

Application of Machine Learning and Predictive Models in Healthcare – A Review

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Abstract: The use of predictive analytics or models in healthcare has the potential to revolutionize patient care by identifying high-risk patients and intervening with targeted preventative measures to improve health outcomes. This makes the application of analytics in healthcare a concept of utmost interest, which has been explored in various fashions by several scholars. From predicting patients' ailments to prescribing appropriate drugs, predictive models have seen massive interest. This work studied published works on predictive models in healthcare and observed that the implementation of predictive models in healthcare is experiencing a notable upswing, with a particular focus on research in the United States, where a majority of the top publications originated. Surprisingly, all of the leading nations in this sector have affiliations spanning many continents, with the exception of Africa and South America, together producing a substantially larger volume of research than other countries. The United States also shone out, accounting for 60% of the top five researchers. Notably, although it was published in 2017 (relatively later), Jiang et al. had the most citations (1,346). These studies' core themes were clinical standards, machine learning terminology, and model accuracy. The Journal of Biomedical Informatics topped among journals, with 54 articles, while Luo Gang emerged as the top-performing author, with 12 publications.

Index Terms: Prediction, machine learning, predictive models, healthcare, patients

1. Introduction

In recent years, there has been a growing interest in using predictive analytics in all aspects of life [1 – 4]. One such key area is to identify patients who are at high risk for developing specific health conditions, such as diabetes or heart disease [5, 6]. Predictive analytics involves the use of machine learning algorithms to analyze large datasets and identify patterns or risk factors that may be associated with certain health conditions [5]. Predictive models in healthcare analytics have reshaped how healthcare organizations work, administering insights into patient care, resource allocation, and control of illness. Medical providers may now use sophisticated analytics to accurately project patient outcomes, identify at-risk groups, and optimize care pathways to increase patient outcomes while reducing costs. Predictive models are utilized in a variety of situations in healthcare, including hospitals, clinics, and health insurance

firms. This method includes analyzing massive datasets with machine learning and statistical algorithms to anticipate outcomes and uncover patterns that would otherwise be difficult to identify [3]. Predictive models have become a vital tool for healthcare practitioners in this era of big data, allowing them to make data-driven choices and deliver better treatment for patients. Owing to the growing availability of extensive and intricate healthcare data sources, such as electronic health records, claims data, and genetic information [7, 8] the utilization of predictive models in healthcare analytics has surged in recent years. These predictive models assist medical professionals in recognizing high-risk patients while creating tailored treatment approaches to treat them. This method also allows healthcare providers to manage their operations by forecasting service demand, lowering wait times, and enhancing patient flow. Regarding disease monitoring, global epidemic identification, and public health management, predictive models have proved very helpful. These models enable hospitals and other medical facilities to keep tabs on trends in diseases, anticipate probable outbreaks, and put preventive measures in place like vaccination drives and quarantine protocols. But while the use of predictive analytics has the potential to improve patient care, it also raises important ethical considerations that must be carefully considered and addressed [5]. Using algorithms for prediction in the field of healthcare analytics brings with it unique challenges such as data and information privacy, partiality, and comprehension of outcomes. The objective of this paper is to study existing literature, specifically, works published by scholars relating to innovations and the use and implementation of predictive models in healthcare, in order to establish the intellectual structure of scholars, and their possible collaboration on how predictive models were implemented in healthcare so as to assess their global impact.

