Review

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Internet of Things and Bigdata Analytics in Preventive Healthcare: A Synthetic Review

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Internet of Things and Bigdata Analytics in Preventive Healthcare: A Synthetic Review

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Abstract: Background: IoT and Big Data are newer technologies that can provide substantial support for healthcare systems and help overcome their shortcomings. The aim of this paper was to analyze literature production descriptively, thematically, and chronologically from an interdisciplinary perspective in a holistic way to identify the most prolific research entities and themes. Methods: The synthetic knowledge synthesis qualitatively and quantitatively analyzes the production of literature through a combination of descriptive bibliometrics, bibliometric mapping and content analysis. For this analysis the Scopus bibliometric database was used. Results: In the Scopus database, 2272 publications were found, which were published between 1985 and June 10, 2024. The first article in this field was published in 1985. Until 2012 the production of literature was steady increasing, after that exponential growth began, which reached its peak in 2023. The most productive countries were the USA, India, China, the United Kingdom, South Korea, Germany and Italy. The content analysis resulted in 8 themes (four from the perspective of computer science and four from the perspective of medicine) and 21 thematic concepts (eight from the perspective of computer science and 13 from the perspective of medicine). Conclusions: The results show that IoT and Big Data have become key technologies in preventive health. The study outcomes might represent a starting point for the further development of research that combines multidisciplinary aspects of healthcare.

Keywords: Internet of Things; Big Data; preventive healthcare; epidemiology; bibliometric

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1. Introduction

The COVID-19 pandemic once again exposed the shortcomings of traditional healthcare systems in coping with sudden, unpredictable situations. Major technologies that can support healthcare systems in such crises as well as in routine work are smart and connected wearables (Internet of Things - IoT), which can collect context-oriented data related to patient physical, behavioural, and psychological health and big data analytics, which can mine collected data in real-time, extracting knowledge and making predictions/inferences enabling health professionals and decision maker to improve the healthcare system and their services [1–5].

Some recent review papers [3,6–8] and bibliometric studies [9–11] on the use of IoT or Big data analysis in healthcare have already been published, but none of them didn't focus on predictive medicine/healthcare. Additionally, review synthesis outcomes were based on the analysis of small samples of publications, thus not giving a comprehensive and holistic insight into the field. Additionally, traditional bibliometric studies have already published just quantitative aspects of the research, lacking the formal qualitative analysis, thus missing the insight into prolific themes, topics, concepts, maturity of the research, and identification of the core sources of information based on

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bibliometric laws. Furthermore, most publications didn't analyze IoT and data concurrently, overlooking the integrative effect.

To fill this gap, our study aims to inform the research community and practicing medical and healthcare professionals to improve their understanding of this fast-growing and highly innovative area. It can also inform novice researchers, health institution managers, and patients lacking this specific domain knowledge to develop a perspective on essential research dimensions and possible fields of practical use. Finally, the study might inform and catalyze further research and serve as a starting point for more formal knowledge and evidence synthesis approaches. To achieve this aim, our objective is to answer the following research questions:

- What are the volume and dynamics of the research on using IoT and Big Data in preventive medicine?
- How is the research geographically distributed?
- Which are the core and most prolific information sources that first inform the scientific community and second enable the community to present its research results?
- Which funding bodies are the most productive?
- What are the most prolific research themes, concepts, and future directions?
- How did the research themes envolve historically?
- What are the possible research gaps?

2. Materials and Methods

The research landscape of IoT and Big-data employment in preventive medicine was induced by Synthetic Knowledge Synthesis (SKS) [12]. SKS was developed to face new challenges in synthesizing research evidence due to exponential rates of knowledge development and the digital revolution. SKS triangulates quantitative and qualitative knowledge synthesis by combining descriptive bibliometrics, bibliometric mapping, and content analysis. SKS overcomes some weaknesses of traditional knowledge synthesis approaches by reducing needed resources and automating part of the synthesis. As such, it can synthesize thousands or even ten thousand publications, solving the sampling issue and increasing reproducibility [13,14]. Furthermore, triangulation used in SKS provides a more complete picture of the phenomena in question. It helps to increase the validity, credibility, dependability, confirmability, and transferability (ecological validity) of research synthesis [15]. To further increase the study's validity and reduce bias, we performed the content analysis from two perspectives: medical and computer science. SKS was executed with the algorithm below:

1. Research publications were harvested from the Scopus bibliographic database using the search string *TITLE-ABS-KEY (("internet of things" OR iot OR big-data) AND prevent*) AND (LIMIT-TO (SUBJAREA,"MEDI") OR LIMIT-TO (SUBJAREA,"HEAL") OR LIMIT-TO (SUBJAREA,"NURS")).*
2. Descriptive bibliometric analysis was performed using Scopus's built-in functionality and the Bibliometrics software [16].
3. Author keywords were used as meaningful units of information in content analysis. First, bibliometric mapping was performed using VOSViewer [6]. Next, using content analysis on the most popular authors' keywords, the node size, links, and proximity between author keywords in individual clusters and their borders presented in the bibliometric map were analyzed from the medical and computer science viewpoints to form categories, identify concepts and name the research theme.
4. Next, the representative themes and subcategories' author keywords/terms were applied to form search strings to locate relevant publications associated with describing categories and themes' scope.
5. The timeline authors' keywords landscape was induced and used together with Reference Publication Year Spectroscopy (RPYS) [17] to historically analyze knowledge development [18]. The future research themes were identified by comparing different time slices of the timeline landscape [19].

