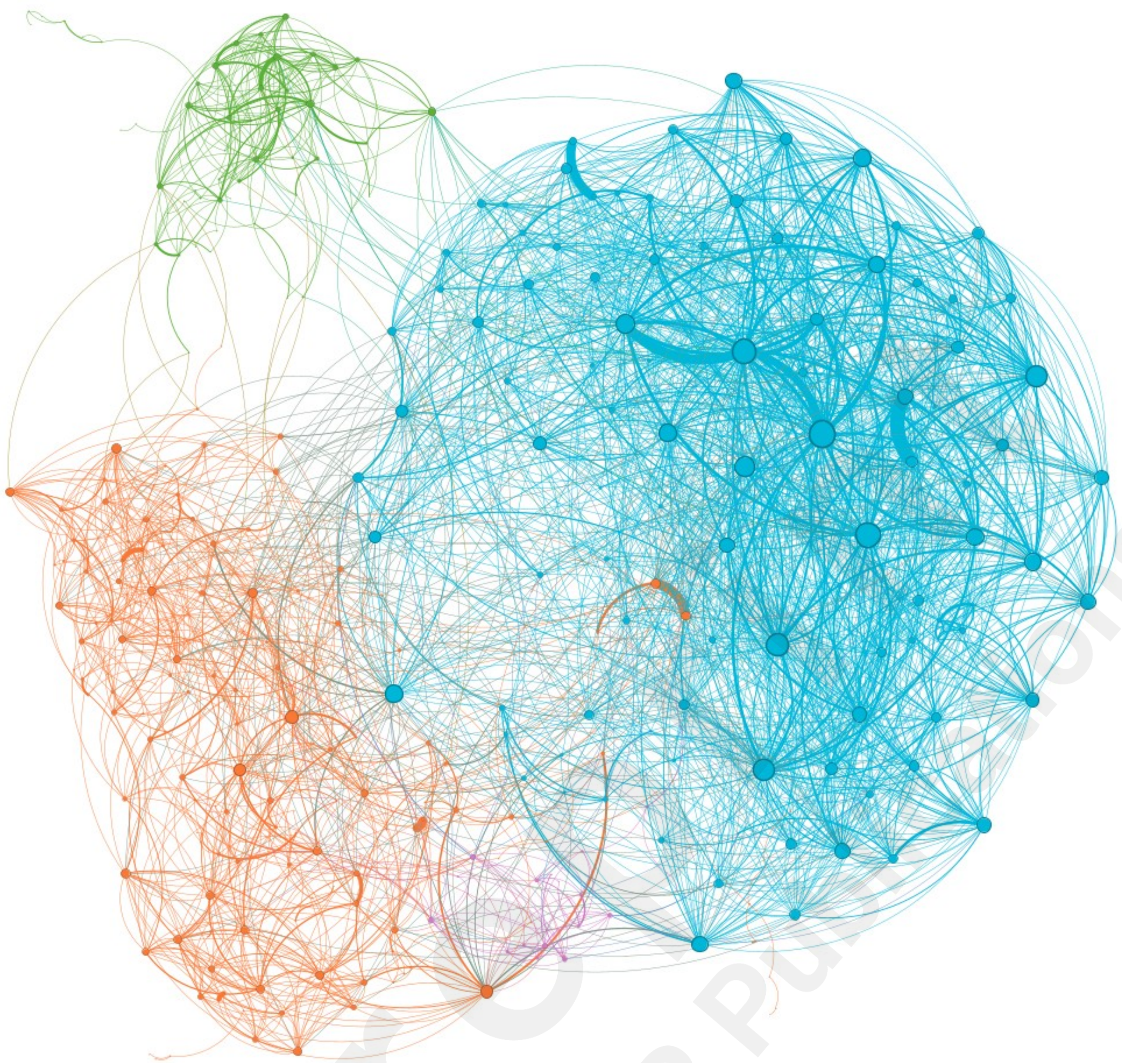


Table 1. Cluster description and principal statistical values

Modularity Class	Color	Position	Number of nodes	Average citation rank	Average degree centrality rank
1	Light blue	Top right	162 (34.6%)	243.9	185.8
2	Green	Top left	57 (12.2%)	178.4	247.3
3	Orange	Bottom left	223 (47.6%)	231.3	261.5

4	Purple	Bottom center	26 (5.6%)	318.0	277.9

In order to better understand the diversity of articles in terms of citation rank and degree centrality, we also represented these data as bar plots and box plots (Figure 7, 8, 9) showing dispersion, skewness, minimum rank, maximum rank, median rank (horizontal line), average rank (cross) and interquartile rank range.