2. Methodology and Data Source

This research used existing literature to establish its findings. Scholarly articles in line with machine learning (predictive) models in health care were carefully extracted and mined from the Scopus database on 6th June 2023. This database provides comprehensive access to various scientific articles in all fields including healthcare [9 – 11] and is updated with current literature on a daily basis. It is also the world's largest citation and abstracts database compared to Web of Science (WoS) and PubMed [12]. The search strategy used a combination of healthcare predictive OR prediction models OR analysis OR analytics AND machine learning as phrases. The inclusion criteria for the search were all relevant fully published literature, without limitation to source type, from 2013 to 2022. This range was chosen to ensure coverage of the most recent at the same time detaching obsolete literature. To ensure comprehensive yet absolute relevance to the topic, the search was fine-tuned to articles published only in 11 key health-related disciplines; Medicine, Decision Sciences, Biochemistry Genetics and Molecular Biology, Health Professions, Environmental Sciences, Neuroscience, Nursing, Pharmacology Toxicology and Pharmaceuticals, Agriculture and Biological Sciences, Immunology and Microbiology and Dentistry. The exclusion criterion was all papers that were retracted. Retracted papers in computer science and any other field of study may be caused by among others, questionable research practices and incorrect or erroneous analysis as posited by [13]. This inclusion and exclusion criterion was used in the search strategy to ensure that only articles that were relevant were collated for the study. As indicated in the work of [14], specificity in searching for literature ensures more accuracy. The search resulted in 2,051 published articles, Fig 1. Based on similar studies conducted by [12, 15], relevant articles were saved and exported in a comma-separated value (.CSV) file format, to collect bibliographic information regarding 1. Publication growth, 2. Authors, 3. Type of document, 4. Countries, 5. Source title or journals and 6. Citations. The Visualization of Similarities (VOS) viewer tool, version 1.6.14 (<https://www.vosviewer.com/>), a free software tool for visualization was used to visualize the relationships that exist between authors, citations, and keywords. VOSviewer uses a technique that puts topics into different clusters, marking them with different colors for easy visualization [15]. There is no specialty however regarding its x and y axes, therefore its orientation does not matter. Generally, the circles and labels represent instances or occurrences, colors for clustering or groups, and connectors or lines represent the connections between occurrences [16–18].

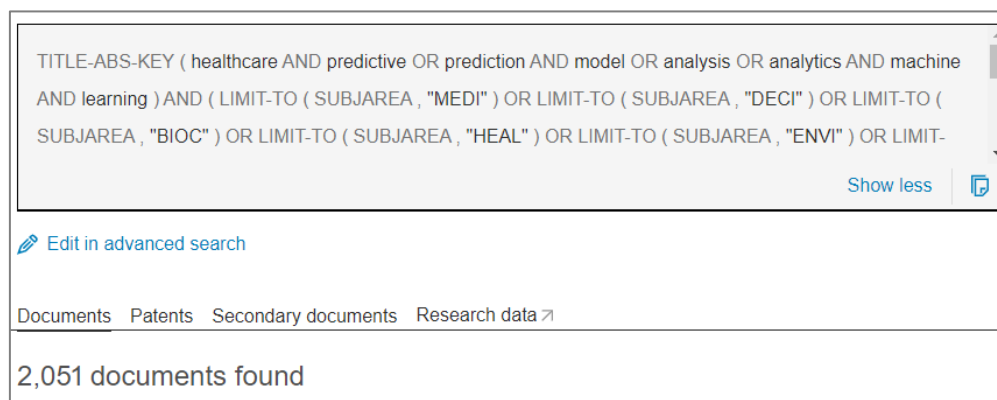


Fig. 1. Search strategy and results

3. Results

3.1 Publication Growth and Geographical Distribution

The bibliometric analysis indicated that there were 2,051 published works that were related to the use of machine learning models in healthcare as of the date of the search. Of these, 57.19% (n = 1,157) were articles, 26.03% (n = 534) were conference proceedings, 204 were Reviews, 86 were chapters, 27 were Conference Reviews, 11 were books, 5 were Editorials, 2 were Errata, 2 short surveys, and 1 letter. Fig. 2 gives a pictorial (pie chart) view of the distribution by source type. The domination of articles indicates among other reasons, an emphasis on rigorousness and scientific progress research in this field. A high number of scholarly papers generally indicates a dedication to furthering scientific or academic understanding of a subject. It indicates a willingness to push the frontiers of knowledge and contribute to the advancement of the area. The analysis again pointed out that the interest in predictive models in healthcare also comes from more than 85 different countries. The top 10 countries alone produced a total percentage of 93.27% (n = 1,913), with the United States of America, India, United Kingdom, and China each publishing more than 100 papers, totaling up to 1,452 representing 70.79% of total publications.

