

Artificial Intelligence and Public Health Research: A Systematic Literature Review

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Submitted to: JMIRx Med
on: October 12, 2025

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Artificial Intelligence and Public Health Research: A Systematic Literature Review

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Abstract

Artificial intelligence (AI) is set to transform various aspects of our lives, particularly in the field of public health. In recent years, there has been a notable increase in research at the intersection of AI and public health. This study aims to investigate the application of AI in public health, its impact on this field, and future research directions related to AI and public health. We conducted a systematic literature review to examine research in this area. Our findings indicate that studies can be categorized into five thematic clusters: AI model development, public health threats and outbreaks, systematic reviews, social and ethical issues in public health, and a cluster focusing on governance, policy, and innovation. Furthermore, we identified gaps in the existing literature and highlighted areas for future research.

(JMIR Preprints 12/10/2025:85709)

DOI: <https://doi.org/10.2196/preprints.85709>

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Original Manuscript

Artificial Intelligence and Public Health Research: A Systematic Literature Review

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Artificial Intelligence and Public Health Research: A Systematic Literature Review

Abstract

Artificial intelligence (AI) is set to transform various aspects of our lives, particularly in the field of public health. In recent years, there has been a notable increase in research at the intersection of AI and public health. This study aims to investigate the application of AI in public health, its impact on this field, and future research directions related to AI and public health. We conducted a systematic literature review to examine research in this area. Our findings indicate that studies can be categorized into five thematic clusters: AI model development, public health threats and outbreaks, systematic reviews, social and ethical issues in public health, and a cluster focusing on governance, policy, and innovation. Furthermore, we identified gaps in the existing literature and highlighted areas for future research.

Keywords: Artificial Intelligence, Public Health, Systematic Literature Review, Themes

1. Introduction

Artificial intelligence (AI) has revolutionized the global economy. The latest advances in artificial intelligence suggest that it will impact almost everything we do in the next few years. It is expected that artificial intelligence will change the field of healthcare and public health, in general. According to the U.S. Congressional Research Service [1], "The application of artificial intelligence (AI) in health care settings has become more pervasive due to recent increases in the availability of health care data and innovations in big data analytical methods. When properly trained on relevant clinical data, AI technologies may identify pertinent information from voluminous data, potentially allowing for the rapid improvement of clinical decision-making." What applies to healthcare also applies to public health. This is supported by Panteli et al. [2], who assert that AI can be utilized in various areas of public health, such as surveillance, epidemiological research, communication, and resource allocation.. They confirm the AI has the potential to revolutionize public health practice and research, as long as accompanying challenges are addressed. Giansanti [3] in their editorial on AI in public health predicted that research in this area is strategic to the development of health systems and is inextricably linked to progress in digital health. Moreover, this research will play a leading role in the future. Benke and Benke [4] argue that a deeper understanding of AI and big data is necessary for public health and policy development.

The application of AI has significantly impacted public health, yet there remains a limited understanding of its role in transforming research within this field. Many important questions about AI's integration into public health studies remain unanswered. For example, what are the major research themes? Which methodologies are most used in AI and public health research? Who are the leading researchers in this area? Which journals publish the most studies on AI and public health? A review of the existing literature in this domain, particularly focusing on the integration of AI technologies and the ethical, regulatory, and environmental implications they bring, could help address these questions [3].

However, current literature reviews typically employ traditional review methods, which often limit their literature searches to a handful of prestigious journals, introducing data selection bias. Additionally, these reviews tend to focus on research topics selected based on the reviewers' interests [4,5]. These issues can be mitigated by employing the Systematic Literature Review (SLR) methodology, which offers scientific rigor and a systematic approach to the literature review process [6].

SLR provides several advantages over traditional literature reviews. By treating the literature review as a scientific process in empirical research and adhering to rigorous review protocols, SLR can reduce bias in the design of the review process [7]. Furthermore, SLR aims to include all relevant literature pertaining to the research questions, resulting in broader coverage and eliminating selection bias compared to traditional methods [8]. To create a more comprehensive picture of AI-related

public health research, our approach also incorporates content analysis, bibliographic analysis, and meta-analysis alongside the SLR process. In contrast, the few SLR studies conducted in this field predominantly rely on qualitative interpretations and a narrative format for their analysis [9].

In this paper, we address the need for research in the area of artificial intelligence (AI) and public health by conducting a systematic literature review. We focus on the various aspects of AI that have been studied in public health research, the areas that have been impacted by AI, and the future directions for its adoption and integration in public health.

Our paper is organized as follows: In the next section, we present a theoretical framework along with our research questions and a justification for using a systematic literature review. We then detail the materials and methods used in our study, followed by an analysis of the performance of AI in public health research. Finally, we conclude with a discussion of our findings and a summary of our overall conclusions.

2. Theoretical Framework

We have introduced the significance of studying artificial intelligence (AI) within the field of public health. In this section, we will review the existing literature on this topic and discuss the need for a systematic literature review (SLR) focused on AI and public health. Literature reviews are a common method used to understand the current state of research in a specific domain [7]. Some of these reviews offer an overview of studies within specific areas, such as digital health, while others focus on research from particular countries or continents. Additionally, some reviews target specific health conditions. Examples of literature examining digital health include studies on online information-seeking behavior [10], the use of social media platforms for public health initiatives [11], and the impact of digital data sources on public health [12]. Studies have been conducted in various regions of the world, including the Middle East and North Africa [13], Thailand [14], and Africa [15]. Literature reviews that have examined specific health conditions include studies on anxiety and depression [15], chronic diseases [16], mental health [17], and dentistry [18], to name a few. While several studies have examined digital health, specific regions, and particular diseases and conditions, a comprehensive review of all research related to AI and public health is still lacking in the existing literature. To address this gap, we propose the following research questions for this study.

2.1 Research Questions

In this study, we aim to explore the broader question of how artificial intelligence (AI) tools and techniques have been integrated into public health, particularly in the realms of healthcare and health policy. We would like to address the following research questions:

RQ1: What aspects of AI have been studied or utilized in public health?

RQ2: What areas of public health have been impacted by the adoption of artificial intelligence tools and techniques?

RQ3: What are the future directions for the application of AI in public health?

There are some subtle distinctions between the research questions presented above. In RQ1, we focus on the AI tools and techniques employed in public health. RQ2 emphasizes the specific areas of public health that have been influenced by advancements in artificial intelligence. Finally, RQ3 explores potential future directions for the application of AI in public health.

2.2 Overview of Systematic Literature Reviews (SLR)

The Systematic Literature Review (SLR) is a structured process that applies rigorous research protocols to collect, review, analyze, and present evidence from the literature aimed at answering specific research questions [19,20]. Unlike traditional literature reviews, SLRs offer enhanced replicability, reliability, and transparency [21,22].

SLRs have been utilized across a wide range of research domains, including information systems and public health. In the realm of information systems research, Anderson et al. [23] adopted the SLR framework proposed by Vom Brocke et al. [24] along with content analysis to identify research themes from case-based learning (CBL) and cybersecurity leadership education. Their goal was to

understand how CBL could contribute to developing often overlooked elements in cybersecurity leadership education. Laine et al. [25] applied the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) framework as developed by Moher et al. [26], to analyze information systems literature on AI auditing, focusing on the contributions of ethics-based AI auditing from the perspectives of various stakeholders. Additionally, Altrichter and Benoit [27] utilized Palmatier et al.'s [28] SLR procedure to create a technology discontinuance framework that distinguishes technology discontinuance from related concepts and various types of technology discontinuance.

SLRs have also proven effective for exploring numerous topics in public health research. For instance, Mustapha et al. [29] followed the PRISMA framework [26] to evaluate the impact of Industry 4.0 on healthcare systems using cross-disciplinary literature. Khanra et al. [30] employed a three-stage SLR protocol [31,32] to investigate the applicability of big data analytics (BDA) in healthcare from five distinct perspectives. Furthermore, Pinto et al. [33] applied the SLR framework by Kitchenham and Charters [34] and Petersen et al. [35] to analyze variables and technologies relevant to the impact assessment of public health campaigns.