Scopus (Elsevier, The Netherlands) was used as the bibliographic database. Scopus is the largest abstract and citation database of the reviewed research literature. They were providing powerful analytics services and enabling 20,000 records to be exported simultaneously. The search query was constructed using the recommendation provided by Farooq et al. [20], namely, analyzing and synthesizing search strategies already used in related review papers. The search was performed on June 10th, 2024. Zipf's law was used to calculate the number of relevant keywords to be used in SKS, and Bradford's law was used to calculate the number of core journals [21].

3. Results and Discussion

3.1. Descriptive and Production Bibliometrics

3.1.1. Volume of Research

The search resulted in 2272 publications. There were 971 articles. 669 conference papers, 363 reviews, 159 book chapters, and 110 other types of publications containing 6195 author keywords. They were published by 9770 authors affiliated with 2446 institutions from 72 countries in 1165 source titles. The average number of co-authors was 5.2 authors; 166 publications were single-authored, and 21.4% of publications were international. On average, a publication received 15.11 citations. During the period 1985-2015, 29 countries contributed to the research; in the period 2016-2000, 40 countries; and in 2021-2024, 71 countries.

3.1.2. The Dynamics of the Research Literature Production

The first paper was published in 1985, and after that, the production was very sparse till 2012, when the exponential growth began, reaching its peak in 2023 with 438 publications (Figure 1). The number of conference papers is still exhibiting a positive trend. However, the number of articles, reviews, and book chapters has declined. The annual growth in the number of publications is 9.5%.

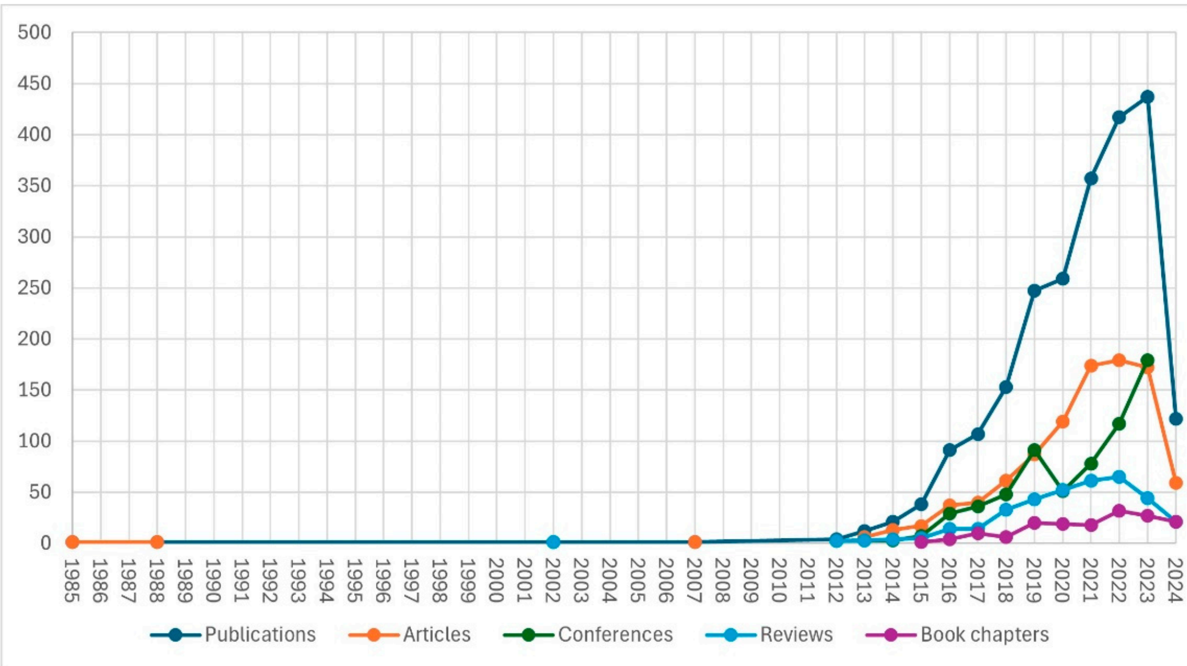

Figure 1. The dynamics of research literature production.

3.1.3. Prolific Information Sources

A total of 1165 source titles have published articles on IoT and Big data in preventive health care. Based on Bradford's Law, 108 source titles are included in the core zone according to their productivity. The large number of core zone journals indicates that the maturity of the research area is still progressing and that archival journals have not yet been established. The 10 most productive source titles are listed in Table 1.

Table 1. Most productive source titles.