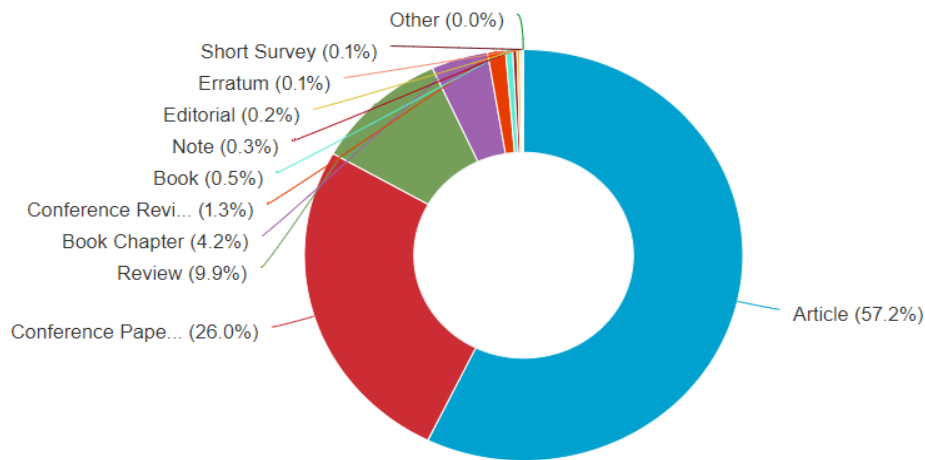


Fig. 2. Distribution by Type of Document

A closer look showed that 9 out of the top 10 countries are members of the G20 [19]. As one of the main aims of this organization is to create sustainable societies committed to achieving equitable health, it may be concluded that these 9 countries had investments to cushion their research, which in consequence aligns with the global aim of equitability in healthcare. The remaining countries have contributed but significantly less than what these G20 countries have done. Looking closely, the top 10 countries had representatives from all continents except for Africa and South America.

Table 1. Top 10 most productive countries

SN	Country	Publications	%
1	USA	681	33.20
2	India	471	22.96
3	United Kingdom	170	8.29
4	China	130	6.34
5	Canada	94	4.58
6	Italy	92	4.47
7	Saudi Arabia	88	4.29
8	Australia	67	3.27
9	Germany	64	3.12
10	South Korea	56	2.73

This observation is intriguing and equally worrying because of the positive impact of predictive models on the human fraternity, which in consequence identifies possible discrepancies in research spending and productivity. It might serve as a wake-up call for these continents to step up their research efforts in healthcare predictive modeling and partner with nations that are at the forefront of the field. It calls into doubt also global health equality. If healthcare predictive modeling research and innovation are focused in a few nations, there may be discrepancies in access to the advantages of these breakthroughs. Table 1 provides the details of the Big 10 regarding the use of predictive models.

Despite the seeming uninterest from some territories, publication growth was however on the rise. From 2013 to 2022, there has been a consistent and steady growth in research into and use of predictive models in healthcare. This can be attributed to a real interest in the field. According to [20] every area of research has three four major stages, 1) the genesis or precursor phase where scholars know little about a topic and hence few or no publications, 2) the stage where scholars begin to have a real sense of the topic through exposure, consequently a relatively slower growth, 3) the maturation phase where scholars have understood the topic and finally 4) the saturation phase where enough knowledge has been generated, leading to a decline in publications. Fig 3 provides a graphical representation of the growth in the publication by year. The years 2013 to 2016 could be adjudged the exposure phase of the use of predictive models in healthcare as publications started appearing to a maximum per year of 35 (year = 2015). The sharp uprise from 2017 (almost a 100% increment compared to its previous year, 2016) makes this research classify 2017 to 2022 as the growth phase of this topic. The graph shows that the maturation phase, where the topic will witness a decline, is yet to come.