Numerous methodological guidelines have been developed to conduct systematic literature reviews (SLRs), including the Systematic Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) protocols [36], recommendations for literature searches by Vom Brocke et al. [24], the PRISMA guidelines [26], Kitchenham's [37] procedures for SLRs, and the Search, Appraisal, Synthesis, and Analysis (SALSA) framework [38]. For this study, we chose to follow the SPAR-4-SLR protocol because it provides comprehensive coverage of the entire SLR process. In contrast, frameworks like Vom Brocke et al.'s [24] and SALSA focus only on specific stages of the SLR process. Compared to other popular frameworks such as PRISMA, SPAR-4-SLR also offers more detailed requirements and justifications for each stage [36,39]. Additionally, it is applicable across multiple disciplines, unlike Kitchenham's [37] framework, which is primarily based in the software engineering context.

SPAR-4-SLR consists of three major stages: assembling, arranging, and assessing. The assembling stage is further divided into two steps: identification and acquisition. In the identification step, SLR researchers must first define their research questions and then establish the scope of the SLR based on these questions. During the acquisition step, researchers create the literature search formula by specifying the time period, keywords, and databases to be used for the literature search.

The next stage is arranging, which is also divided into two steps: organization and purification. In the organization step, reviewers code the retrieved papers based on various characteristics such as the number of citations, research methods, article types, and data types. This process is often guided by an organizing framework, like Theory, Context, Characteristics, and Methodology (TCCM) [36]. In the purification step, the initial set of literature is screened using predefined inclusion and exclusion criteria.

The final stage is assessing, which consists of evaluation and reporting. In the evaluation step, analysis methods such as bibliographic analysis, topic modeling, clustering, and meta-analytical analysis are defined according to the type of SLR and then applied to assess the review articles. In the reporting stage, SLR researchers identify research gaps in the domain that could inform future studies, as well as best practices for academic researchers, industry practitioners, and policymakers. This step highlights the practical and theoretical contributions of the SLR research.

3. Materials and Methods

The Web of Science database was utilized to search for articles on the intersection of artificial intelligence and public health. A general search using these search terms returned 4273 articles. The search was restricted to the years 2021-2025. We restricted our search to these years because the use of artificial intelligence experienced a significant surge after the release of generative AI tools, such

as ChatGPT, in 2022. Articles before this time were not relevant to our study. A copy of the search terms used is provided in Appendix 1.

We restricted the Web of Science categories to those listed in the search query provided in Appendix 1. The search was conducted on September 18, 2025. The search query returned 2071 articles. We followed the protocols outlined in “Systematic Procedures and Rationales for Systematic Literature Reviews” (SPAR-4-SLR). Details are provided in Figure 1.



JMIR Publications	Assembling	Identification ● Research questions – What aspects of AI have been studied or utilized in public health? What areas of public health have been impacted by the adoption of artificial intelligence tools and techniques? What are the future directions for the application of AI in public health? ● Domain – Artificial Intelligence and Public Health ● Source Type – Articles and Review Articles and early access ● Source quality – Web of Science (WoS) – Only used peer-reviewed journal	Dasgupta et al
		Acquisition ● Search mechanism and material acquisition – Web of Science (WoS) ● Search Period – January 2021 to August 2025 ● Search Keywords - "Artificial Intelligence and Public Health" (Topic) ● Publication titles – All refereed publications in the WoS database restricted to 17 categories	
	Arranging	Organizing ● Organizing codes: Bibliometric analysis using keywords	
		Purification ● Article type excluded: No articles were excluded.	
	Arranging	Evaluation ● Total documents for analysis – 2071 documents ● Performance analysis – Analysis of publication and citation trends, top countries, publications, and authors; Topic modeling using bibliographic coupling, cluster analysis, and keyword co-occurrence analysis ● Software – Microsoft Excel, VOSviewers	
Figure 2	: Overview of the SLR and bibliometric analysis: The SPAR-4-SLR [36] protocol with details		
3. Results	Study	Reporting ● Convention – Figures, graphs, and tables ● Limitation – Accuracy and completeness of document data in WoS and scope of the bibliometric analysis ● Sources of support – No financial support received	

Artificial Intelligence is a rapidly evolving field that has garnered significant interest, as evidenced by the rising volume of research publications. The number of publications increased from 213 in 2021 to 659 in 2025, reflecting this growth. After a slow start in 2021 and 2022, there was a noticeable surge in publications from 2023 to 2025, with 400, 576, and 659 publications released in those respective years. This upward trend in the number of publications is illustrated in Figure 2 below.

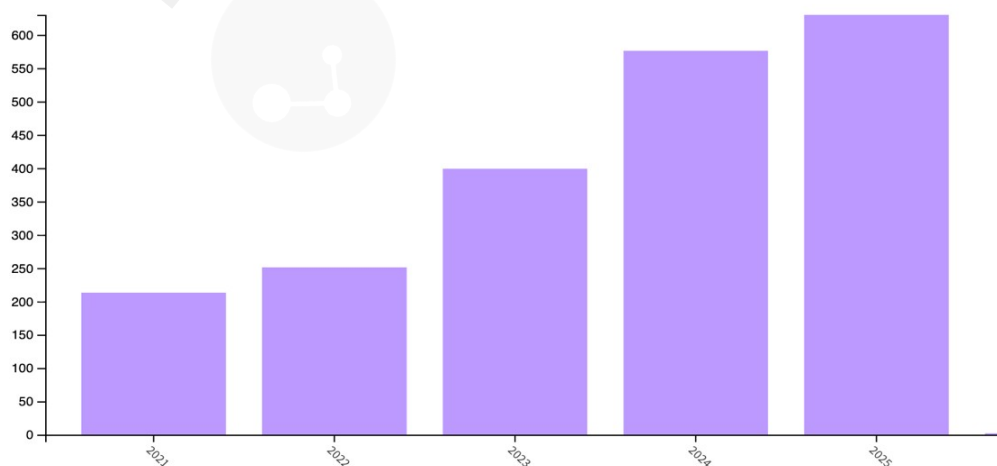


Figure 2: Number of Publications by Year

While the number of papers has increased, so has the number of citations. Table 1 below provides details of the publications by year, along with the number of citations. There has been a significant increase in recent years. As shown in Figure 3, the number of citations has increased dramatically since 2023. This also reflects the increasing interest in the field of AI.

Year	Publications	Citations
2021	231	371
2022	252	1739
2023	400	4408
2024	576	8945
2025	659	10799

Table 1: Publications and Citations by Year (Updated: September 27, 2025)