Source Title	Number of publications	H-Index in Scopus	Scopus SJR	Quarter
Eai Springer Innovations In Communication And Computing	55	26	0.15	Q4
International Journal Of Environmental Research And Public Health	54	198	0.81	Q2
Journal Of Medical Internet Research	36	197	2.02	Q1
Studies In Health Technology And Informatics	28	67	0.29	Q3
Frontiers In Public Health	27	101	0.90	Q1
Journal Of Healthcare Engineering	24	57	0.51	Q2
Safety Science	20	154	1.28	Q1
Accident Analysis And Prevention	17	188	1.90	Q1
BMC Public Health	12	197	1.25	Q1
BMJ Open	12	160	0.97	Q1

The H-index of the above source titles lies between 26 and 197, and the SJR (Scopus Journal Rank) is between 0.15 and 2.02, placing most of the source titles into the Q1 category, indicating the high quality of prolific information sources. However, the five top cited papers (Table 2) have not been published in the most prolific source titles, except for the most cited paper in Q1 journals, with mostly higher than most productive source title SJRs. All five of those journals belong to the core zone journals.

Table 2. Most cited papers.

Authors	Title	Publication year	Source title	Cited by	SJR 2023	Core journal
Tomczak K. et al.	The Cancer Genome Atlas (TCGA): An immeasurable source of knowledge	2015	Wspolczesna Onkologia	1452	0.532 (Q2)	Yes
Peeri N.C. et al.	The SARS, MERS, and novel coronavirus (COVID-19)	2021	International Journal of Epidemiology	987	2.663 (Q1)	Yes

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	epidemics are the newest and biggest global health threats. What lessons have we learned?					
Vaishya R.; et al.	Artificial Intelligence (AI) applications for the COVID-19 pandemic	2020	Diabetes and Metabolic Syndrome: Clinical Research and Reviews	927	1.313 (Q1)	Yes
Dimitrov D.V.	Medical internet of things and big data in healthcare	2016	Healthcare Informatics Research	645	1.628 Q1)	Yes
Brisimi T.S. et al.	Federated learning of predictive models from federated Electronic Health Records	2018	International Journal of Medical Informatics	552	1,493 (Q1)	Yes

3.1.4. Geographical Distribution of Research

The most productive countries publishing more than 100 publications were the United States (n=477), followed by India (n=445), China (n=388), the United Kingdom (n=179), South Korea (n=131), Germany (n=114), and Italy (n=109). The ranking of scientific production is comparable with the Scimago Country Rankings (Elsevier, Amsterdam, Netherlands), where China, the United States, and India are the three first-ranked in Computer science and the United States, China, and the United Kingdom in medicine. Other top productive countries are among the 11 most productive in both categories. All top productive countries are also members of G20 [22]. The United States, China, and the United Kingdom also prevail among the most productive institutions; among the first 20, 19 are from those three countries.

The most cooperative countries (Figure 2) are The United States, Canada, The United Kingdom, Australia, and Germany, with 28, 27, 26, 26, and 24 co-authors-based cooperation links, respectively. The strongest cooperation exists between The United States and Canada; Australia and The United Kingdom; The United Kingdom, Germany, Netherlands, and Sweden; and India, The United States, and Malaysia. The cooperation indicates the regional/cultural concentration of research, which should be overcome in the future to enable the translation of global preventive healthcare knowledge to less developed regions and enable regional researchers to contribute to the development of worldwide knowledge and share unique datasets, specialized equipment, regional knowledge, and distinct research environments.

The United States, Canada, Denmark, and Sweden have, on average, the oldest publications, and Belgium, Russian Federation, India, Japan, Hong Kong, Malaysia, Pakistan, and Saudi Arabia are the youngest, indicating countries where preventive health care research has started and where more focus to it has been gained lately.

The eight most productive institutions publishing more than 20 publications are Harvard Medical School (n=35), University of Oxford (n=26), Peking University (n=24), University of Toronto (n=24), Harvard T.H. Chan School of Public Health (n=23), Standford University (n=22), Brigham and Women's Hospital (n=22) and Chinese Center for Disease Control and Prevention (n=22).

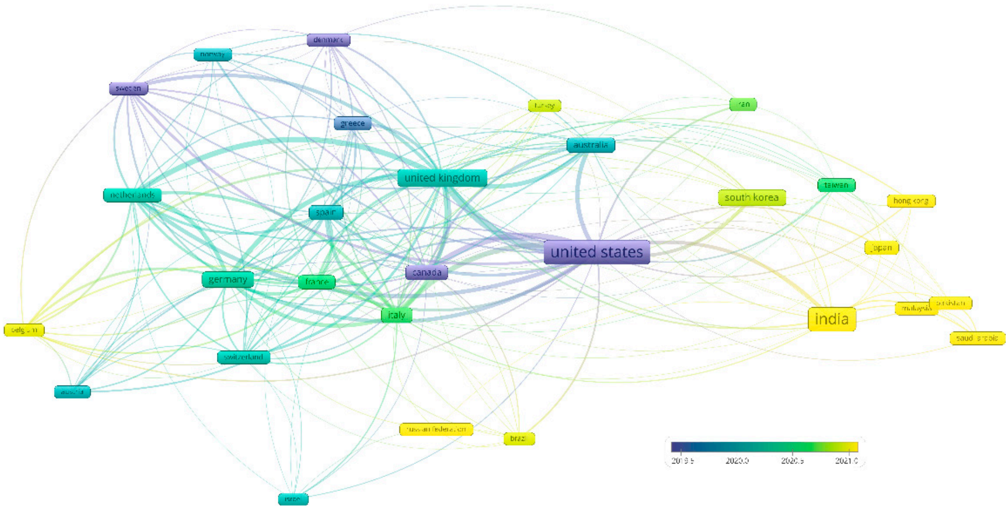

Figure 2. Country co-operation network.