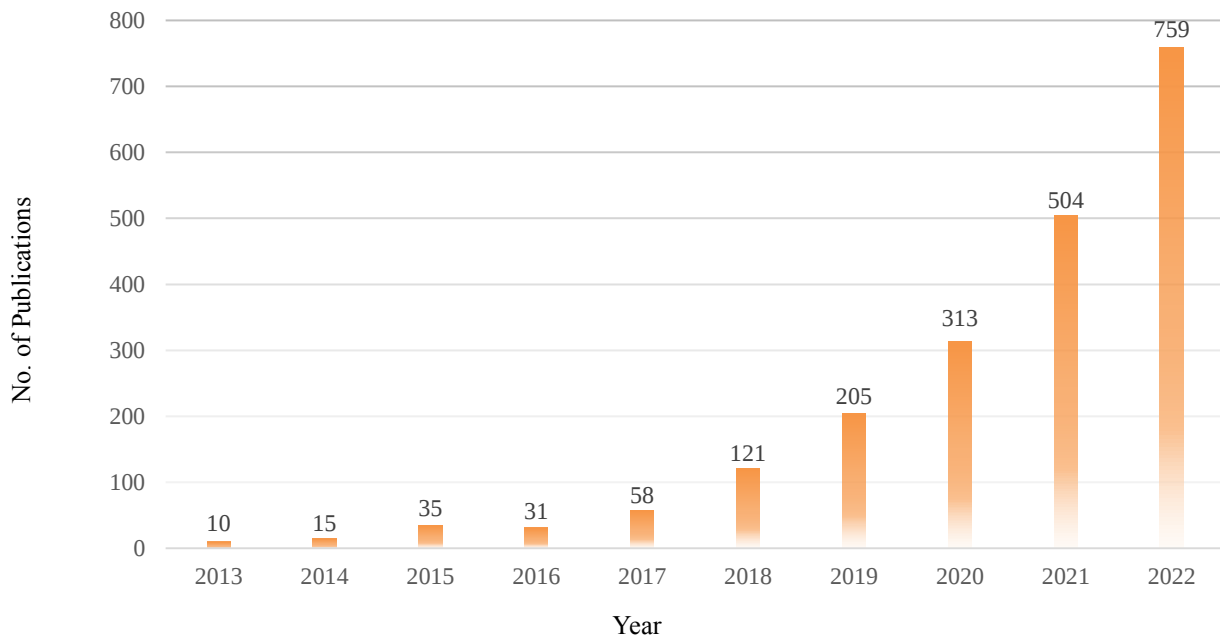


Fig. 3. Publication growth by year

3.2 Authors and Citation

The field of science, more especially computing in addition to healthcare, can get very dynamic. Day in and out novel findings, hence information appears in each scene. The ability of technocrats to work together is paramount to progress and new discoveries in the field [21]. The bibliometric analysis pointed out that the most productive author in line with research related to predictive models in healthcare was Luo, G who published a total of 12 papers. Table 2 shows the performance of the top 5 most productive authors and the details of their works.

Table 2. Author Performance

SN	Author	Territory	No. of publications	Avg. Citations	h-index
1	Luo, Gang	United States	12	14.5	8
2	Kahade, Aditya Vishwas	United States	10	33.1	7
3	Schwab, Joseph Hasbrouk	United States	10	33.1	7
4	Scherieier, Gunter	Austria	9	3.1	4
5	Leung, Carson K.	Canada	8	2.3	3

*SN is independent of the statistics. It has no bearing on the author's performance.