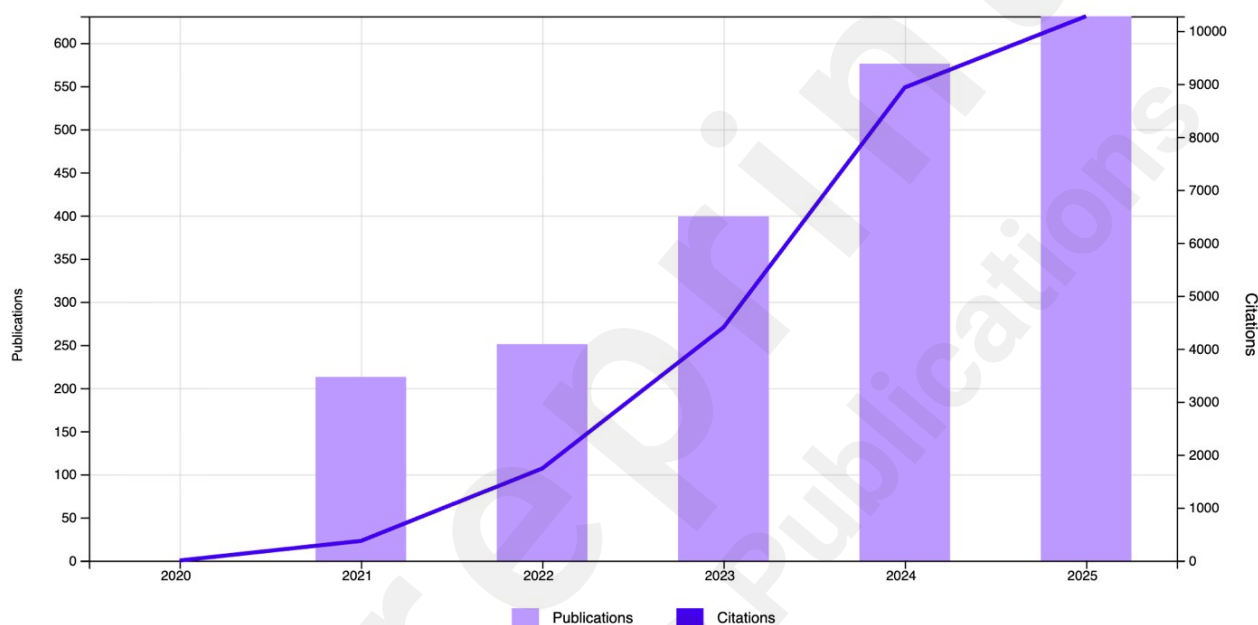


Figure 3: Number of Publications and Citations

In addition to the increase in the number of papers published from 2021 to 2025, it is also important to determine which countries are at the forefront of research in the area. Figure 4 below illustrates the number of publications by country from 2021 to 2025. The United States has the highest number of publications, totaling 586, which accounts for 27.9% of all publications. China follows with 364 publications (17.3%), England with 240 (11.4%), India with 191 (9.1%), and Australia with 152 (7.2%). Canada is also notable, contributing 147 publications (7%). Together, these six countries represent 79% of all publications during the five-year period analyzed in this study. The countries with the highest numbers are the Western developed nations, such as the U.S.A., England, Australia, and Canada, as well as countries that are strong in emerging computer and information technologies, including China and India. Additionally, publications related to artificial intelligence and public health can be found globally. The figure below displays the number of publications by country.

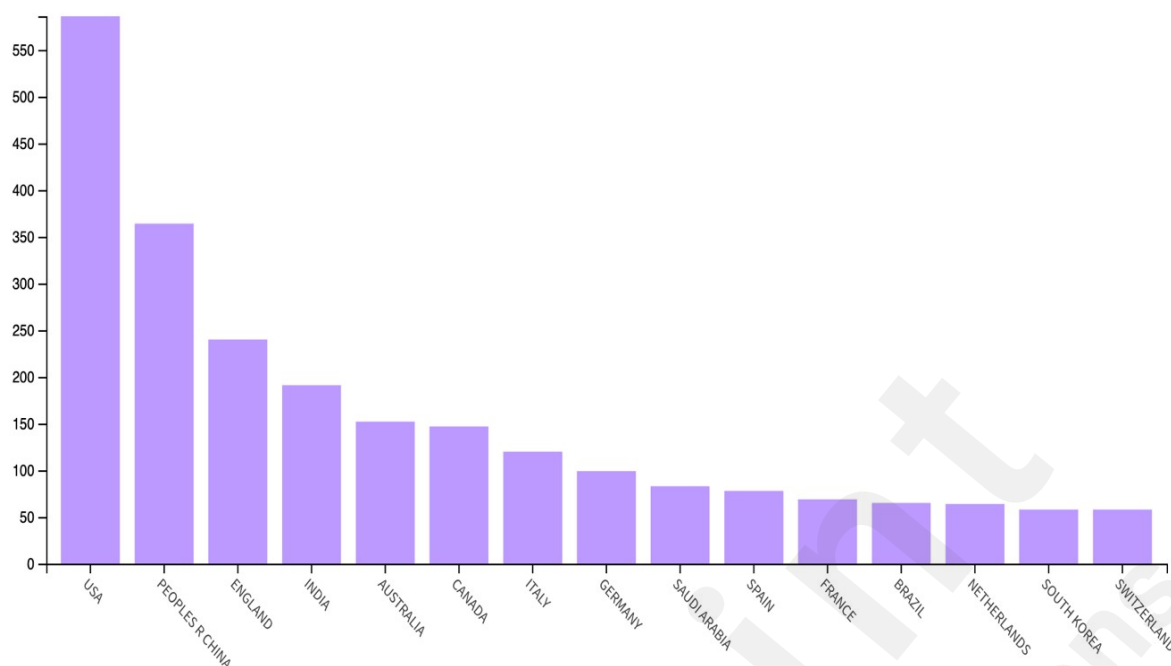


Figure 4: Publication by Country

After analyzing the number of publications in AI and public health by country, it would be interesting to explore the data at a more detailed level by examining the number of publications by institution. Figure 5 below displays the top 10 institutions with the highest number of publications in this field.

Harvard University and its medical affiliates, including its medical school, lead the list with a total of 149 publications. The University of London follows with 86 publications. The University of California system has reported 63 publications, while the University of Toronto has 38. Two other institutions from London, University College London and Imperial College London, have 35 and 38 publications, respectively. Finally, the list of top institutions is rounded out by Johns Hopkins University and the National University of Singapore, both of which have 33 publications each.



Figure 5: Publication by Institution (Tree chart)

Now that we have examined the research output of institutions in the field of AI and public health, we can review the most prolific researchers in this area. The list of researchers and the number of academic publications is provided in Figure 6 below. Since this is a new, evolving field, the number of articles published by our leading author is nine.

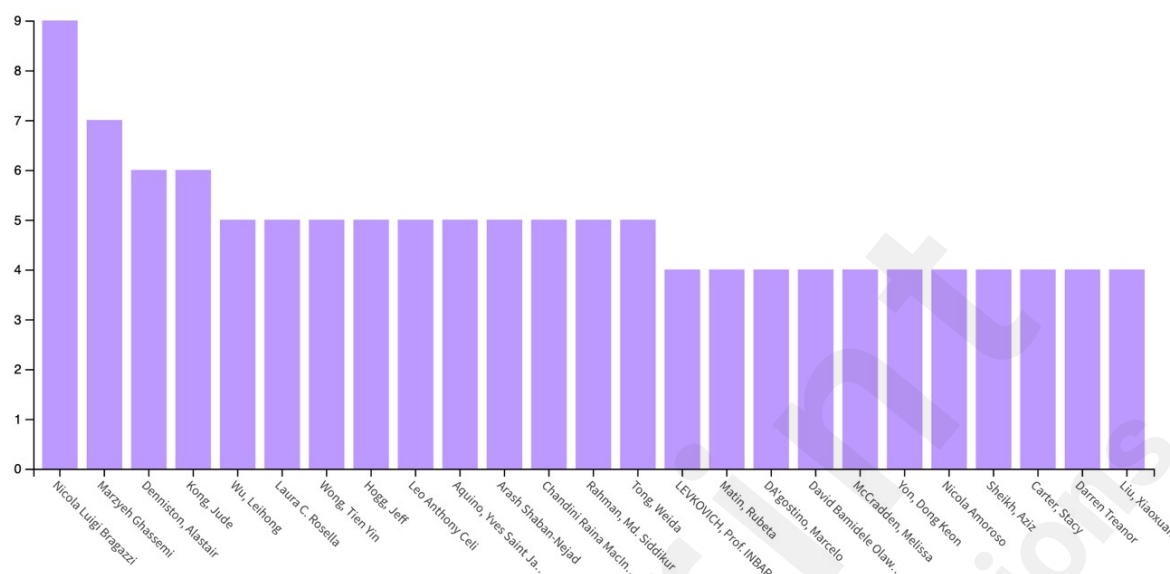


Figure 6: Publication by author

Next, we examine the common research areas in the field of AI and public health. As illustrated in Figure 7, studies have primarily concentrated on five key areas: healthcare sciences and services, public environmental and occupational health, medical informatics, general internal medicine, and science and technology-related topics. These research domains account for 1,900 of the 2,071 articles included in our study.



Figure 7: Research areas tree map chart

In this section, we have presented the results of our performance analysis of AI in public health research. We reviewed the annual number of publications for the past five years, the increasing number of citations, publications by country, publications by leading authors in the field, and main topics of study. In the next section, we present a co-occurrence network analysis of keywords.

4. Analysis and Results

4.1 Co-occurrence network analysis of keywords

We utilized VOSViewer to analyze articles and conduct a co-occurrence network analysis of keywords, titles, and abstracts. This analysis involves creating a keyword co-occurrence network (KCN) to represent a collection of texts. In this network, keywords are treated as nodes or points, and a line is drawn between keywords that frequently appear together (known as co-occurrence) within a specified unit of text, such as a document or a sentence. The frequency of this co-occurrence—often referred to as the strength—determines the weight of the link between the keywords. The first map (Figure 8) is a co-occurrence map or visualization that shows how keywords group together into thematic clusters based on their frequency of co-occurrence across all WoS records.

The structure of the network reveals patterns, connections, and the underlying knowledge framework of the text [40]. This technique is commonly used in systematic literature reviews and bibliometric analyses.