3.1.5. Most Prolific Funding Bodies

Another important indicator of the research state of a scientific field/sub-field is the rate of research funding [23]. Our analysis showed that 37.0% of publications were funded, notably more than in many other fields [18]; however, less than in broadly comparable subfields, namely the use of AI in pediatrics, where 47.4% [24] and the use of AI in software engineering where 41.1% [25] were funded. The most productive funding sponsors, funding more than 20 publications, were the National Natural Science Foundation of China (n=96), the National Institutes of Health, USA (n=85), the Horizon 2020 Framework Programme, EU (n=28), National Key Research and Development Program of China (n=28), National Research Foundation of Korea (n=23), and National Science Foundation, USA (n=22). As expected, the majority of the most productive funding sponsors are from China and the United States of America. That is not surprising, considering that the USA is one of the countries spending the most on preventive health care [26], and China recently implemented a comprehensive health system reform with strong political and financial support [27].

3.2. Most Prolific Research Themes

Content analysis was performed using SKS Steps 3 and 4 and VOSViewer software, version 1.6.20 (Leiden University, Leiden, The Netherlands). According to Zipf's law, 79 authors' keywords are relevant enough to be used in SKS and, respectively, in content analysis, meaning that all keywords occurring ten or more times were included in the analysis. The author's keyword landscape is shown in Figure 3, and the synthesis of the results is shown in Table 3. Content analysis resulted in 8 themes (four from a computer science viewpoint and four from a medical point of view) and 21 Concepts (eight from a computer science viewpoint and 13 from a medical point of view).

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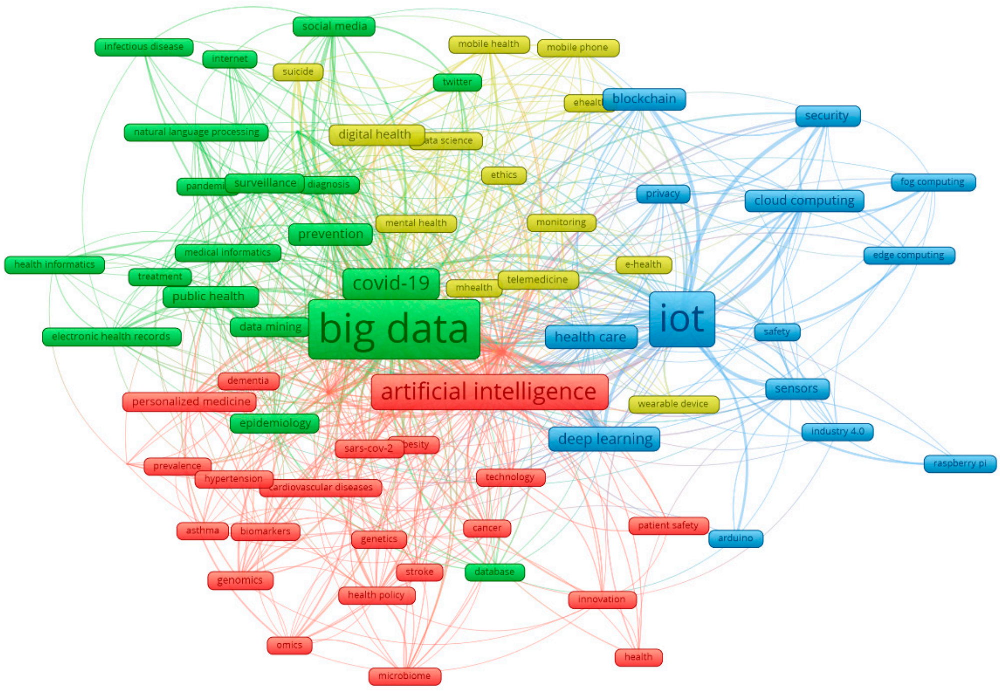

Figure 3. Author keywords landscape, including author keywords occurring ten or more times. Each coloured cluster presents a theme.

Table 3. The Concepts and Themes in IoT and BigD.

Cluster color (number of keywords)	**Representative author keywords (ICT viewpoint in upper cell / medical viewpoint in lower cell)**	**Concepts (ICT viewpoint in upper cell / medical viewpoint in lower cell)**	**Theme (ICT viewpoint in upper cell / medical viewpoint in lower cell)**
Red (n=26)	Artificial intelligence (n=206), Machine learning (n=205), Precision medicine (n=64), Personalised medicine (n=32), Risk prediction (n=31), Health policy (n=17),	-The use of artificial intelligence and Omics in personalized and precision medicine according to health policies; -The use of machine learning in risk prediction; -The role of personalized medicine in chronic disease management	The role of artificial intelligence in personal, precision, and preventive medicine