Figure 7. Number of nodes for each cluster

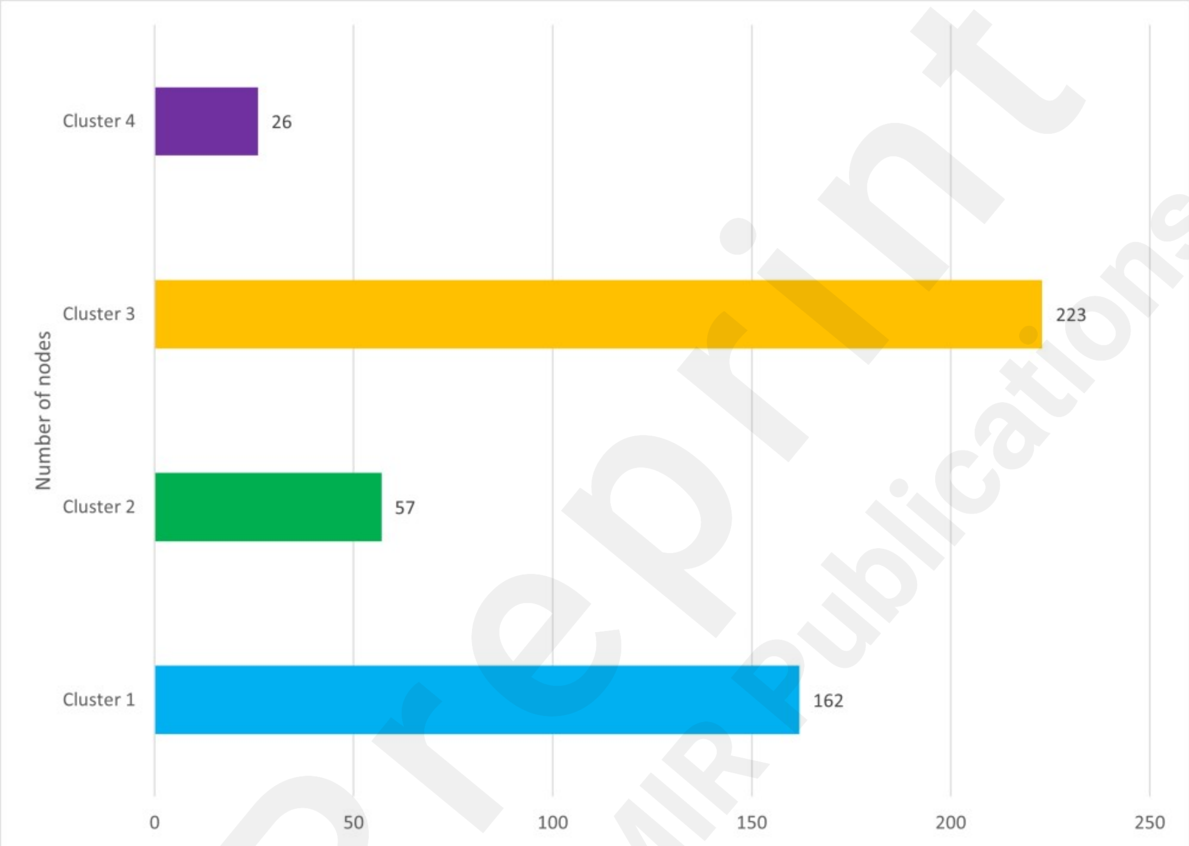


Figure 8. Box plot of the global citation rank distribution for each cluster

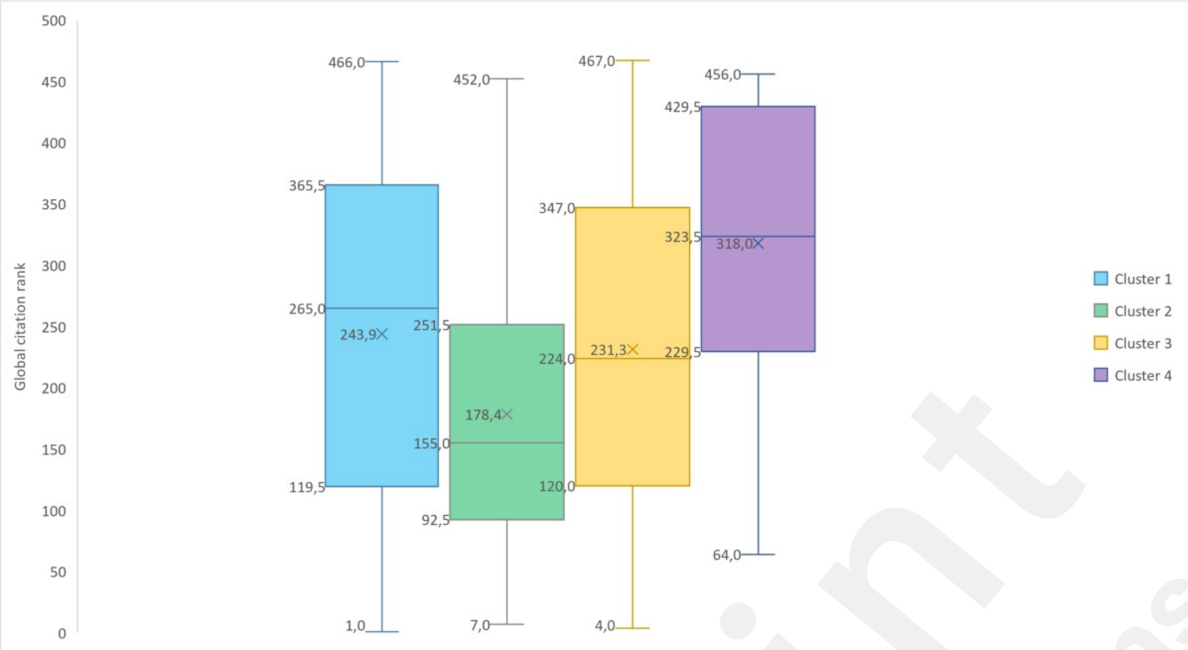
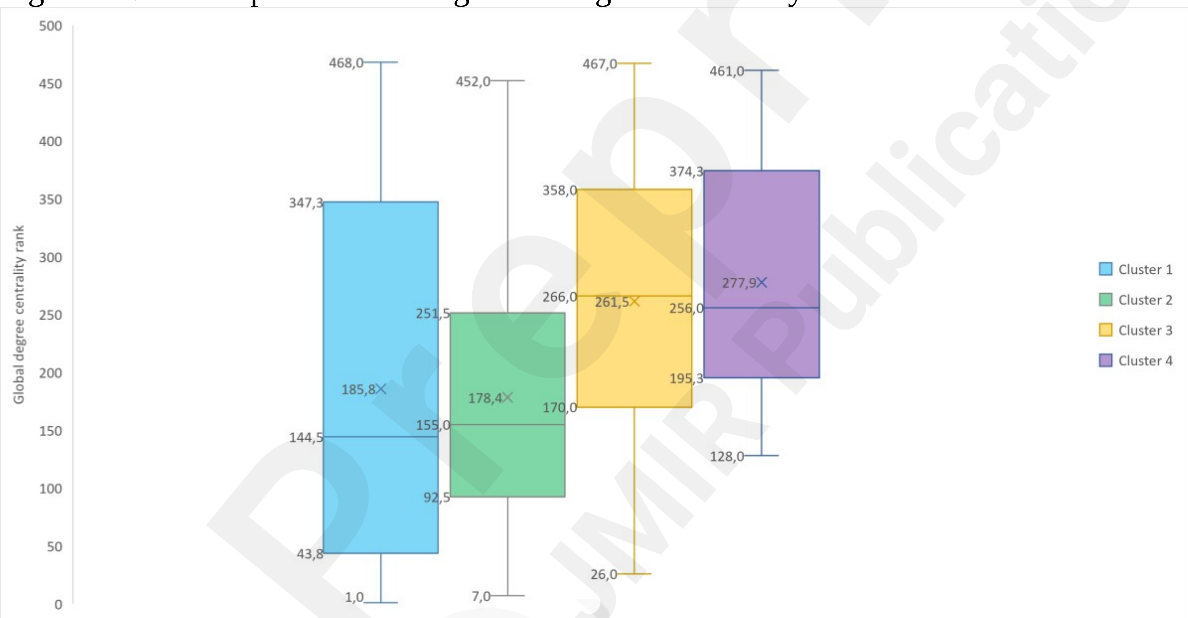


Figure 9. Box plot of the global degree centrality rank distribution for each cluster



The mere presence of clusters constitutes a significant finding, as scientific fields can exhibit varying degrees of cohesion, ranging from uniform interconnections among papers to complete absence of clustering.

Cluster 1: User Adoption and Engagement in mHealth

The first cluster, represented in light blue (Figure 6), has 162 nodes (34.6% of the total number of nodes), with an average centrality degree of 18.9 which makes it the most highly connected among its own nodes. It is the second bigger cluster. It contains the globally higher centrality degree nodes but is also the most dispersed and has an important positive skew meaning that there are more low ranks (high centrality degree) than high ranks (low centrality degree) among cluster 1. In terms of citation dispersion, there is a slightly negative skew ad an overall high dispersion.

Thanks to content analysis, we are able to explain this first cluster as “User Adoption and

Engagement in mHealth”. The cluster 1 primarily focuses on user adoption and engagement in mhealth services. It also examines the adoption of mhealth services in developing countries, specifically India and Bangladesh. The cluster 1 explores emotional bonding with mhealth apps, gamification, and cross-country analyses of adoption patterns. Additionally, it investigates the impact of these technologies on the quality of life, preventive healthcare, and patient knowledge creation through telemedicine technologies. There are lots Technology Acceptance Model (TAM) research papers in the cluster 1 along with some paper addressing information privacy stakes (Table 2).

Table 2. Top 3 papers according to their degree centrality from Cluster 1

Degree centrality	Title	Year	Authors	Total cit[1]	Principal findings
78	Do mobile health (mHealth) services ensure the quality of health life? An integrated approach from a developing country context [18]	2022	Alam M.Z.; Alam M.M.D.; Uddin M.A.; Mohd Noor N.A.	17	The principal factors having a significant impact on adoption of mHealth services among Genation Y are performance expectancy, effort expectancy, facilitating condition, social influence, hedonic motivation, system quality, and services quality. Consequences are to build trust, satisfaction, and improve quality of health life.
72	Adoption of mobile fitness and dietary apps in India: An empirical study [19]	2020	Sampat B.; Prabhakar B.; Yajnik N.; Sharma A.	5	The most important factors for Mobile fitness and dietary apps adoption are perceived usefulness and trust.
71	Factors influencing the adoption of mHealth services in a developing country: A patient-centric study [20]	2020	Alam M.Z.; Hoque M.R.; Hu W.; Barua Z.	189	The behavioral intention to adopt mHealth services in a developing country is positively influenced by performance expectancy, social influence, facilitating conditions and perceived reliability. Other factors such as effort expectancy and price value have no significant influence on

					behavioral intention to adopt mHealth services. Genders are also discussed as a moderating effect on mHealth services adoption.

[1] Last update on February 26th, 2024

This content analysis seemed to be strengthen by the independent keyword analysis (Table 3). Apart from “mhealth”, “ehealth” and “telemedicine” which were included in the inclusion criteria, various keywords appeared in the top 10 such as “adoption” (including “adoption”, “adoption model”, “adoption fit”, “adoption intention”…), “UTAUT” (Unified Theory of Acceptance and Use of Technology, including “utaut”, “utaut2” and “utaut model”), and “behaviour” (including “behaviour”, “behavior”, “behavioral”, “behavior intention”, “theory of planned behaviour”…).