As mentioned in the previous sections, we had a dataset of 2071 articles that we considered for this analysis. We used a keyword occurrence threshold of 25, which means that a keyword had to appear at least 25 times in the entire dataset for it to be considered in our analysis. There were 572 such terms in the dataset. A higher threshold was necessary according to KCN analysis because we had a large number of articles in our dataset. We limited weighted links between keywords to 200. The network visualization in VOSViewer shows that there are 4 clusters that include 194 items. These clusters include 12,484 links with a total link strength of 57,820.

Figure 8 displays a map illustrating the co-occurrence of keywords, revealing stable thematic clusters that form the structural backbone of the research landscape. The subsequent map, Figure 9, presented in the next section, illustrates the evolution of these themes over time. For instance, trending topics such as LLMs, ChatGPT, and governance are relatively new. Together, these maps highlight both the existing themes and the direction in which the field is evolving.

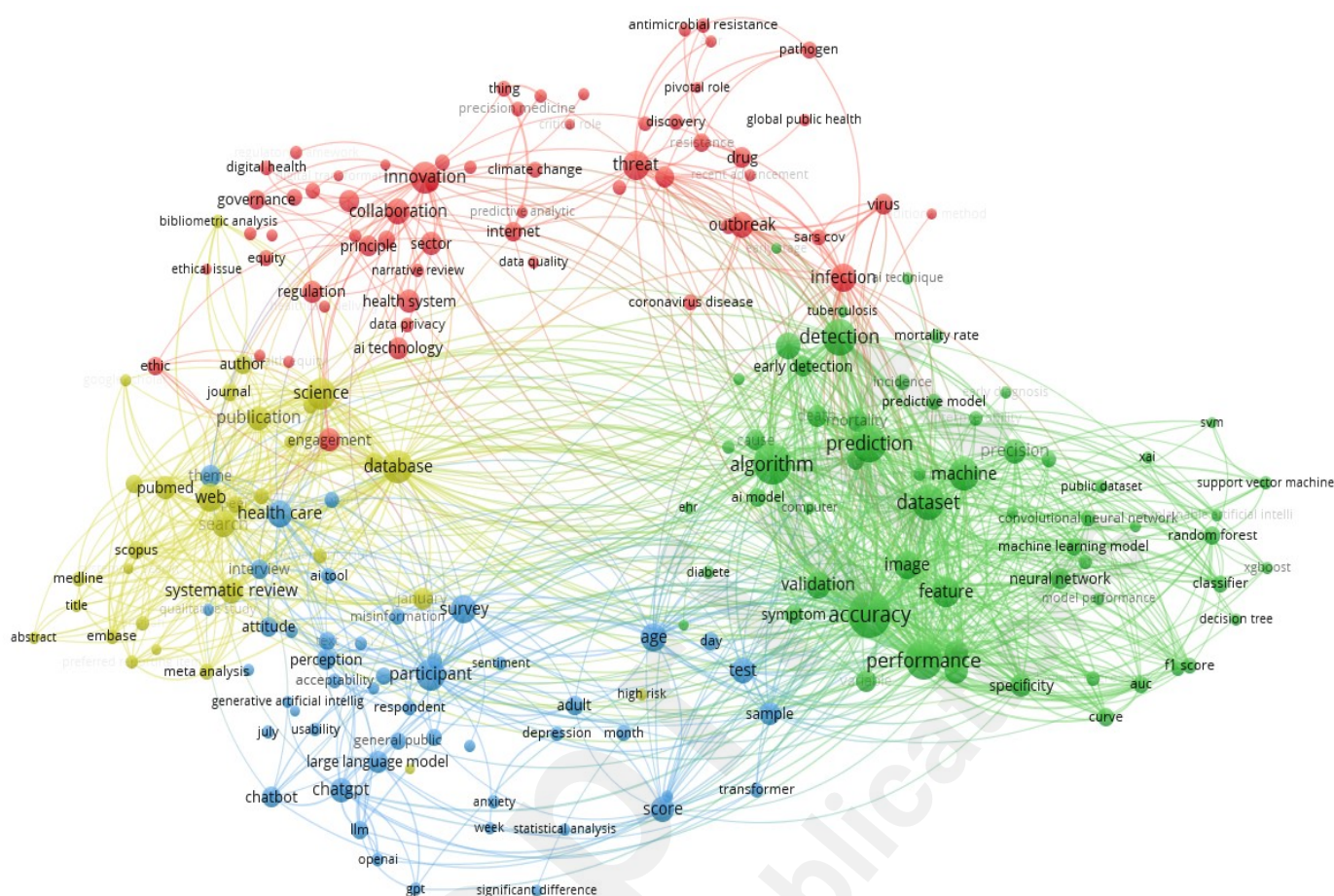


Figure 8: Co-occurrence Analysis of Keywords

The co-occurrence analysis of keywords from the WoS records revealed five major thematic clusters in the application of artificial intelligence (AI) to public health. They are identified using different colors in Figure 8, and they are listed in Table 2.

Cluster 1, represented by the green cluster, is the technical backbone of the field. It emphasizes algorithms, datasets, and performance metrics, including neural networks, random forests, decision trees, and support vector machines. This cluster comprises 60 keyword items, highlighting research focused on model development, validation, and accuracy in diagnostic and predictive tasks. Some papers within this cluster have explored hybrid models for the prevention and monitoring of infectious diseases [41], predicting COVID-19 infections using machine learning [42], and a novel machine learning model for predicting multiple unplanned hospitalizations [43]. All papers in this cluster share a common theme: AI models and algorithms.

The red cluster, referred to as Cluster 2, consists of 61 keywords and focuses on public health threats and outbreaks. It is closely related to terms such as outbreak, virus, tuberculosis, antimicrobial resistance, and drug discovery. This cluster illustrates how artificial intelligence (AI) has been utilized in epidemiological monitoring and the detection of infectious diseases. Several representative papers within this cluster address public health threats and outbreaks. For instance, McKee et al. [39] provide a guide for health professionals on how to use AI in response to future pandemics. Some studies even concentrate on the application of specific tools, such as ChatGPT, for medical knowledge [44]. It is not surprising that many studies discuss the use of AI during and after

the COVID-19 outbreak across various regions of the world.[45–50]

Cluster 3, represented by the yellow cluster, includes 29 keywords. This cluster focuses on systematic reviews, databases, and bibliometric evidence, linking healthcare applications with large scientific databases such as PubMed, Scopus, Medline, and Embase, as well as meta-analytic approaches. Several studies are present within this cluster. The systematic literature review (SLR) methodology is utilized to explore topics such as the impact of artificial intelligence on health disparities related to income [51], self-administered interventions derived from natural language modeling [52], and proactive health management strategies [53]. However, since this cluster primarily consists of methodology-based research, it does not address research in the field of AI and public health, nor does it provide answers to our research questions.

The blue cluster, or cluster 4, has 42 keywords. It captures the social and ethical issues in public health. It includes participants, surveys, and public perception, including emerging terms such as ChatGPT, large language models (LLMs), and usability. This reflects a growing strand of research into the acceptability, trust, and ethical use of AI-driven tools among patients and the public. For example, Mlakar [54] studied the expectations, attitudes, and ethical acceptability of humanoid robots in nursing. Another study employed machine learning techniques for mental health monitoring using wearable devices and smartphones [55]. All these papers have a common focus – they examine the social and ethical issues related to AI and public health.

Finally, a red–yellow intersection cluster (cluster 5) emphasizes governance, policy, and innovation, with terms such as governance, equity, regulation, and digital health. This cluster shows how ethical, legal, and policy issues intersect with technical and clinical adoption of AI. There are several papers on governance, both for AI [56] and data [57]. There are papers that examine innovations [58], opportunities and barriers to digital health [59], and interventions for depression in low and middle-income countries [60]. These papers show that AI in public health is an emerging field. There are issues of governance, equity, and regulation that still need to be resolved. More importantly, the field is changing faster than governance and regulation can keep up with.

The overlay visualization further highlights the temporal dimension of these themes. Earlier research, prior to 2023, was more closely associated with systematic reviews, databases, and traditional machine learning methods. More recent work, from 2024 onward, is increasingly focused on LLMs, such as ChatGPT, and governance-related concerns. These findings suggest that the field has evolved from building and validating predictive models to evidence synthesis and bibliometrics, and is now moving toward addressing the social, ethical, and governance challenges of AI in healthcare.