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	Artificial intelligence (n=206), Personalised medicine (n=32), Sars-cov2 (n=23), Cardiovascular diseases (n=20), Genetics (n=17), Genomics (n=19), Obesity (n=15), Asthma (n=15), Cancer (n=12), Dementia (n=11),	-Use of AI in the genetics and genomics of cardiovascular diseases, cancer, dementia, obesity, asthma -Investigating an individual's risk for the most common chronic diseases -Use of AI in Sars-Cov2 management	The role of AI in personalized medicine (genetics, genomics) in the field of the most common diseases of the modern population (cardiovascular diseases, dementia, obesity, asthma, sars-cov2, cancer)
Green (n=20)	Big data (n=494), Covid-19 (n=153), Prevention (n=52), Social media (n=33), Public health (n=43), Predictive analytics (n=33), Epidemiology (n=32)	-Big data mining of social media and electronic health records used in epidemiology, predictive analysis, and prevention; -Big data analysis in public health surveillance	The role of big data in public health
	Big data (n=494), Covid-19 (n=153), Prevention (n=52), Public health (n=43), Surveillance (n=29)	-Use of big data and databases in the field of public health -Use of databases in epidemiology -Planning and researching prevention and survival in covid19	The role of big data and databases in public health, especially in the field of prevention, epidemiology, and surveillance
Blue (n=14)	IoT (n=439), Deep learning (n=83), Health care (n=63), Cloud computing (n=49), Blokchain (n=48)	-IoT, Cloud Computing and deep learning, blockchain in secure and safe healthcare	The role of IoT, Cloud Computing, deep learning, and blockchain in secure and safe healthcare
	IoT (n=439), Deep Learning (n=83), Health care (n=63), Security (n=49), Sensors (n=38), Privacy (n=24)	-Application of deep learning and IoT in healthcare -Security and privacy of IoT and deep learning -Sensitivity of the sensors for the acquisition of IoT -Importance of sensors for deep learning	The role of IoT and deep learning in the security and privacy of health care

Yellow (n=13)	Digital health (n=39), Telemedicine (n=39), Mobile health (n=30), Monitoring (n=17), suicide (n=16)	-Mobile health and wearable devices in monitoring mental health; -Digital health use in telemedicine	The role of digital health in monitoring and Telemedicine
	Telemedicine (n=39), Digital Health (n=39), Monitoring (n=26), Mental health (n=15), eHealth (n=14), Ethics (n=12),	-Ethical aspects of digital health and telemedicine -Data monitoring for eHealth -Ethical aspects of monitoring an individual's mental health	The role of ethics in telemedicine and digital health

The role of artificial intelligence in personal, precision, and preventive medicine / The role of AI in personalized medicine (genetics, genomics) in the field of the most common diseases of the modern population (cardiovascular diseases, dementia, obesity, asthma, sars-cov2, cancer)

The use of artificial intelligence and Omics in personalized and precision medicine according to health policies

3 PM (Precision, preventive and personalized) medicine, in combination with omics, environmental data, and big data analytics, is one of the emerging approaches in modern public health, with vast implications for future health policy formulation [28]. It emerged as a response to epidemics of non-communicable diseases and suboptimal but still reversible health conditions [29], for example, sleep disorders [30], kidney injury, and diabetes [31].

The use of machine learning in risk prediction

Big data and machine learning have been used to predict the risk [32] of various diseases like stroke [33], coronary artery diseases [34,35], diabetes [36], COVID-19 [37], Breast cancer [38], and suicide [39]. Likewise, they were used in occupational medicine.

The role of personalized medicine in chronic disease management

The use of AI and big data in combination with mobile health has significantly increased and showed promise that it can considerably assist individuals and healthcare professionals in managing and preventing chronic diseases in the scope of a person-centered paradigm [40,41].

Use of AI in the genetics and genomics of cardiovascular diseases, cancer, dementia, obesity, asthma

Pathogenetic processes are most often the result of interactions between various environmental and genetic factors. The use of AI, based on available biological and clinical data sets, can contribute to greater accuracy in predicting the risk of developing the most common chronic diseases in a given person [42]. In addition, it is also widely used to aid in the diagnosis and prognosis of diseases, the optimization of treatment, and the development of new drugs [43]. In the pathophysiology of the diseases above, AI relies mainly on the emerging fields of molecular biology (genomics, glycomics, proteomics, lipidomics, and transcriptomics) [44].

Investigating an individual's risk for the most common chronic diseases

AI is essential for researching an individual's risk of developing chronic diseases. It refers to the network formed by the physical environment, human factors, technological devices, and health care quality. Studies show that AI is a promising tool for increasing patient safety, identifying and analyzing disease risk, and identifying errors in the clinical environment. However, it still requires human supervision and cannot fully replace the skills of clinical staff [45]. The strength of AI in risk identification is its ability to accurately and efficiently analyze vast amounts of data [46]. At the same time, AI serves as a critical tool to improve communication with patients and is part of supporting applications in the field of healthcare [47].

Use of AI in Sars-Cov2 management

Digital technologies utilizing smartphone sensors have been widely deployed to support the response to COVID-19, focusing on cooperation between big data analysts, telecoms, and public health authorities [48] to promote healthy lifestyles among the elderly [49], COVID-19 diagnosing management [50] and vaccination [51] and to enhance surveillance of zoonotic diseases [52].

