Original Paper

Artificial Intelligence in Public Health: Integrated SPAR-4 Systematic Literature Review and Bibliometric Analysis

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Abstract

Background: Artificial intelligence (AI) is increasingly transforming multiple sectors, including public health. Recent years have witnessed a substantial increase in research on integrating AI into public health systems, reflecting a growing interest in its potential to improve surveillance, diagnostics, policy development, and health outcomes.

Objective: This study aims to identify how AI has been applied in public health, examine its impact on the field, and determine future research directions at the intersection of AI and public health.

Methods: A systematic literature review was conducted to analyze existing scholarly research on AI applications in public health. Relevant studies were collected, screened, and categorized to identify dominant research themes and gaps in the literature.

Results: The analysis revealed five primary thematic clusters within the literature: (1) AI model development and performance, (2) public health threats and outbreak management, (3) systematic reviews and evidence synthesis, (4) social and ethical issues in public health, and (5) governance, policy, and innovation. The review also identified underexplored areas and inconsistencies across studies, highlighting significant research gaps.

Conclusions: AI has demonstrated substantial potential to enhance public health practice and research. However, further investigation is needed to address ethical, governance, and implementation challenges. Future research should focus on strengthening policy frameworks, improving transparency and accountability in AI systems, and promoting interdisciplinary collaboration to ensure the responsible and equitable integration of AI into public health.

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Keywords: artificial intelligence; public health; systematic literature review; research themes; bibliometric analysis

Introduction

The Impacts of Artificial Intelligence on Public Health Care

Artificial intelligence (AI) has revolutionized the global economy. The latest advances in AI suggest that it will impact almost everything we do in the next few years. In general, it is expected that AI will change the field of health care and public health. Before exploring the significance of this field, it is essential to define AI and public health as they are presented in the literature. Zúñiga et al [1] defined AI as, "the tangible real-world capability of non-human machines or artificial entities to perform tasks, solve problems, communicate, interact, and act logically as it occurs with biological humans." Dahlke [2] presented a sociotechnical definition: "Artificial intelligence (AI) refers to digital machine-based systems that process inputs, infer concepts, and generate outputs for explicit or implicit objectives. It can be expected to perceive and influence its environment to varying degrees of autonomy. The purpose of fulfilling these objectives is to automate human labor and/or augment human intelligence." Public health, on the other hand, is defined as "the art and science of preventing disease, prolonging life and promoting health through the organized efforts of society" [3]. We will use these definitions of AI and public health to limit the scope of our study.

According to the US Congressional Research Service [4], "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 health care applies to public health as well. This is supported by Panteli et al [5], who assert that AI can be utilized in various areas of public health such as surveillance, epidemiological research, communication, and resource allocation. They confirm that AI has the potential to revolutionize public health practice and research, provided the accompanying challenges are addressed. Giansanti [6] 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 [7] 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; however, there remains a limited understanding of its role in transforming public health research. Many important questions about AI's integration into public health studies remain unanswered in the research domains of information systems (IS), health care, and public policy. For example, what are the major research themes in the studies of AI and public health? Which methodologies are most used in AI and public health research? Who are the leading researchers studying the application of AI in public health from IS, public policy, and health care research fields? Which peer-reviewed academic journals publish the most studies on AI and public health, in the cross-disciplinary fields of IS, public policy, and health care? A review of the existing literature in these domains, particularly focusing on the integration of AI technologies and their ethical, regulatory, and environmental implications, could help address these questions [6].

Research Gap and Research Questions

The current literature reviews typically employ traditional review methods that often limit their searches to a handful of prestigious journals, thereby introducing data selection bias. Additionally, these reviews tend to focus on research topics selected based on the reviewers' interests [7,8]. 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 [9].

The 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 [10]. Furthermore, the SLR aims to include all relevant literature pertinent to the research questions, thereby providing broader coverage and eliminating selection bias compared to traditional methods [11]. 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 in this field predominantly rely on qualitative analysis and a narrative format [12].