Table 3. Top 10 grouped keywords of cluster 1

Grouped keywords	Count
mhealth	64
adoption	50
ehealth	40
telemedicine	31
ehr	20
utaut	19
behaviour	14
hit	12
research	11
literacy	11

Cluster 2: Adoption and Trust in mHealth Services

The second cluster, represented in green (Figure 6) has 57 nodes (12.2% of the total number of nodes), with an average centrality degree of 7.4, which makes it the second less connected among its own nodes. It contains the globally most cited articles with low dispersion and a positive skew, meaning that there are more low ranks (highly cited articles) than high ranks (low cited articles) among cluster 2. In terms of degree centrality, the analysis is similar with the lowest dispersion compared to other clusters, with a positive skew, meaning more low ranks than high ranks. One could also notice that the cluster 2, with the lowest average citation rank of 178.4, is the globally most cited cluster.

Thanks to content analysis, we are able to explain this second cluster as “Adoption and Trust in mHealth Services”. The cluster 2 centers around the adoption and acceptance of mhealth services which seems quite similar to cluster 1. However, cluster 2 explores factors influencing mhealth adoption, including emotional attachment, trust, and the paradox between privacy and personalization. The cluster 2 delves into the acceptance of telemedicine services in different cultural contexts and incorporates artificial intelligence in healthcare, examining user engagement and learning perspectives within mhealth apps. Numerous research papers from cluster 2 are based on the United Theory of Acceptance and Use of Technology (UTAUT) along with research papers addressing the risk−trust relationship to predict intention to use mobile health apps (MHA) and sensors in the medical context (Table 4).

Table 4. Top 3 papers according to their degree centrality from Cluster 2

Degree centrality	Title	Year	Authors	Total cit[1]	Principal findings
23	Effects of emotional attachment on mobile health-monitoring service usage: An affect transfer perspective [21]	2021	Xiaofei Z.; Guo X.; Ho S.Y.; Lai K.-H.; Vogel D.	42	Patients with chronic illnesses develop emotional attachment to Mobile health-monitoring services. Their satisfaction with the services influences their affective evaluation of using the services. The effects of device satisfaction and feedback satisfaction on services perceived value is positively moderated by the patients health rationality.
21	An extension of technology acceptance model for mHealth user adoption [22]	2021	Rajak M.; Shaw K.	38	Patients trust with mHealth services positively impacts perceived usefulness and perceived ease of use. Perceived risk, resistance to change and perceived physical condition negatively impact behavioural intention. Social influence, trust and behavioural intention positively influences adoption of mHealth services.
19	The role of trust in intention to use the IoT in eHealth: Application of the modified UTAUT in a consumer context [23]	2021	Arfi W.B.; Nasr I.B.; Kondrateva G.; Hikkerova L.	122	Risk-trust relationship is the principal factor for IoT adoption for eHealth whereas performance expectancy has no impact on intention to use IoT for

					eHealth.

[1] Last update on February 26th, 2024

Again, the content analysis seems to be strengthen by the independent keyword analysis (Table 5). Apart from “mhealth”, “ehealth”, “EHR” (Electronic Medical Records) and “telemedicine” which were included in the inclusion criteria, various keywords appeared in the top 10 such as “adoption” (including “adoption”, “adoption model”, “adoption fit”, “adoption intention”…), “behaviour” (including “behaviour”, “behavior”, “behavioral”, “behavior intention”, “theory of planned behaviour”…), “UTAUT” (including “utaut”, “utaut2” and “utaut model”), “apps” (including “apps”, “mobile apps” and “health apps”), and “trust” (including “trusting” and “virtual trust”).

Table 5. Top 11 grouped keywords of cluster 2

Grouped keywords	**Count**
mhealth	18
EHR	11
adoption	9
healthcare	7
telemedicine	7
ehealth	7
behaviour	6
hit	6
apps	5
covid	4
management	4

Cluster 3: Digital Transformation in Healthcare

The third cluster, represented in orange (Figure 6), has 223 nodes (47.6% of the total number of nodes), which makes it the biggest cluster of this bibliometric analysis, with an average centrality degree of 7.6. Both the citation rank and the degree centrality have a very slight skew. The dispersion for degree centrality rank is noticeably low.

Thanks to content analysis, we are able to explain this third cluster as “Digital Transformation in Healthcare”. The cluster 3 revolves around the digital transformation of the healthcare industry. It explores various aspects of technology adoption, including patient engagement through telemedicine, electronic health record assimilation, and the impact of health information technology on healthcare quality and cost. The cluster 3 delves into the ethical considerations of digital healthcare, focusing on responsible design, patient empowerment through digital health trackers, and mostly the challenges of introducing digital technologies in healthcare ecosystems. The research papers are mostly about value cocreation, ecosystems and implementing Health Information Technology (HIT) in organizations (Table 6).

Table 6. Top 3 papers according to their degree centrality from Cluster 3

Degree centrality	**Title**	**Year**	**Authors**	**Total cit[1]**	**Principal findings**
38	The digital transformation of the	2020	Hermes S.; Riasanow T.; Clemons E.K.;	111	New roles are discovered in the digital transformation

	healthcare industry: exploring the rise of emerging platform ecosystems and their influence on the role of patients [24]		Böhm M.; Krcmar H.		of the healthcare industry. The evolution of the role of patients as co-creators of value and these new roles in the context of digitalization of healthcare tackle the simple linear value chains to a platform-mediated multi-sided market.
37	Value cocreation in service ecosystems: Investigating health care at the micro, meso, and macro levels [25]	2017	Beirão G.; Patrício L.; Fisk R.P.	191	Resource access, resource sharing, resource recombination, resource monitoring, and governance/institutions generation enable service ecosystems actors to integrate resources in multiple dynamic interactions to cocreate value outcomes helping with population well-being and ecosystem viability.
37	Reflective Technology Assimilation: Facilitating Electronic Health Record Assimilation in Small Physician Practices [26]	2017	Baird A.; Davidson E.; Mathiassen L.	30	Reflective technology assimilation enables ongoing technology assimilation such as electronic health records by facilitating deeper learning and reflection within small organizations. Reflective action research with facilitative involvement of physicians is efficient to help actors to create their own solution with the help of researchers.

[1] Last update on February 26th, 2024

The keyword analysis (Table 7) is totally in accordance with the content analysis. Apart from “EHR”, “telemedicine”, “ehealth”, “digital health”, and “telehealth” which were included in the inclusion criteria, lots of related keywords appeared in the top 10 such as “HIT”, “management” (including “management”, “project management”, “network management”, value management”, "growth management"…), "organization" (including "organization", "organization theory", "organizational change", "organizational factors", "healthcare organization"…), "data" (including "data", "data justice", "data interaction" and "data capitalism"), "study" (including "longitudinal study" and "exploratory study"), "adoption" (including "adoption", "adoption model", "adoption fit", "adoption intention"…), "research" (including "empirical research", "action research", "qualitative research", "service research", "qualitative research" and "intervention research"), "process", "ecosystem" (including "ecosystem analysis", "platform ecosystem", "healthcare ecosystem"…), "marketing" and "strategy" (including "hospital strategy", "strategic alignment", "growth strategy"…).

Table 7. Top 10 grouped keywords of cluster 3

Grouped keywords	Count
ehr	84
hit	37
telemedicine	35
management	31
health	27
organization	24
ehealth	19
data	15
0	13
study	13

Cluster 4: Implementation Challenges and Ethical Considerations

The fourth cluster, represented in purple (Figure 6), has 26 nodes (5.6% of the total number of nodes) which makes it the smallest cluster of this bibliometric analysis, with the minimum average centrality degree of 6 among all clusters. The citation rank has a very slight skew while the degree centrality rank has a positive skew meaning that there are more low ranks (highly cited articles) than high ranks (low cited articles) among cluster 4. With an average citation rank at 318, cluster 4 remains globally less cited than other clusters.

Thanks to content analysis, we are able to title this fourth cluster as "Implementation Challenges and Ethical Considerations". Cluster 14 addresses challenges and ethical considerations in implementing digital health technologies. It examines the secondary use of EHR data and emphasizes responsible design in virtual reality rehabilitation programs. The cluster explores the role of digital health tools in empowering specific communities, such as Indigenous Australian women, and assesses the limitations and potential of mobile health technologies in healthcare ecosystems. Additionally, it investigates the practical aspects of technology implementation, including image quality in telehealth and the effectiveness of information tools for care coordination during patient handovers. The research papers are strongly connected with behavior change or patients empowerment following Electronic Medical Record (EMR), self-tracking devices or new usages (Table 8).