The bibliometric co-occurrence network revealed four distinct thematic clusters and one intersection cluster of research on AI and public health. Below is a summary of each cluster (with representative keywords) followed by a narrative synthesis.

Cluster Number	Cluster	Key Terms	Focus
1	Green Algorithms, Models, and Performance	algorithm, dataset, prediction, accuracy, performance, machine, neural network, convolutional neural network, random forest, decision tree, support vector machine, f1 score, specificity	Development and evaluation of AI/ML models for diagnostics, classification, and health-related predictions.
2	Red – Public Health Threats & Outbreaks	outbreak, threat, virus, SARS-CoV, coronavirus disease, detection, tuberculosis, antimicrobial resistance, pathogen, drug discovery, global public health	Application of AI in epidemiology and infectious disease surveillance, outbreak detection, and global health threats.

Cluster Number	Cluster	Key Terms	Focus
3	Yellow Systematic Reviews, Databases, Evidence and	systematic review, meta-analysis, healthcare, PubMed, Scopus, Medline, Embase, publication, science, journal	Evidence-based research foundations, systematic reviews, bibliometrics, and meta-analyses of AI in healthcare.
4	Blue – Social and Ethical Issues in Public Health	participant, survey, perception, acceptability, chatbot, ChatGPT, large language model, LLM, GPT, OpenAI, usability, respondent, general public, anxiety, depression	Engagement and perception of AI by patients, participants, and the public, with focus on LLMs, chatbots, usability, and trust.
5	Red-Yellow Intersection Governance, Policy, and Innovation	innovation, collaboration, governance, equity, regulation, ethical issue, health system, data privacy, AI technology, digital health	Ethical, legal, and social implications of AI in healthcare, emphasizing governance, equity, privacy, and innovation.

Table 2: Main Thematic Clusters after Co-occurrence Analysis

Here are a few additional insights from the thematic cluster analysis.

- Technical methods (green, cluster 1) are strongly connected to disease/outbreak applications (red, cluster 2). This shows AI's important role in public health surveillance and diagnostics.
- Systematic reviews & evidence synthesis (yellow, cluster 3) form the foundation for how knowledge is validated in the field.
- Social and ethical issues in public health (blue, cluster 4) is a newer but fast-growing area that highlights concerns about the acceptability, trust, and usability of AI in health.
- Governance/innovation (red/yellow mix, cluster 5) emphasizes how policy, ethics, and regulation increasingly interact with the deployment of AI. This is another important area of AI and public health.

Next, we present an overlay visualization of AI and public health.

5.2. Overlay Visualization

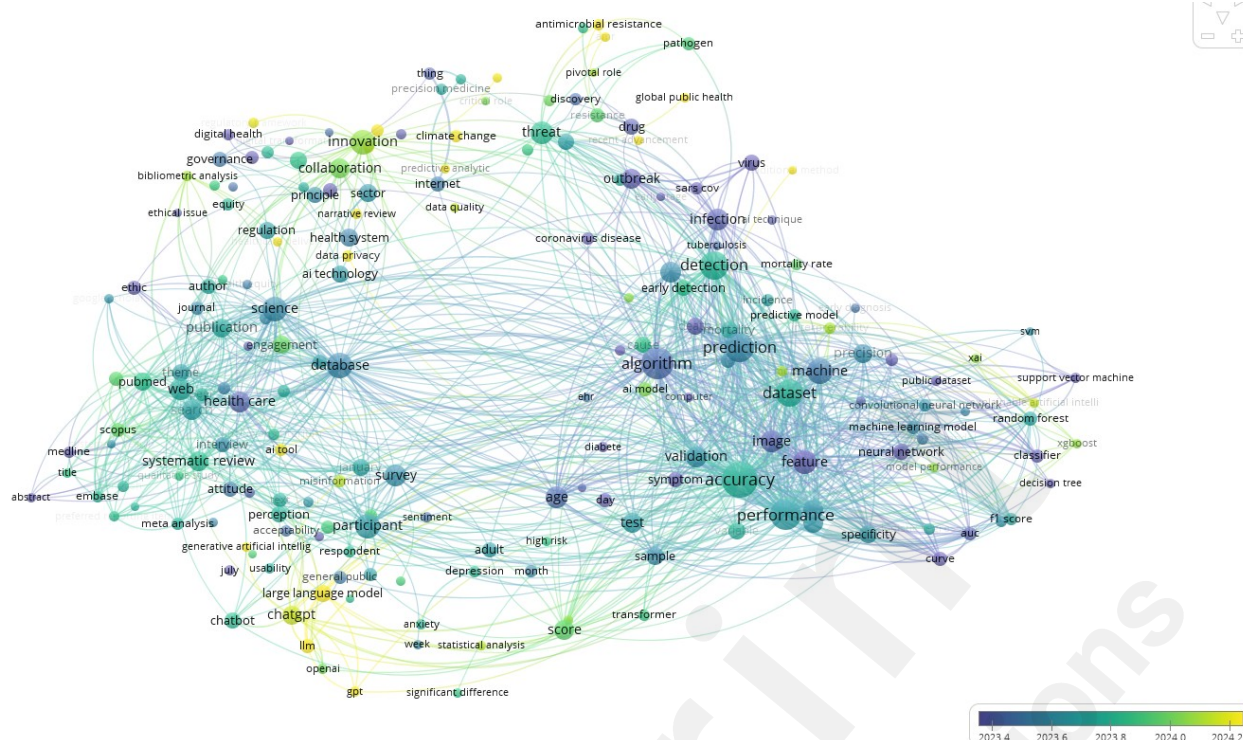


Figure 9: Overlay Visualization

We performed an overlay visualization using VOSViewer that provides insight into the temporal evolution of research themes at the intersection of artificial intelligence (AI) and public health. In this map, the size of each node corresponds to the keyword frequency of each keyword, while the color gradient, ranging from dark blue (earlier average year of publication) to yellow (most recent average year), represents the temporal dimension of keyword emergence.

The analysis indicates that foundational methodological terms such as algorithm, model, dataset, accuracy, detection, and diagnosis cluster predominantly in teal and green hues, reflecting their sustained prominence in publications across 2023. In contrast, terms such as innovation, pathogen, discovery, and significant difference are rendered in yellow, signifying that these research foci have become more prevalent in the 2024 literature. These keywords indicate a growing focus on translational applications, novel biomedical discoveries, and emerging disease modeling. Conversely, darker blue terms, including systematic review, participant, behavior, and survey, were more prevalent in the earlier stages of the analyzed time period, suggesting that early scholarship focused on reviews and human-centered studies before the field shifted to more technical, model-driven research.

Overall, the overlay map illustrates a temporal shift in emphasis: while earlier work focused on review and survey-based methods to assess feasibility and human impact, more recent publications increasingly highlight technical innovation, precision modeling, and application to emerging public health challenges. This evolution aligns with broader patterns in digital health scholarship, where AI has shifted from exploratory evaluation to deployment in clinical and epidemiological contexts [2,61,62].

5. Discussion

In our research, we conducted a systematic literature review on AI in public health. We employed this methodology to address all three research questions presented earlier in this study. We identified aspects of AI that have been studied or utilized in public health. We examined those areas of public health that have impacted the adoption of AI. We propose areas where additional research is needed. We identified that research in the area falls into five thematic clusters. Cluster 1 was AI-related research. Cluster 2 addressed public health threats and outbreaks, Cluster 3 consisted of papers

related to systematic literature reviews, Cluster 4 encompassed research on social and ethical issues in public health, and finally, Cluster 5 was the intersection of governance, policy, and innovation. We also used an overlay visualization that showed trends of publications over time. Recent studies are increasingly AI-related, focusing on technical innovation, precision modeling, and applications to emerging public health challenges. In the following sections, we identify the challenges, research gaps, and future directions.