[22] in trying to understand why citation and references are necessary, indicated that citation gives recognition to a published article and helps identify its sources. A general analogy has it that the more cited a work is, the more valuable or "rich" its content is. However, according to [15], this analogy is flawed and only falls to one side of citation as bigger citations could generally also be attributed to the year of which, hence how long a published work has been in existence [23]. A citation may fall into two broad categories; works cited by an author in a current work and works that cited the work of an author. For this research, citation analysis is based on the latter, works that made reference to the works of the authors, which this work will call direct citations. [24] pointed out that direct citations provide more accurate information hence finding invalidations is limited. Table 3 provides details of the top 10 most cited articles. Analysis of the citations indicated that among the top 10 works related to the use of predictive models in healthcare, works that were published in 2018 ($n = 6$) totaled 40% of the total citations ($n = 2,225/5,556$), with 2017 gathering 25%

($n = 1,346/5,556$). This observation aligns with the judgment deduced from Fig 2, adjudging 2017 as the year in which the topic started to grow. [20] again posited that higher citations could be attributed to the duration of years of a publication or the impact of the publication. A closer look at Table 3 reveals that the publications that received the highest citation were rather recent i.e., from 2017 to 2020. This would corroborate the latter position of [20] on the impact of publication

Table 3. Top 10 most cited publications

SN	Title	Author(s)	Country of the first author	Source Title	Year	Time Cited	*FWCI
1	Artificial Intelligence in Healthcare: Past, Present and Future	Jiaing et al.	Hong Kong	Stroke and Vascular Neurology	2017	1346	26.08
2	An overview of deep learning in medical imaging focusing on MRI	Lundervold et al.	Norway	Zeitschrift für Medizinische Physik	2019	943	45.03
3	Artificial Intelligence (AI) Applications for COVID—19 pandemic	Vaishya et al.	India	Diabetes and Metabolic Syndrome: Clinical Research and Review	2020	694	60.37
4	Deep EHR: A Survey of Recent Advances in Deep Learning Techniques for Electronic Health Record (EHR) Analysis	Shicket et al.	USA	IEEE Journal of Biomedical and Health Informatics	2018	556	30.1
5	Fully automated echocardiogram interpretation in clinical practice: Feasibility and diagnostic accuracy	Zhang et. al	USA	Circulation	2018	388	19.88
6	Artificial Intelligence in retina	Schmidt-Erfurth et al.	Austria	Progress in Retinal and Eye Research	2018	380	12.29
7	Federated learning of predictive models from federated Electronic Health Records	Brisimi et al.	USA	International Journal of Medical Informatics	2018	357	12.07
8	P4 medicine: How systems medicine will transform the healthcare sector and society	Flores et al.	USA	Personalized Medicine	2013	348	2.11
9	Ensuring fairness in machine learning to advance health equity	Rajkomar et al.	USA	Annals of Internal Medicine	2018	274	13.25
10	Converging blockchain and next-generation artificial intelligence technologies to decentralize and accelerate biomedical research and healthcare	Momashina et al	USA	Oncotarget	2018	270	12.01

*Field Weighted Citation Impact (FWCI) considers the Year of Publication, Document Type, and Disciplines associated with its source to determine the appropriateness of the article in comparison with similar articles. A bigger value (above 1.00) indicates its performance is above average.

3.3 Source Titles and Keywords

The total number of papers used for this review appeared in more than 30 different journals. Of these, none had made a publication of more than 100. However, one made an appearance in more than 50. Four of these journals have made more than 30 publications, and the remaining falling to less than 30. Table 4 provides a listing of the most influential journals and their details

Table 4. Most Influential journals (ranked on the basis of the total number of publications)

SN	Source Title	Total publications	Impact Factor	*SJR (2022)	Cite Score
1	Journal of Biomedical Informatics	54	8.0	1.083	8.2
2	BMC Medical Informatics and Decision Making	38	3.3	0.940	6.2
3	Journal of The American Medical Informatics Association	33	7.9	2.440	11.7
3	Studies in Health Technology and Informatics	33	0.3	0.285	1.4
5	IEEE Journal of Biomedical and Health Informatics	32	7.0	1.672	11.9
6	International Journal of Medical Informatics	28	4.7	1.197	9.5
7	Smart Innovation Systems and Technologies	27	-	0.170	1.1
8	International Journal of Environmental Research and Public Health	26	4.6	0.828	5.4
9	Sensors	25	3.9	0.764	6.8
10	BMJ Open	22	3.0	1.059	4.4
10	Npj Digital Medicine	22	15.4	3.552	23.6
12	Journal of Healthcare Engineering	20	3.8	0.404	3.2