Table 8. Top 3 papers according to their degree centrality from Cluster 4

Degree centrality	Title	Year	Authors	Total cit[1]	Principal findings
15	Information quality life cycle in secondary use	2021	Hausvik G.I.; Thapa D.; Munkvold B.E.	8	The information quality life cycle in secondary use of

	of EHR data [27]				EHR data can be divided in 3 processes : information generation (data extraction, data organization and data presentation), communication, and use. Communication quality influences the actionability of the information for application and enactment.
15	Leading change: introducing an electronic medical record system to a paramedic service [28]	2016	Baird S.; Boak G.	1	Adoption of electronic medical records in a paramedic service is primarly influenced by perceived ease of use and user interfaces. Barriers to acceptance seem to be removed by introducing flexibility of use.
14	The expected and perceived well-being effects of short-Term self-Tracking technology use [29]	2017	Kari T.; Koivunen S.; Frank L.; Makkonen M.; Moilanen P.	16	Living with a self-tracking technology can have a negative influence on the daily life of the user a negative effect on perceived well-being. Receiving positive feedback was expected to give well-being while negative feedback to not have a significant impact on the well-being. Perceived effect of the technology was small on the well-being which was attributed to the activity tracked by itself. Increase in psychological well-being helps the user

					to continue using the self-tracking device.

[1] Last update on February 26th, 2024

The keyword analysis (Table 9) helps to complete the content analysis. Apart from “EHR”, “mhealth”, “digital health”, “ehealth”, and “telehealth” which were included in the inclusion criteria, various keywords appeared in the top 10 such as “technology”, “apps” (including “apps”, “mobile apps”, “health apps”…), “tracking” (including “tracking”, “trackers”, “self tracking” and “activity tracking”), “design” (including “responsible design”, “value sensitive design”, “codesign”, “design approach”, and “design science”)”, “data” (including “data”, “data justice”, “data interaction” and “data capitalism”), “ethics” (including “ethics” and “guidance ethics”) and “virtual reality”.

Table 9. Top 10 grouped keywords of cluster 4

Grouped keywords	Count
technology	8
apps	7
ehr	5
tracking	5
design	5
mhealth	5
health	4
digitalhealth	4
data	4
ethics	3
developingcountry	3

Discussion

Principal Results

Our principal result is twofold: the existence of four clusters on Digital Health topics in Management science thanks to Gephi, and the understanding of their significance. We used the degree centrality to describe each one of them thanks to their most representative nodes. “User Adoption and Engagement in mHealth”, “Adoption and Trust in mHealth Services”, “Digital Transformation in Healthcare”, and “Implementation Challenges and Ethical Considerations” are highly related. Some papers seemed to be simultaneously part of two clusters. The biggest cluster was Cluster 3 (“Digital Transformation in Healthcare”) with 47.6% of all nodes, making it the most researched field without being the most interrelated field. The highest global degree centrality remained for Cluster 1 (“User Adoption and Engagement in mHealth”), making it the most connected field without being the most globally cited field. The highest globally cited cluster was Cluster 2 (“Adoption and Trust in mHealth Services”). Last, the Cluster 4 (“Implementation Challenges and Ethical Considerations”) seemed to be both the smallest cluster with only 26 papers but also the one with the most recent papers. The oldest paper from this cluster was from 2010 and more than half of them were published after 2020.

Additionally, our analysis brings light to a secondary result: a global statistical analysis on digital health business, accounting and management papers. Medicine and Computer sciences are the two main secondary fields for Management science papers about digital health. The main sources were Health Care Management Review, Journal Of Healthcare Management, and Journal Of Commercial

Biotechnology. The papers came from various countries, mostly United States.

Last but not least, the analysis highlighted a methodology to select keyword when different notions overlapped when the ability to choose the best keywords was not guaranteed. Thanks to comparison of similar keywords with various request, we were able to identify those which best represented the digital health business, accounting and management academic ecosystem and have a keywords-only request to avoid articles that were off-topic.

Limitations

Our study focused exclusively on English-written research papers available on Scopus, a widely recognized citation database that is supposed to be more complete in this field than other databases [11]. Due to the vast number of papers included in our analysis, it was not feasible to comprehensively review each paper one by one, so we had to select among the articles. Additionally, there is no universally agreed-upon method to rank articles and identify the most representative ones within each cluster. As a result, we explored various metrics such as co-citation PageRank, total citations, and degree centrality in the network to assess article significance. Furthermore, the clusters varied significantly in size, and certain papers were found to be borderline between multiple clusters depending on the cluster algorithm used. It's worth noting that papers from developing countries were relatively underrepresented in our dataset.

Comparison with Prior Work

Our study diverges from previous research in several significant ways. Firstly, unlike prior analyses that encompass a broad spectrum of digital health literature, we narrow our focus specifically to the field of management science within digital health. This targeted approach allows for a more in-depth exploration of key themes and trends within this specific domain. Additionally, we employ cluster analysis, leveraging network methodologies, rather than relying solely on traditional bibliometric indicators such as citation count or PageRank ranking. This nuanced approach enables us to uncover intricate relationships and patterns among research articles within each cluster. Moreover, we provide detailed interpretations for each cluster, offering insights into the thematic content and significance of the included articles. Besides, our analysis of the "most significant articles" is conducted cluster-wise rather than globally, providing a more granular understanding of influential works within each thematic cluster. Furthermore, our keyword analysis delves deep by regrouping related keywords and is performed at the cluster level, offering again a comprehensive perspective on the thematic landscape within each cluster. Importantly, we provide statistical measures such as dispersion, average citation rank, and average centrality degree rank, enhancing the robustness of our findings and allowing researchers to gain deeper insights into their position within specific clusters. This approach not only fosters a better understanding of one's research community but also offers valuable insights into the areas of high research activity within the domain of management science in digital health.

Conclusions

Digital Health in Business Management research is a very heterogeneous field that one might formalize as being part of a subgroup such as “User Adoption and Engagement in mHealth”, “Adoption and Trust in mHealth Services”, “Digital Transformation in Healthcare”, or “Implementation Challenges and Ethical Considerations”. This last cluster is also the most recent one and could benefit from more research about ethical considerations as a motor of implementation of digital health in services, ecosystems and society to helps cope with big challenges.

We also think that a more longitudinal analysis could help understand the dynamics of cluster emergence and allow anticipating stakes and subject that could benefit from more research.

Acknowledgements

This study was conducted as part of the exploration of the field for a PhD Thesis at Ecole des Mines, Paris, France. The goal was to better understand what was already been done and to structure the knowledge around management science for digital health.

Conflicts of Interest

None declared

Abbreviations

DH: Digital Health
EHR: Electronic Health Records
EMR: Electronic Medical Records
HIT: Health Information Technology
JMIR: Journal of Medical Internet Research
MHAs: Mobile Health Applications
TAM: Technology Acceptance Model
UTAUT: Unified Theory of Acceptance and Use of Technology