5.1 Challenges

Integrating AI into public health research presents several interconnected challenges. First, issues related to data quality, heterogeneity, and access barriers hinder the reliability of AI models. Public health data is often sourced from various platforms, such as electronic health records, surveys, and wearables, which can differ significantly in format and may contain missing values or biases. Additionally, privacy regulations can restrict the sharing of data [2,62]. Second, concerns about algorithmic bias and equity arise when the training data fail to adequately represent marginalized groups. This lack of representation can cause AI systems to perpetuate or even exacerbate existing health disparities [63,64]. Third, the issues of transparency and explainability pose significant challenges. Many high-performing AI models function as “black boxes,” making it difficult for public health practitioners and decision-makers to trust, validate, or interpret their outputs [65,66]. Fourth, concerns surrounding privacy, security, and ethical governance complicate the deployment of AI technologies. Sensitive health data must be managed in compliance with evolving regulations while ensuring participant confidentiality [56,67]. There are several regulatory and integration challenges when incorporating AI systems into existing healthcare infrastructures. AI tools must comply with medical device regulations, fit seamlessly into clinical workflows, and ensure compatibility with current systems [2,61]. Lastly, limitations in capacity and workforce, such as a shortage of technical skills among public health professionals, insufficient computational infrastructure, and resistance to adopting new technologies, hinder the scaling and implementation of AI initiatives [2,62].

5.2 Research Gap and Future Directions

While the literature strongly emphasizes technical development of AI models for disease diagnosis, detection, and prediction (green cluster, or cluster 1), and separately addresses public health policy, governance, and pandemic response (red cluster, cluster 2), there remains a notable absence of robust, integrated research at their interface. In particular, few studies systematically examine how AI models can be effectively integrated into public health decision-making settings in ways that are transparent, trustworthy, and actionable [68–70]. Furthermore, although user- and participant-oriented studies (blue cluster) evaluate perceptions, acceptability, and outcomes, these are rarely co-designed with technical teams, meaning that human factors, implementation constraints, and contextual realities do not sufficiently inform model architecture, evaluation metrics, or deployment strategies. The ethics/equity (yellow) cluster, although recognized, appears peripheral rather than central: fairness, accessibility, bias mitigation, transparency, patient consent, and power dynamics are often treated as afterthoughts rather than foundational design principles [71].

Gaps remain in the following areas. First is the governance of distributed AI systems. Federated learning in healthcare is promising for privacy but currently lacks adequate governance frameworks; only a few studies explicitly address this issue. Research in the area lacks Interdisciplinary co-design and evaluation. In most cases, technical performance (accuracy, specificity) is prioritized over adoption, usability, acceptance, and equity outcomes in real-world settings.

Addressing these gaps will require transdisciplinary research that co-develops models, governance protocols, and evaluation frameworks in collaboration with clinicians, public health actors, ethicists, and end-users. Only by embedding ethics, equity, transparency, and implementation realities from the outset can AI in healthcare realize its full potential as a policy-relevant, trustworthy, and just tool.

6. Conclusions

In this study, we have examined the existing literature in AI and public health. We identified the different types of research in AI and public health using SLR. We classified studies into multiple clusters and identified their common focus areas. We examined gaps in the research and identified areas for future research.

7. References

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Appendix 1

Search query used:

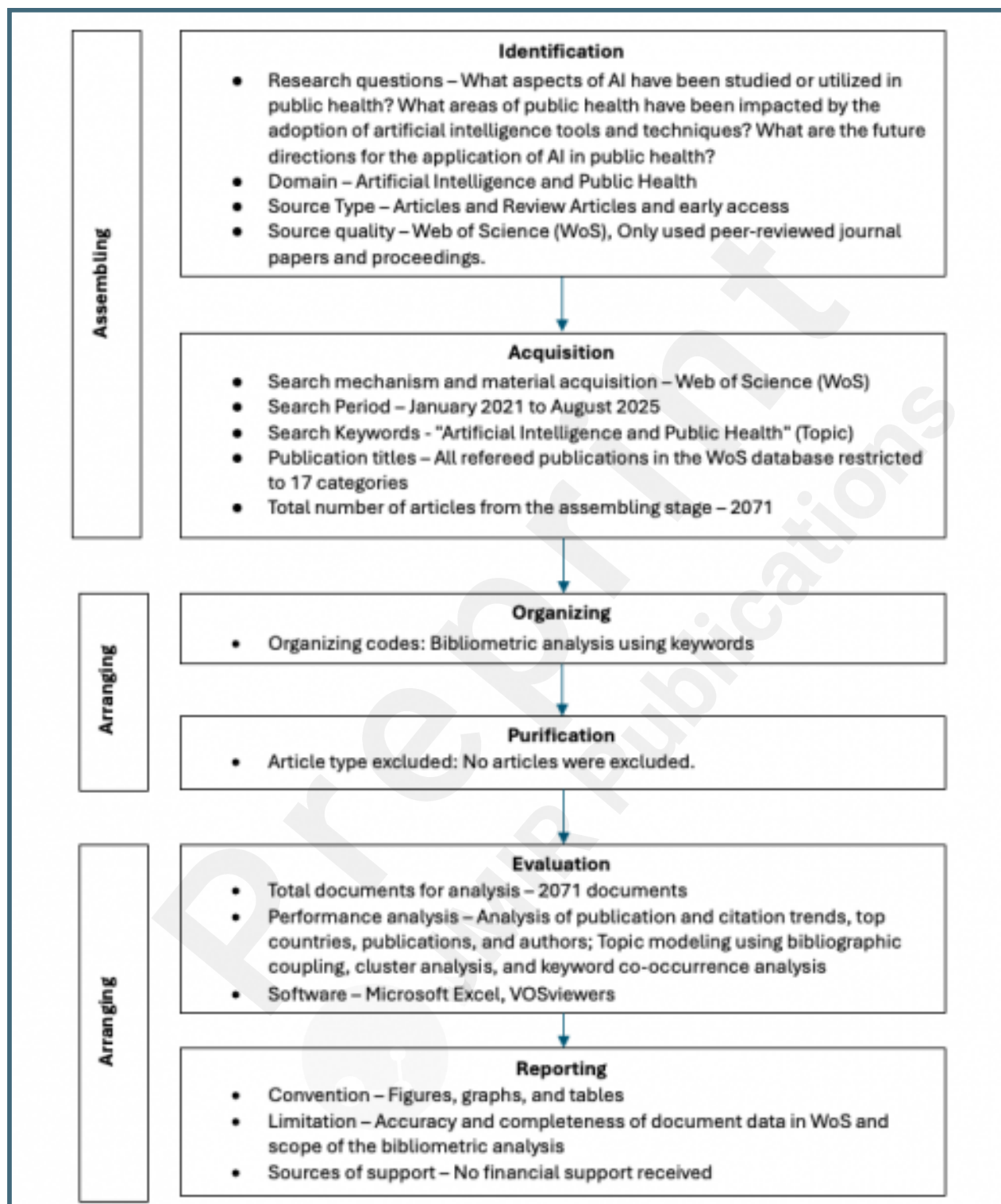
artificial intelligence and public health and 2021 or 2022 or 2023 or 2024 or 2025 or 2026 (Publication Years) and Health Care Sciences Services or Public Environmental Occupational Health or Medical Informatics or Medicine General Internal or Multidisciplinary Sciences or Environmental Sciences or Health Policy Services or Engineering Biomedical or Medicine Research Experimental or Pharmacology Pharmacy or Infectious Diseases or Chemistry Multidisciplinary or Microbiology or Biotechnology Applied Microbiology or Oncology or Psychiatry or Biochemistry Molecular Biology (Web of Science Categories)