*SJR is a measure of the scientific influence of journals that accounts for both the number of citations received by a journal and the importance or prestige of the journals where such citations come from. It measures the scientific influence of the average article in a journal, it expresses how central to the global scientific discussion an average article of the journal is.

Research for the themes or keywords for publications related to predictive models in healthcare were visualized and presented in word cloud visualization by mapping of co-occurrences of terms in the title and or abstract for the entire number of articles under study. From the 2,051 published works, 13,933 unique keywords were realized. Of this number, 1,639 appeared in at least 5 works, 828 in at least 10 works and 415 terms occurred at least 20 times. With a keyword threshold of at least 50 appearances, VOSviewer clustered the keywords into four (4) broad categories, represented in Figure 4. The clusters, for the purposes of visual discrimination, were colored as follows; Cluster 1 (color = Red) which involved terms like “adult”, “age”, “male”, “female”, “age”, “body mass” and “intensive care unit”, all which may be considered as clinical and hospital related terminologies; Cluster 2 (color = Green) mostly had terms like “machine learning”, “forecasting”, “predictive analytics”, “nearest neighbor search”, “medical computing”, “predictive analytics” and “logistic regression”, which all related to predictive models, machine learning and data analytics. Cluster 3 (color = Blue) entailed words like “accuracy”, “medical informatics”, “healthcare systems”, “diagnostic imaging” and “predictive medicine”, which seemed more like a combination of computing and healthcare terminologies, and thus may be referred as medical technology, and Cluster 4 (color = Yellow) contained terms like “Bayes Theorem”, “Decision Tree”, “Support Vector Machine” and “random forest”, which are machine learning algorithms.