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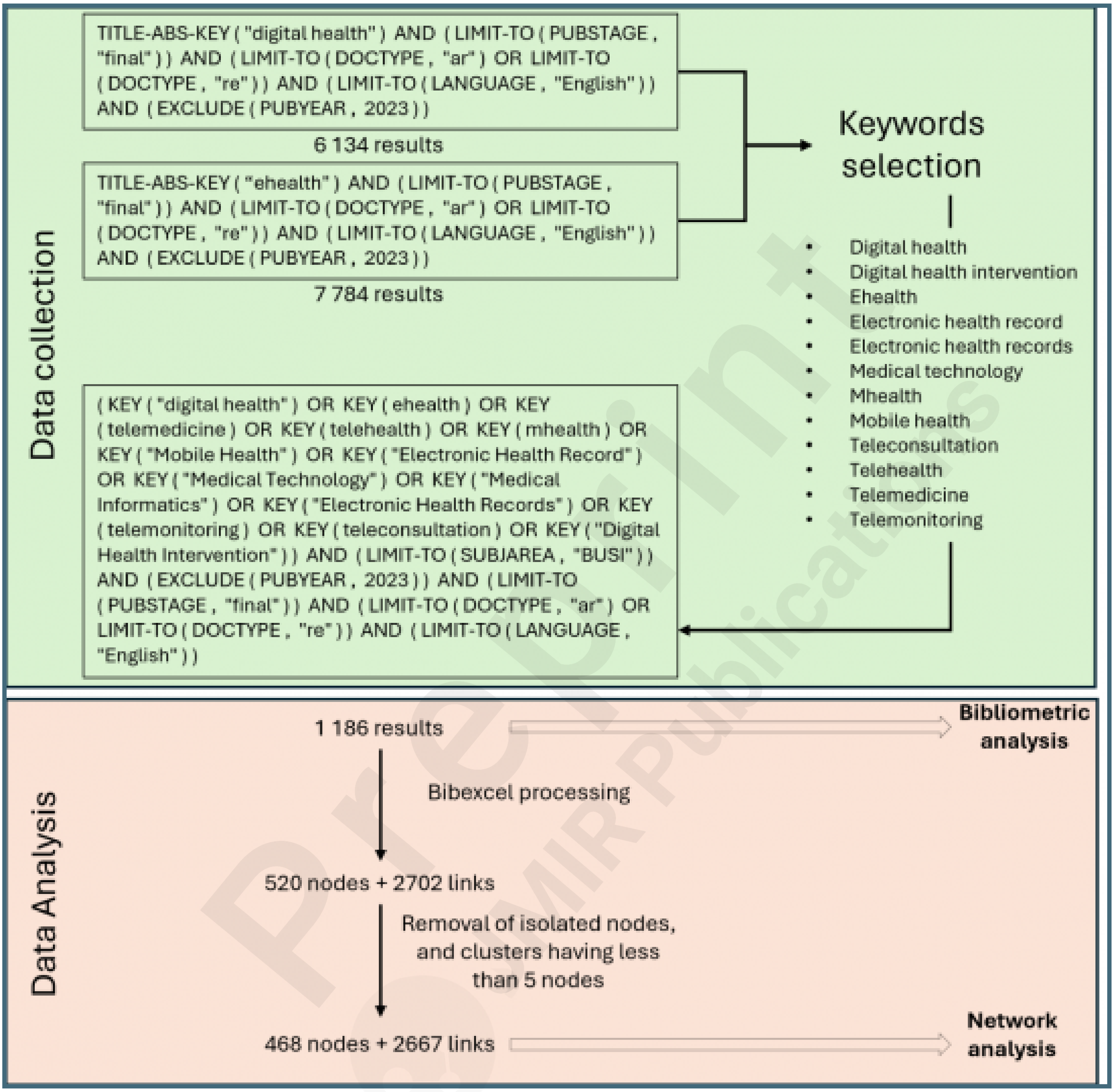
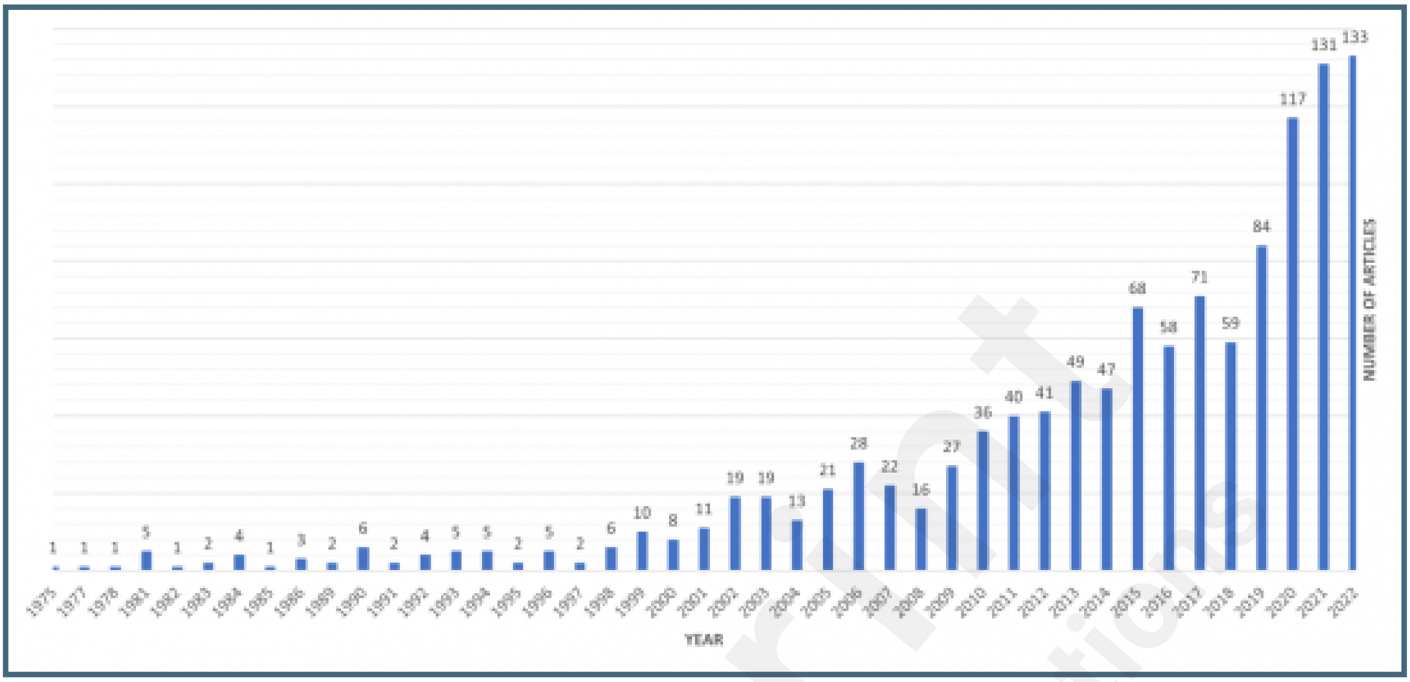
Supplementary Files

Figures

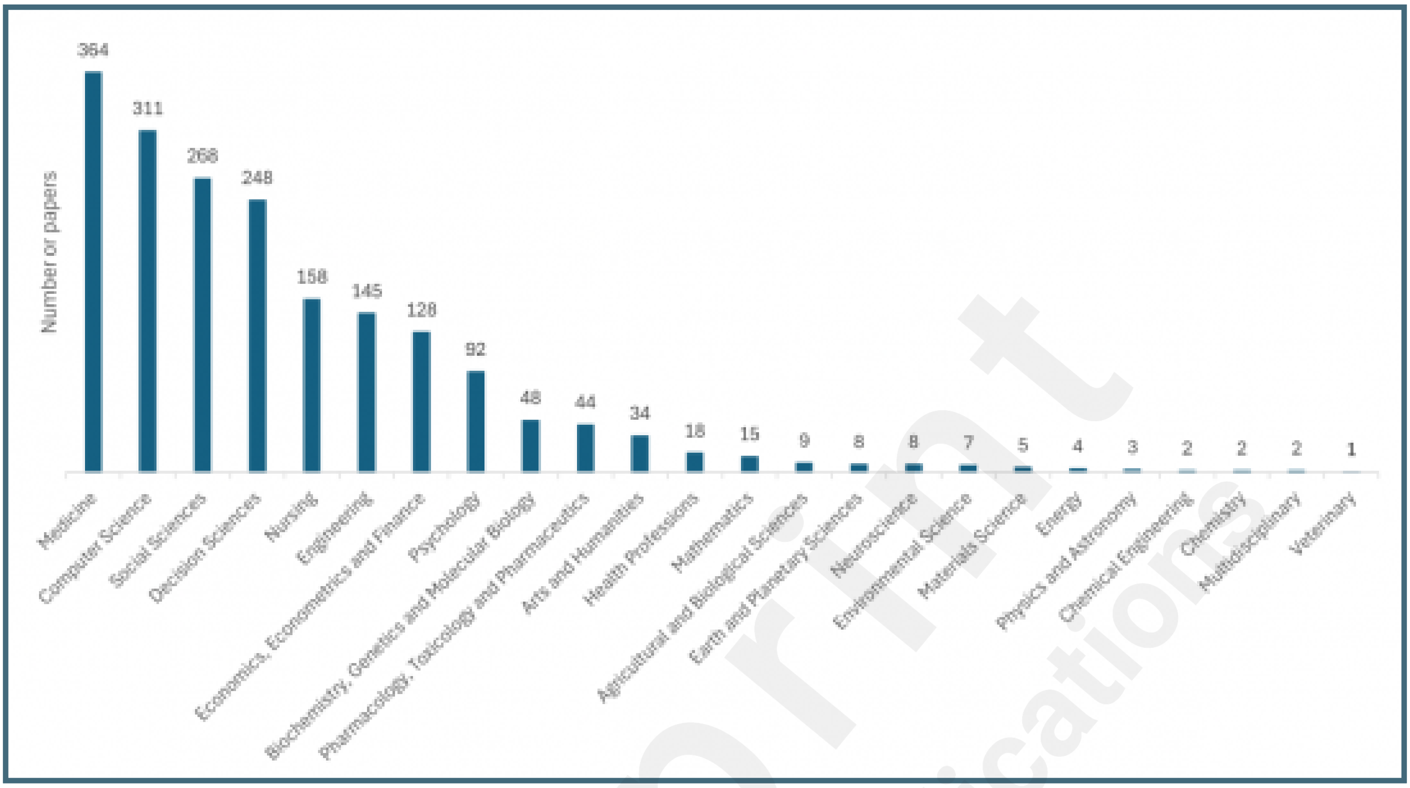
Methodology description from data collection to data analysis.