in Web of Science Core Collection | Session: September 18, 2025

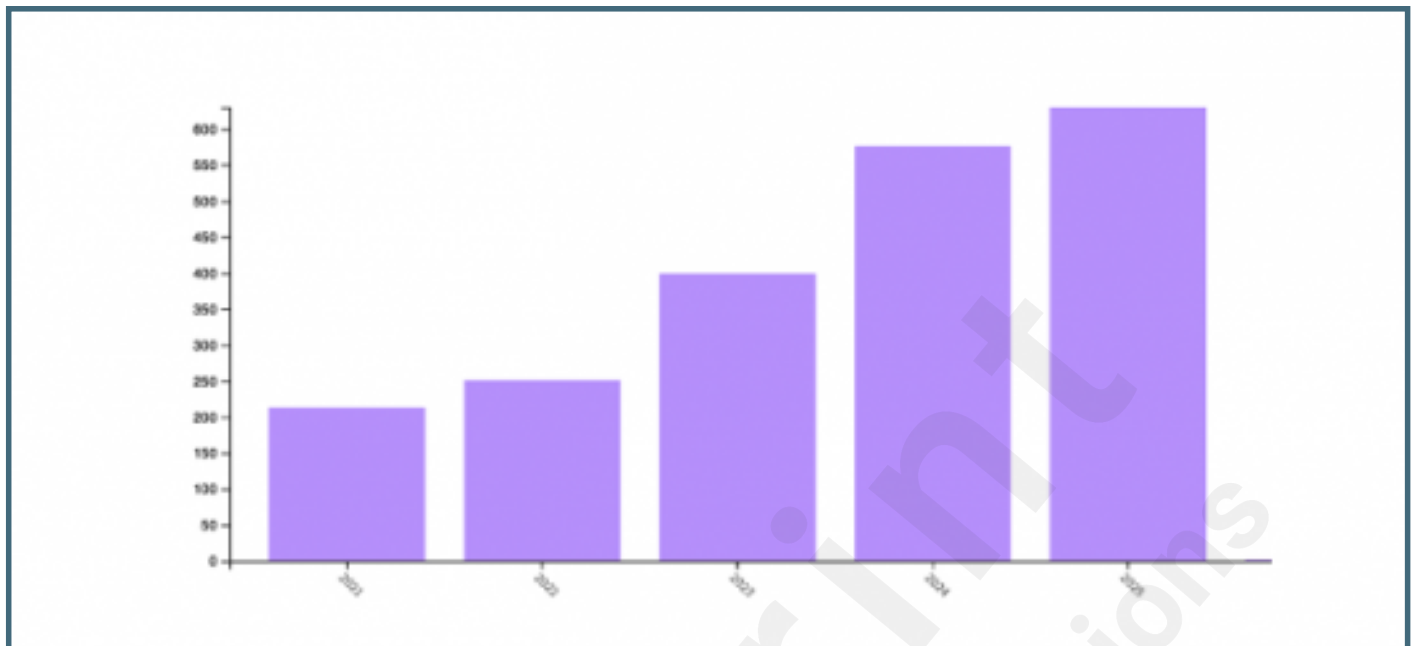
Supplementary Files

Figures

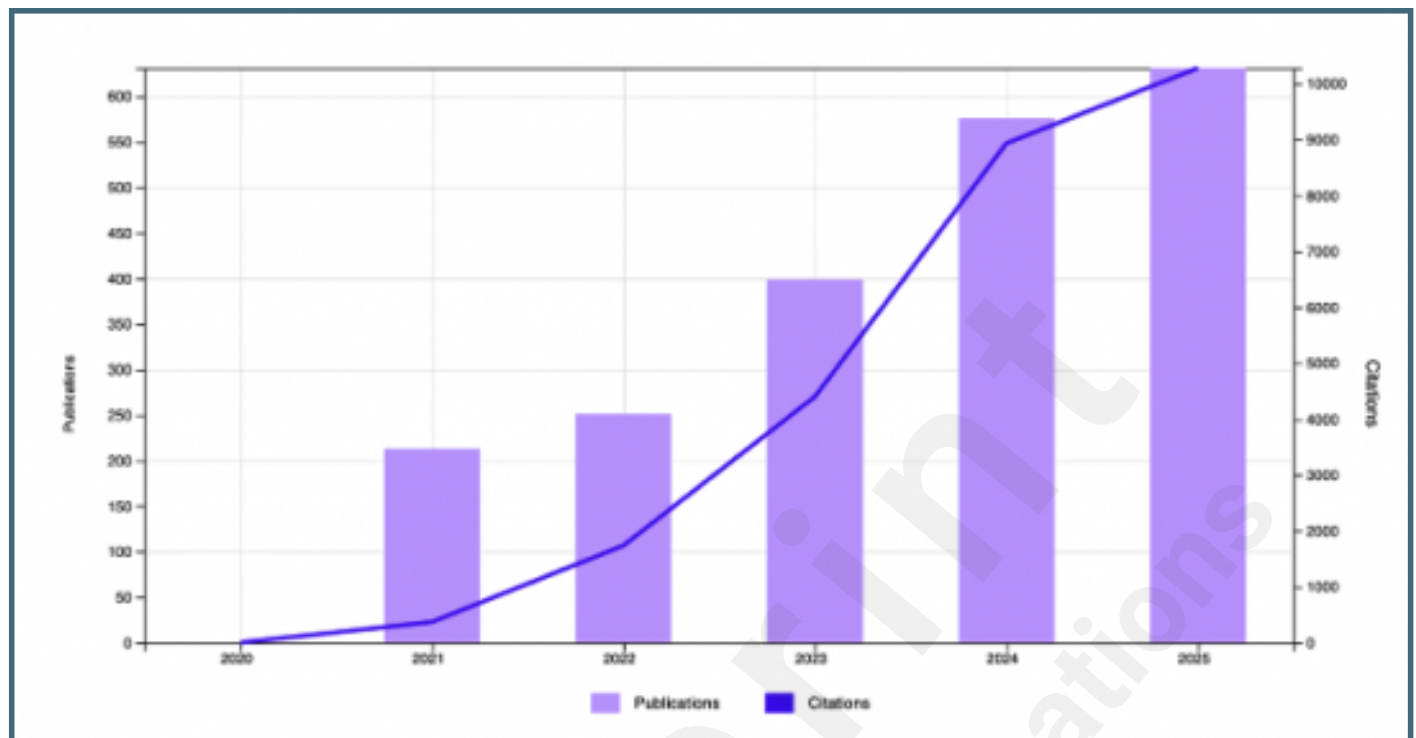
Overview of SLR and Bibliometric Analysis.



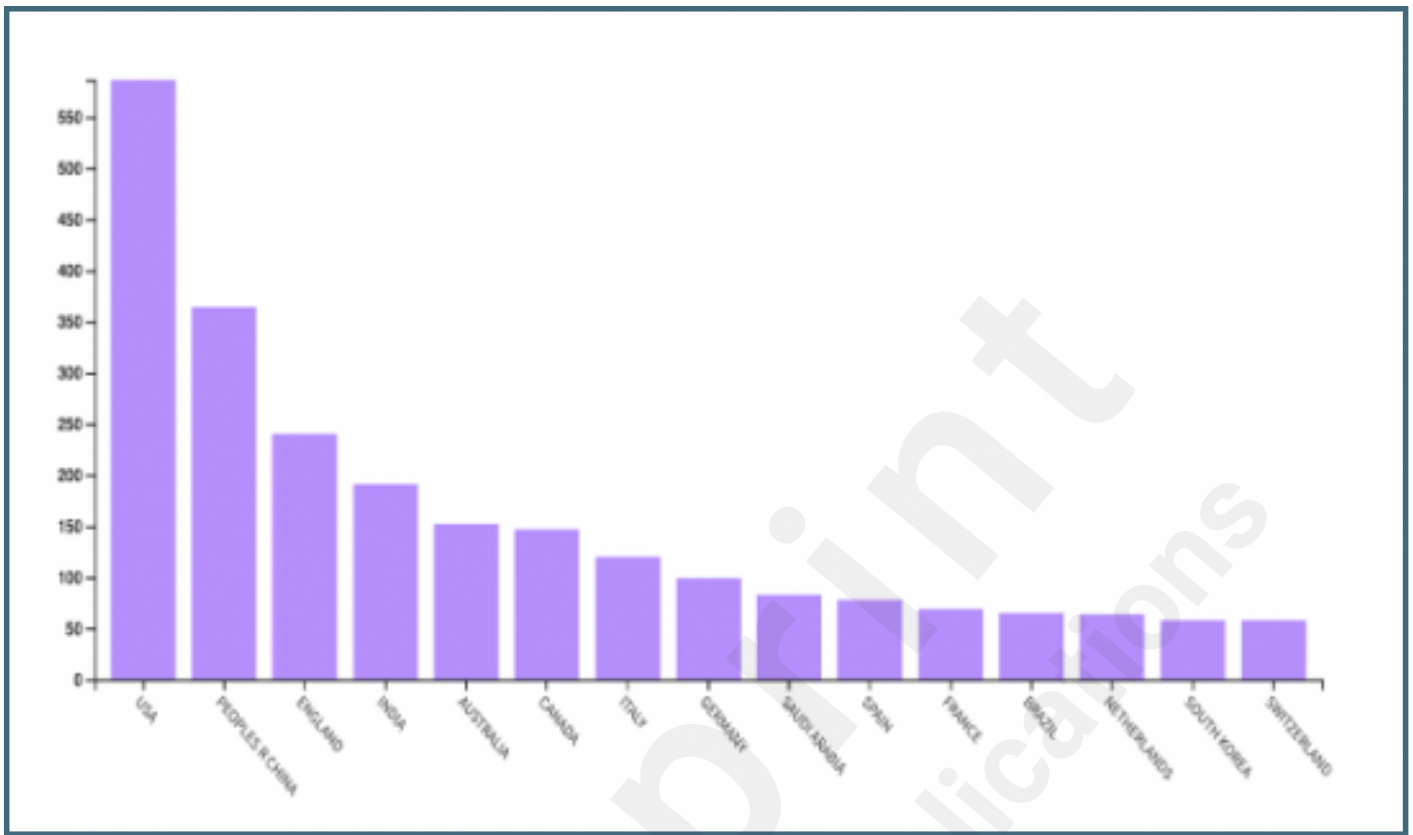
Number of Publications by Year.