The role of big data in public health/ The role of big data and databases in public health, especially in the field of prevention, epidemiology, and surveillance

Big data mining of social media and electronic health records used in epidemiology, predictive analysis, and prevention

Big data mining of real-world data [53–55] has been increasingly utilized in predictive epidemiology to manage epidemics [56], urban epidemiology control [57], or predicting Hospital-Induced-Delirium [58]

Big data analysis in public health surveillance

Digital epidemiology emerged as a novel discipline that employs Big Data Analytics and IoT to enhance traditional surveillance [59]. In addition to COVID.19 it has been used in response to infectious diseases in Bangladesh [60] and urban epidemiology control [57]. Influenza trend surveillance [61] and zoonotic disease response [52].

Use of big data and databases in the field of public health

AI has gained importance in public health and covers essential points: detection of diseases at an early stage of development, interpretation of disease progression, optimization of treatment regimens, and research into newer intervention strategies [62]. At the same time, big data analysis in public health involves collecting, processing, and analyzing large-scale data sets from heterogeneous sources, including electronic health records, social media, and portable devices. The latter provides insight into disease patterns, risk factors, health care, and population health trends [63]. At the same time, big data analysis [64]enables real-time monitoring of disease incidence, spread, and transmission patterns [64]; analyzing data from social media and mobile health applications provides insights into health-related behaviors and attitudes of residents. By understanding the population's health behaviors, policymakers can more easily design targeted health promotion campaigns [53,65].

Use of databases in epidemiology

AI and the databases based on it play an essential role in diagnosing and treating diseases and making it easier to control them during a pandemic. Databases are critical for epidemiology, as they enable the rapid control of infectious diseases, help implement and assess trends, track the source of infection and treatment of diseases, and develop vaccines and drugs [66]. This is important because the epidemiological picture of the disease is crucial for studying the distribution, pathogenesis, and spread of the disease [67]. At the same time, the databases enable the identification of demographic, environmental, genetic, and behavioral risk factors and help to develop predictive models for the assessment of the probability of an individual developing the disease [68,69].

Planning and researching prevention and survival in COVID-19

AI-enabled more effective disease control and prevention in the COVID-19 pandemic [66] based on passive (existing epidemiological data on the disease) and active surveillance (specific search for information on the disease) [70]. The information gathered through surveillance improved the efficiency and effectiveness of health services [71].

The role of IoT, Cloud Computing, deep learning, and blockchain in secure and safe healthcare/ The role of IoT and deep learning in security and privacy of healthcare

IoT, Cloud Computing, deep learning, and blockchain in secure and safe healthcare

Blockchain, mobile health, the Internet of Things, and other recent ICT technologies have been used to determine safe COVID-19 vaccination strategy, safe management of vaccination and provide

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safe and transparent vaccination certificates postvaccination surveillance [51,72] and to develop safe, dependable, and efficient Healthcare 4.0 applications [73].

Application of deep learning and IoT in healthcare

The primary task of IOT in healthcare is to make patients' lives easier by monitoring their health status. This facilitates the decisions of their attending physician [74]. IoT offers a wide range of applications in healthcare, including remote monitoring of the patient's health status, tracking of patient treatments, and administration of medication to patients [75,76]. In addition, IoT represents an important area of progress in nursing homes [77] and has great potential for improving the quality of health services and reducing costs based on early detection and prevention of diseases [78,79].

Security and privacy of IoT and deep learning

IOT-based deep learning is essential in bio- and medical informatics, as it enables the analysis and interpretation of large amounts of complex and diverse data in real-time. This can increase the efficiency of healthcare. Deep learning applications include diagnostics, treatment recommendations, clinical decision support, and new drug discovery [80].

Security and privacy IOT and AI applications are essential in disease self-management and remote patient health monitoring [81,82].

Sensitivity of the sensors for the acquisition of IoT

IoT can introduce new services and solutions in various applications [83,84]. This is possible through smart sensors that can assess the population's health. These have gradually emerged in public health as multiplexed biosensors and data acquisition systems with flexible substrate and body attachments for improved wearability, portability, and reliability. These sensors have the potential for early detection, diagnosis, and management of diseases. They enable real-time assessment of abnormal conditions of physical or chemical components in the human body [85].

Importance of sensors for deep learning

IoT and related deep learning refer to sensors that collect crucial patient health data. Various sensors are used to monitor health, including sensors for blood pressure, pulse, oxygen level, airflow, patient position, muscle and heart activity [86], breathing patterns, and glucose level [87]. This technology allows remote monitoring of patients in medical institutions and their home environment, thereby improving the quality of medical care and reducing costs [86]. In medical applications, sensors as part of machine learning were important in recognizing and assessing diseases (epilepsy, dementia, autism, stroke, depression, sudden cardiac arrest, Parkinson's disease [88]. As an integral part of IoT, medical sensors are the foundation of wireless sensor networks (WSN). Using them, healthcare professionals can continuously monitor patients' vital functions [87].