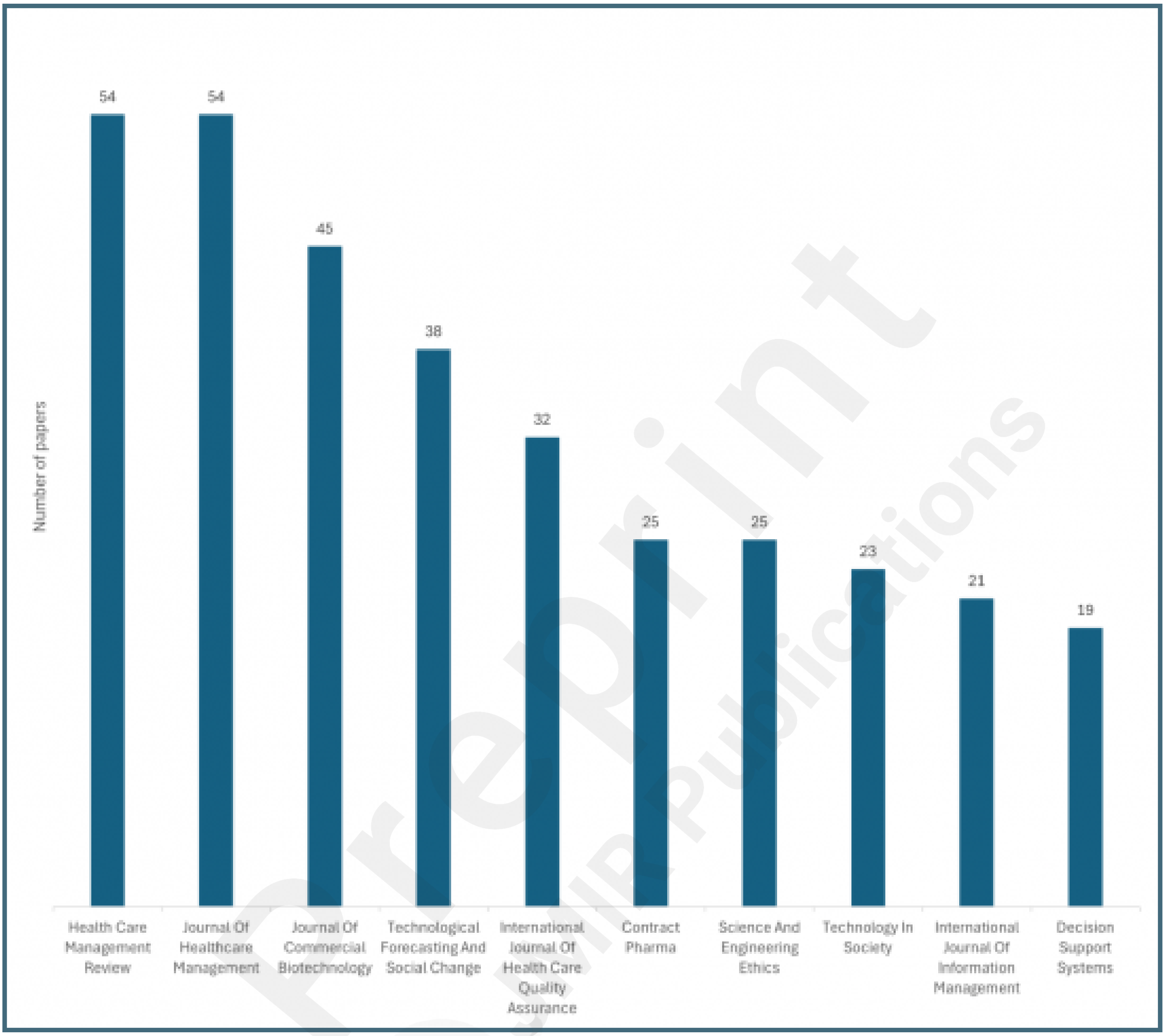
Year of publication of the 1186 papers of the bibliometric analysis.



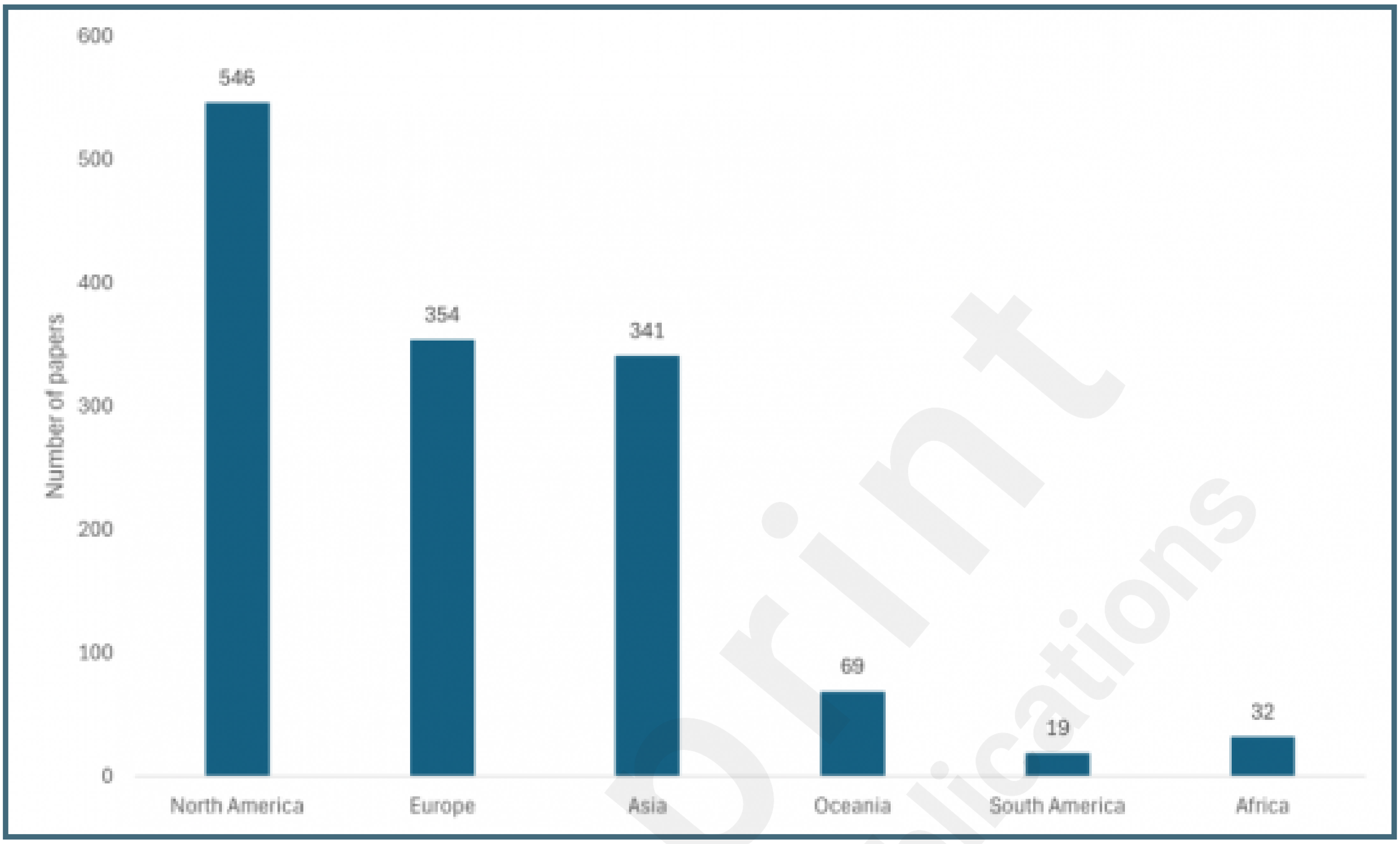
Secondary subject area of the 1186 papers of the bibliometric analysis .