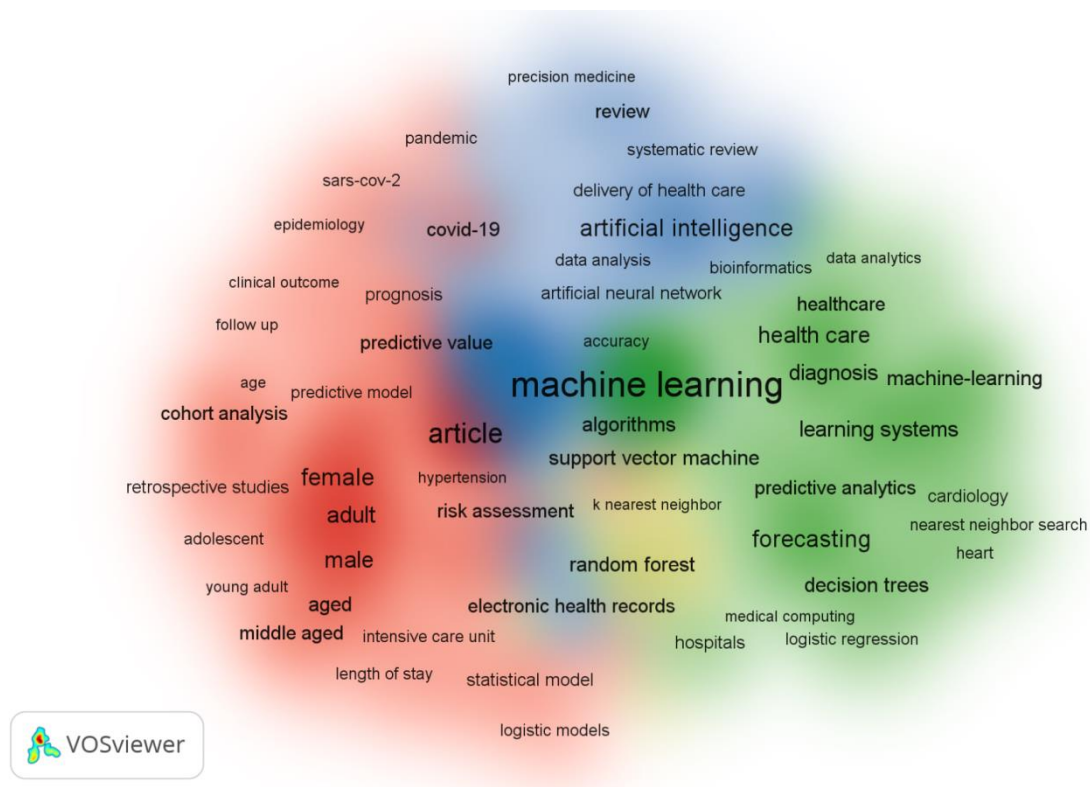


Fig. 4. Word cloud of keywords

4. Findings

The study revealed that there presently is a massive interest in research associated with the use of predictive models in healthcare. This is apparently because of the benefits predictive models bring to bear, not only in health but across all other major sectors ranging from industry to education. Health practitioners are particular in the use of predictive models as they help them detect trends in patients' sicknesses, among others.

The study proved that publication interest in this topic relating to number started hitting the 100s in the year 2018, with a steady rise even up to 2022, in which year publications have seen up to seven times the fold of that of 2018. This surge and sudden increase point out that predictive model implementation in the health sector is on the rise and technocrats are showing real interest in the field.

Interest in this topic is mainly biased towards researchers in the United States as they produced more research and publications than any other country in the top 10, with 60% of top publishers emanating from the same country, the USA. This geographical disparity relating to this theme indicates an opportunity for more international collaboration among countries which could widen the scope of research relating to predictive models.

All the top 10 countries had affiliations with various continents except for Africa and South America, and have produced significantly more combined, compared to the remaining countries. This finding indicates that efforts would have to be taken to guarantee that the advantages of medical research are distributed in greater proportion across the other parts of the world.

Despite being published later (in 2017) compared to the earliest (in 2013) among the top 10 most cited publications, the work of Jiaing et al. received the most citations 1,346 times, suggesting that the general ideology of oldest publications having the highest citations may be flawed.

The essence of keywords in research enhances searchability, increases precision, and establishes interdisciplinary connections. Incorporating thoughtfully selected keywords will improve a research's exposure and citations. Significant keywords used in the collated papers hovered around clinical terms, machine learning terminologies, and model accuracy.

Regarding authorship and source titles, the best-performing author was Luo Gang, who produced 12 publications and the most recognized source title was the Journal of Biomedical Informatics being the sole journal with more than 50 publications. Total publications were 54.

5. Conclusion

Healthcare is one, if not the most important thing to humans and all living things. To make the health sectors even more effective has seen the introduction of major developments and innovations from the side of technology among others. One such technological measure is the use of predictive models or analysis in healthcare. The dynamism of the field of science generally necessitates contemporary knowledge. This work fundamentally provides the research environment with a current and vivid overview of the trends relating to knowledge of predictive models relating to healthcare. With such updated knowledge, the research community will have a rudimentary idea of which areas to gear their studies. In this updated research, consideration was given to all works done in line with predictive models in healthcare which were published in Scopus over 10-year duration. The study spanned articles published from 2013 to 2022. It used a bibliometric analysis, paying close attention to the trends in publication, the performance of authors, articles, and journals, and also the relationship between keywords

Availability of Data

The data for this work is available on

https://drive.google.com/file/d/1D2br5F21CZ-Xq3XJn5dDQXSg99FOZc78/view?usp=drive_link

Conflict of Interest

The authors declare that there is no conflict of interest regarding this work. This study was conducted with the sole purpose of disseminating and enhancing knowledge.

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