The role of digital health in monitoring and Telemedicine/ The role of ethics in telemedicine and digital health

Mobile health and wearable devices in monitoring mental health

The concept of intelligent health (iHealth) in mental healthcare integrates AI and Big Data analytics [89]. It was introduced in community mental health services [90], preventive mental health care [91], student mental health care prediction [92], or management of mental well-being [93].

Digital health use in telemedicine

COVID-19 has transformed the global healthcare infrastructure and triggered the transformation of healthcare into digital healthcare encompassing AI, Big data, telemedicine, robotics, IoMT, federated learning, computer vision and audition, blockchain, cloud and fog computing, and various other ICT technologies [40,94,95]. Recently, IoT and Big data Analytics augmented telemedicine has been used in the management of chronic obstructive pulmonary disease [96], sleep medicine [30], transgender healthcare services [97], and cardiac arrhythmia [98].

Ethical aspects of Digital Health and Telemedicine

Digitization is a global phenomenon that permeates professional and private life [99]. It lists three levels of e-health services: 1. general online services (provide advice, information, and guidance on health and social services), 2. various ordering services in social and health care (tracking personal data), and 3. digitized services (various video conferencing and remote services in education,

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diagnosis and provision of medical care). Telemedicine and e-health are the main e-environments in digitized healthcare [100]. [101]Kaplan the variety of newly introduced telemedicine services is an ongoing natural experiment, which also brings with it questions of legal and ethical aspects, such as the issue of privacy, accuracy, security, responsibility, availability, and transparency of data [102] and patient consent [63,103].

Data monitoring for eHealth

The expansion of knowledge and technical possibilities has brought greater digitization and automation of data exchange in health systems [104]. E-health technology, together with AI, has integrated with already existing health information and communication systems (electronic health records), which has brought many advantages: privacy, accuracy, security, responsibility, availability, and transparency of data [104]. These include, among others, improved interoperability [105], the possibility of data re-use [106], and improved decision support [107]. E-health has specifically developed technologically and enables the facilitation of health provision care at the patient's home, thereby moving away from traditional hospital environments using secure data collection [108].

Ethical aspects of monitoring an individual's mental health

Social concepts about what data is public and private, or medical and non-medical, do not have a precise boundary. Recommending the use of digital technology to patients with mental illness may inadvertently cause harm. [109]. E-mental health presents more opportunities in mental health care, especially in pandemic situations. However, its effectiveness and efficiency must be evaluated for its inclusion in the health service system as part of routine mental health care [110]. AI can offer innovative means to support the management of mental health problems and improve its quality [111]. The ethical issue of AI in the field of mental health mainly involves data ownership and obtaining informed consent from patients [112].

3.3. Timeline of the Recent Research and Seminal Publications

Among the seminal papers, the first that should be mentioned is the Lebniz paper published in 1671, in which he develops ideas regarding the development of new medical knowledge using an empirical and experimental approach and discusses public health [113]. The following two influential papers, published about 350 years later, in 1920 and 1953, dealt with public health [114] and observation and experimentation in medicine [115]. The two remaining seminal papers deal with epidemics analysis, first presenting its mathematical theory [116] and the second, published in 2019, on employing computer science and informatics in preventive medicine to detect influenza epidemics [117].

Historically (Figure 4), the use of big data and IoT in preventive medicine started with more traditional ICT technologies like data mining/science, Internet, Twitter, mobile health, telemedicine, personalized medicine, and genomics in managing chronic diseases. In the next phase, cloud and fog computing, data mining/science, natural language processing, and more advanced social media were used for predictive analytics, management of incestuous diseases, preventive medicine, epidemiology, and similar. In the most recent period, digital health and advanced sensors and AI and machine learning are used in health policy-making, epidemic prevention, prognosis, and surveillance.