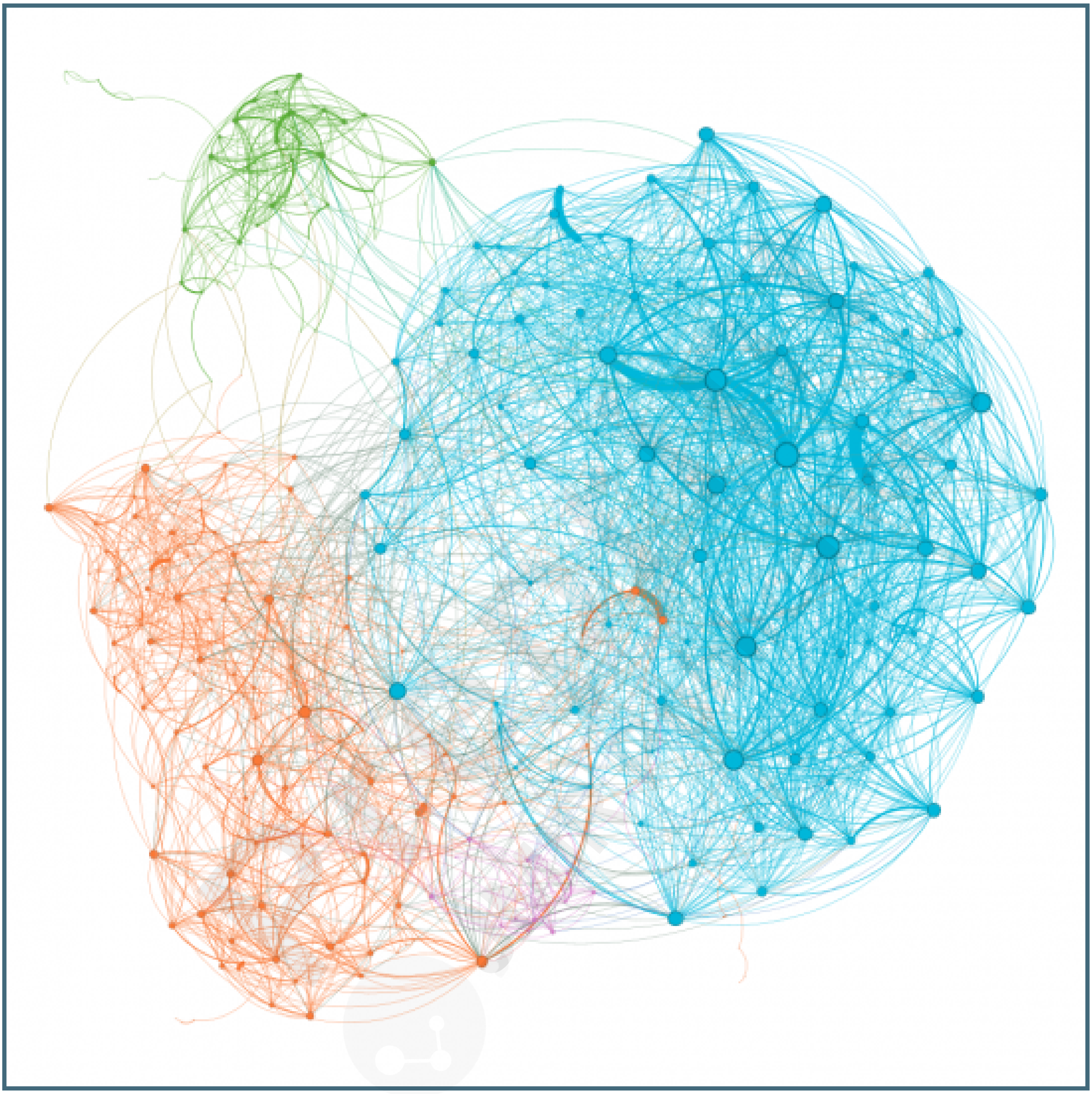
Sources of the 1186 papers of the bibliometric analysis.



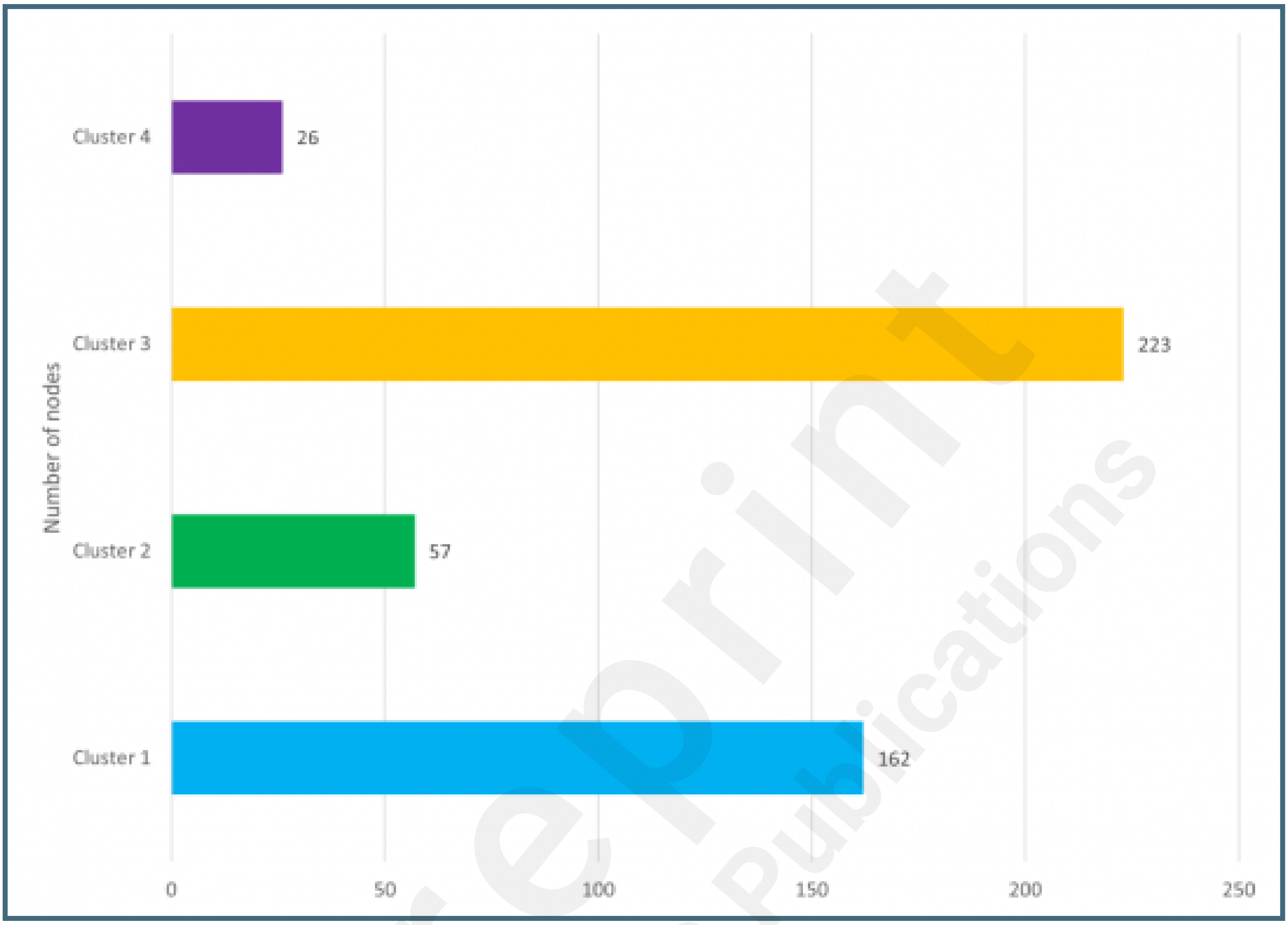
Affiliation zone of the 1186 papers of the bibliometric analysis.