Number of Publications and Citations.



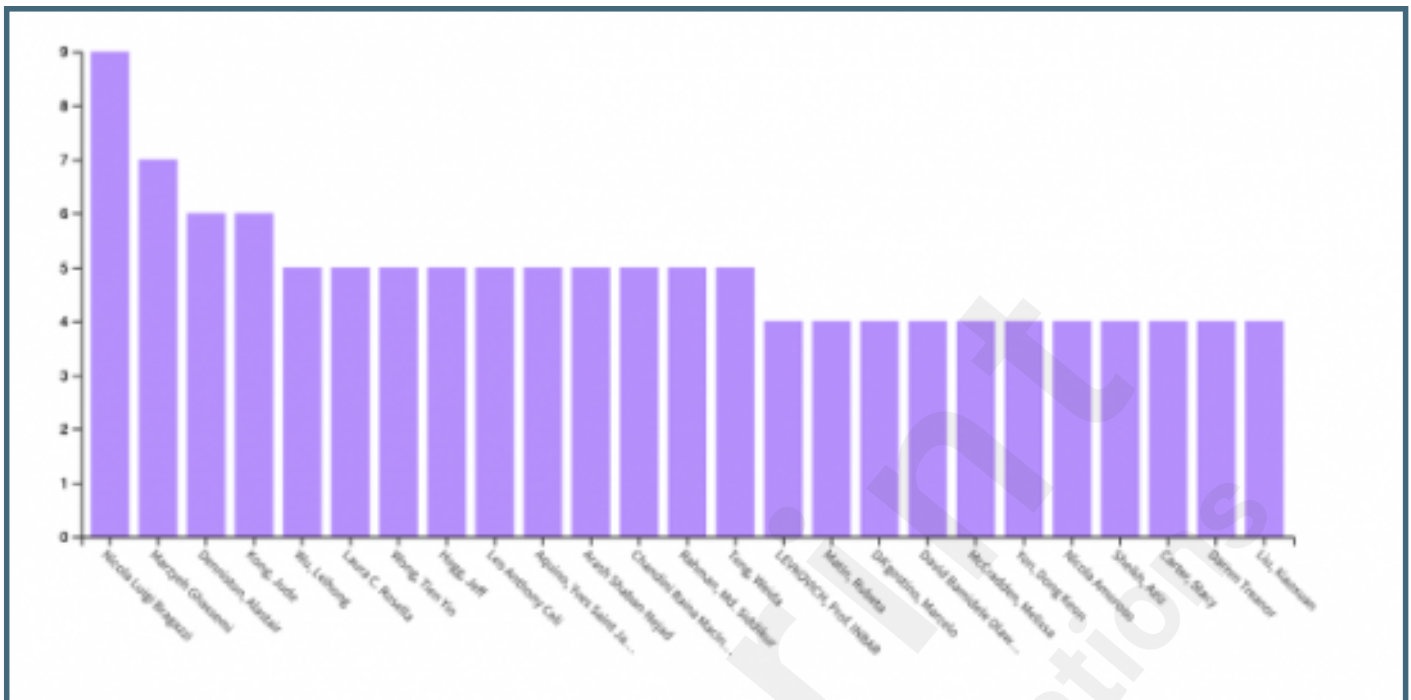
Publication by Country.



Publication by Institution (Tree Chart).



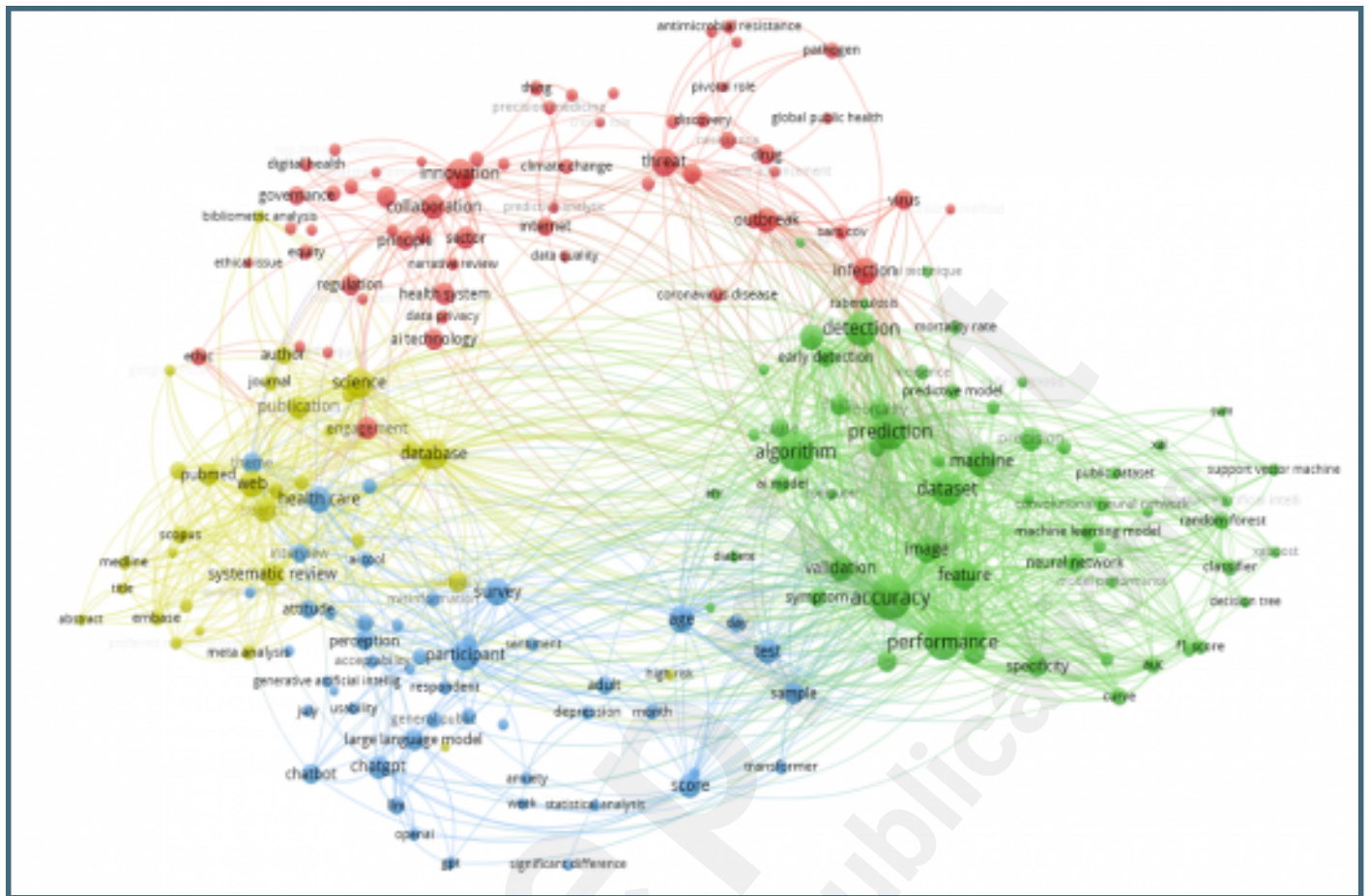
Publication by Author.



Research areas tree map chart.



Co-occurrence Analysis of Keywords.



Overlay Visualization.