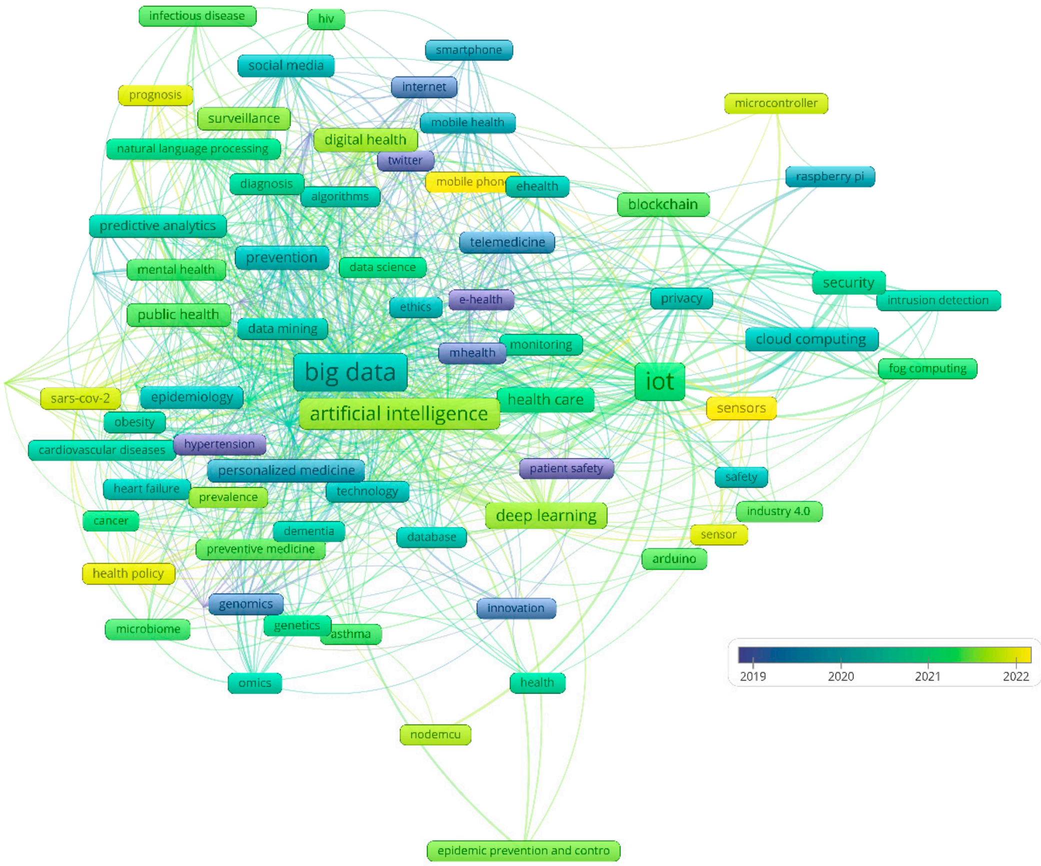

Figure 4. Timeline keywords landscape, including authors' keywords occurring ten or more times.

3.4. Hot Topics and Future Research Directions

Some interesting hot spots were identified by comparing different time slices in the research landscape. The Internet of Medical Things is used in occupational safety monitoring [118], in rapid diagnostic of viral respiratory infections [119], and in precision medicine [120]. In combination with federated learning, it is used for handling privacy-sensitive medical data [121], analyzing wireless long-tailed data [95], and smart healthcare [122]. IoT and Big data collected from smartphones in combination with machine learning and AI are used to improve the management, diagnosis, and treatment of high-prevalence diseases like hypertension [123], dementia and cognitive impairment [124] or sleep disorders [125], trends analysis [126], injury prevention [127] and how to solve privacy [128] and safety issues [129].

3.5. Research Gaps and Challenges

The heterogeneous nature of equipment and devices involved in the use of Bigdata and IoT in preventive medicine [130] posed several challenges:

- Cyber security threats and managing trust: Healthcare data poses excellent security and privacy risks, but adding IoT and big data significantly increases the risk of exposure [131].
- Regulatory challenges: Clinical-grade medical devices need approval and clearance from various regulators, which can present new challenges for the regulatory and legislative bodies [132].
- Interoperability of data and Standardization issues: To obtain meaningful and clinically relevant decisions from data collected from the various IoMT devices, all IoMT devices and big data algorithms must be interoperable [133].
- High infrastructure costs: IoT and big data software/hardware systems require a high initial investment that might act as a barrier to IoMT [134].

- Strain on Existing Networks: Many current health institutions' networks are neither secure nor robust enough to operate the new IoMT/big data platforms [135]
- Scale: While IoMT/big data is becoming increasingly popular in preventive medicine, ensuring future growth scalability and broader adoption might be problematic [136].

3.6. Study Strengths and Limitations

This article brings particular strengths and limitations. The first strength is that the article is based on the Scopus database, one of the largest databases of peer-reviewed literature and offers a more extended period of published literature. At the same time, the article combines the computer and medical aspects of IoT and big data in preventive medicine, with its findings significantly contributing to the application of this knowledge in practice. Another strength of the article is the use of SKS, considered a proven knowledge synthesis method and offers a holistic view of knowledge development's thematic, spatial, and historical aspects.

On the other hand, the article also has certain limitations, of which we must mention the qualitative and consequently subjective interpretation of the results obtained with SKS. One of the limitations is that only the Scopus database was included in the study, so there is a possibility that part of the literature in the field under consideration was not considered.

4. Conclusions

Our study presented a holistic and interdisciplinary synthesis of the evidence published in the research literature regarding the use of IoT and BigData in preventive healthcare. The field of preventive healthcare has recently experienced strong and fast development. Big data health databases, especially electronic health records, provide a wide range of data about patients and diseases and provide a basis for health policymakers. Especially epidemiology, where the monitoring and prediction of infectious diseases require fast, reliable, and concrete decisions based on information stored in various health and health-related databases, social media, and other evidence that can be supported with deep learning and IoT. Medical sensors and wearable devices are an integral part of the IoT, enabling continuous monitoring of patient functions and their treatment remotely. As shown in our paper, IoT, Big data, and machine learning under the umbrella of artificial intelligence can support decision-making in personalized and precision medicine, risk prediction in both treatment and risk takings of populations and individual patients, genomic and other omics, chronic diseases management, epidemics prediction and management, and public health surveillance and monitoring. From the information technology point of view, the Internet of Medical Things, Cloud computing fog computing, and deep learning are prevailing technologies. At the same time, it is good to notice that much research also deals with the security, privacy, and ethical problems associated with using advanced information technologies in healthcare.

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