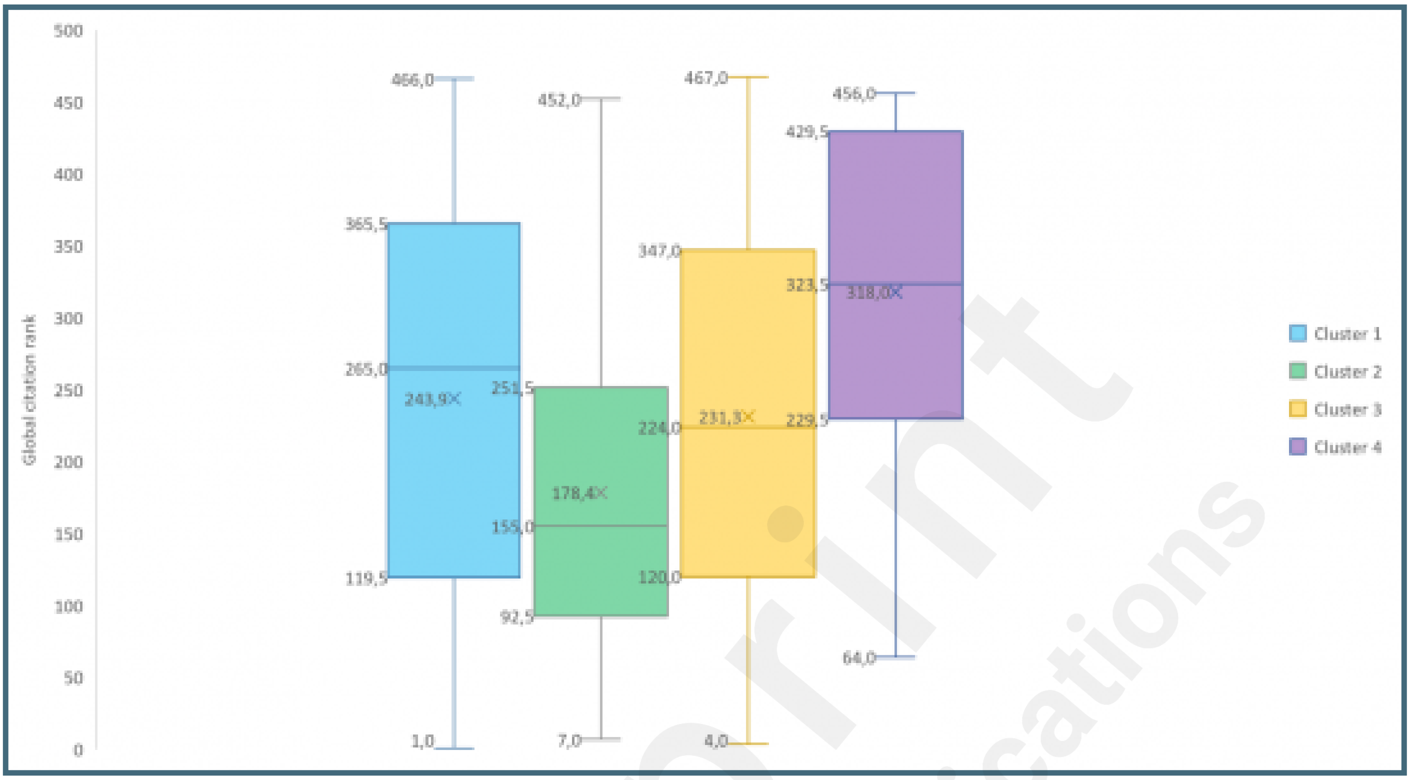
Cluster representation of the 468 papers using Gephi.



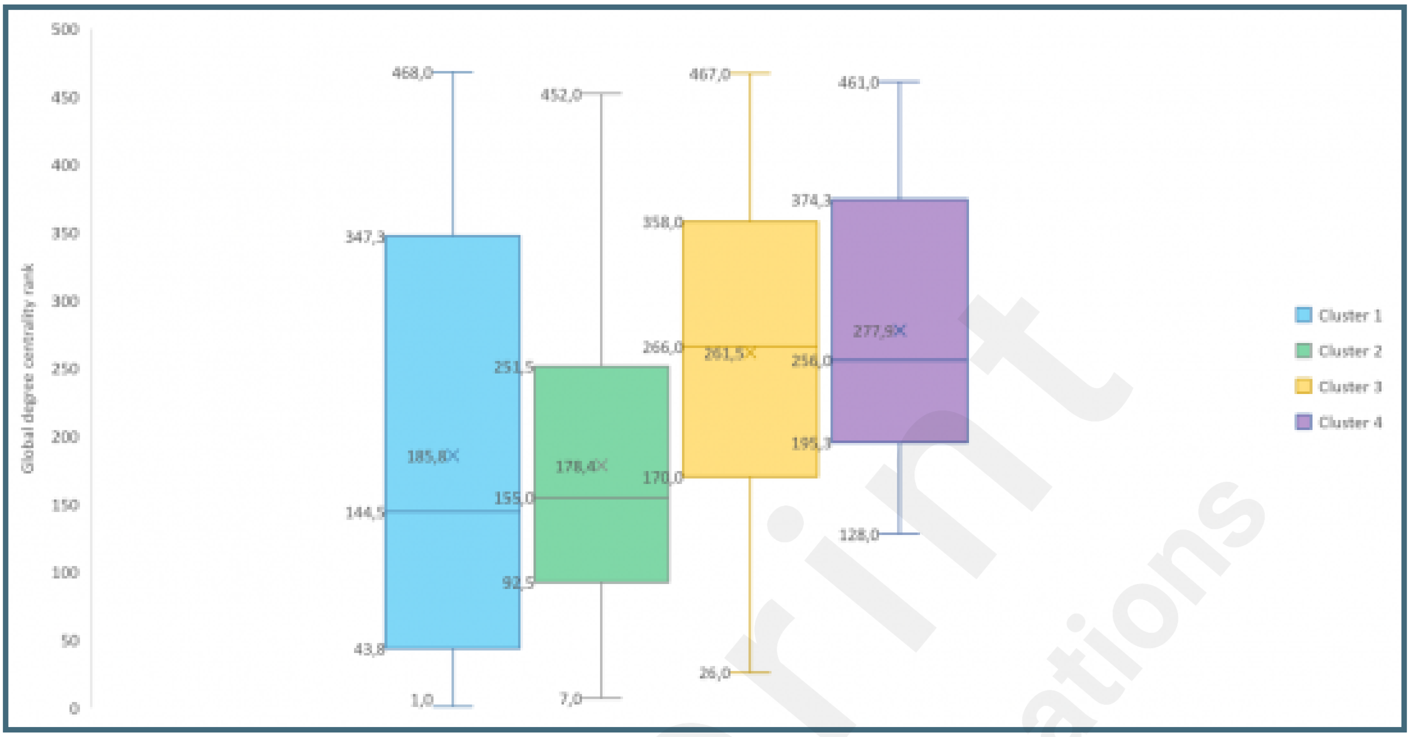
Number of nodes for each cluster.



Box plot of the global citation rank distribution for each cluster.



Box plot of the global degree centrality rank distribution for each cluster.



Multimedia Appendixes

Keywords selection methodology with comparison of keywords for two requests.
URL: http://asset.jmir.pub/assets/895c6a33c4a6d5dd1f025defef521aae.xlsx

All nodes data from clusters 1 to 4.
URL: http://asset.jmir.pub/assets/609c430668c96d6c8d9e954632ab8f77.xlsx

Complete year of publication analysis.
URL: http://asset.jmir.pub/assets/906e9c9afe6e35ef8d09f0a3e4ed59df.xlsx

Complete source of publication analysis.
URL: http://asset.jmir.pub/assets/d5478f286ec9101d33d56828ad270883.xlsx

Complete list of the 160 most represented keywords for the keyword analysis.
URL: http://asset.jmir.pub/assets/619ee9256be40013e98e4861bb65bbb2.xlsx

All grouping of keywords for the keyword analysis.
URL: http://asset.jmir.pub/assets/3903f65a0b5d114182f940d8f09c8940.xlsx

Complete country and zone of publication analysis.
URL: http://asset.jmir.pub/assets/ac9294859a8165191934a8cd0cc27531.xlsx