In this paper, we address the need for research in the area of AI and public health by conducting an SLR. We focus on the various aspects of AI studied in public health research, the areas impacted by AI, and future directions for its adoption and integration in public health. We intend to explore, using our SLR-based framework, the broader question of how AI tools and techniques have been integrated into public health. More specifically, we aim to address the following research questions in the realms of health care and health policy in our analysis

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 AI 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 AI. Finally, RQ3 examines potential future directions for the use of AI in public health.

We have highlighted the significance of studying AI in public health. In this section, we will review the existing literature on this topic and discuss the need for an 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 [10]. 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 [13], the use of social media platforms for public health initiatives [14], and the impact of digital data sources on public health [15]. There have been studies in different regions of the world, including the Middle East and North Africa (Saadah), Thailand (Kaushik), and Africa (Hu). Literature reviews that have examined specific health conditions include studies on anxiety and depression [16], chronic diseases [17], mental health [18], and dentistry [19], to name a few. While several studies have examined digital health, specific regions, and particular diseases and conditions, a comprehensive review of all research on AI and public health remains lacking in the existing literature. To address this gap, we propose the following research questions for this study.

Our paper is organized as follows: In the next section, we detail the materials and methods used in our study, followed by the analysis and results. Finally, we conclude with a discussion of our findings and a summary of our overall conclusions.

Methods

The 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 [20,21]. Unlike traditional literature reviews, SLRs offer enhanced replicability, reliability, and transparency [22,23].

SLRs have been utilized across a wide range of research domains, including IS and public health. In the realm of IS research, Anderson et al [24] adopted the SLR framework proposed by Vom Brocke et al [25] along with the content analysis to identify research themes from case-based learning and cybersecurity leadership education. Their goal was to understand how case-based learning could contribute to developing often overlooked elements in cybersecurity leadership education. Laine et al [26] applied the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework as developed by Moher et al [27] to analyze IS literature on AI auditing, focusing on the contributions of ethics-based AI auditing from the perspectives of various stakeholders. Additionally, Altrichter and Benoit [28] utilized the SLR procedure by Palmatier et al [29] 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 [30] followed the PRISMA framework [27] to evaluate the impact of Industry 4.0 on health care systems using cross-disciplinary literature. Khanra et al [31] employed a 3-stage SLR protocol [32,33] to investigate the applicability of big data analytics (BDA) in health care from 5 distinct perspectives. Furthermore, Pinto et al [34] applied the SLR framework by Kitchenham and Charters [35] and Petersen et al [36] to analyze variables and technologies relevant to the impact assessment of public health campaigns.

Numerous methodological guidelines have been developed to conduct SLRs, including the Systematic Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) protocols [37], recommendations for literature searches by Vom Brocke et al [25], the PRISMA guidelines [27], Kitchenham [38] procedures for SLRs, and the SALSA (Search, Appraisal, Synthesis, and Analysis) framework [39]. 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 such as Vom Brocke et al [25] 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 [37,40]. Additionally, it is applicable across multiple disciplines, unlike the Kitchenham [38] framework, which is primarily based in the software engineering context.

SPAR-4-SLR consists of 3 major stages: assembling, arranging, and assessing. The assembling stage is further divided into 2 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 2 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 such as TCCM (Theory, Context, Characteristics, and Methodology) [37]. 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 papers. 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.

We followed the protocols outlined in SPAR-4-SLR.

In the assembling stage, we utilized the Web of Science (WoS) database to search for papers on the intersection

of AI and public health to address the research questions proposed earlier. It is worth noting that the broad terms "artificial intelligence" and "public health" were used in our search formula. This is due to the heterogeneous, dynamic, and cross-disciplinary nature of both concepts. For instance, the topic of AI includes discussions of traditional AI and generative AI. Some AI studies focus on the technical aspects of AI algorithm development, while others focus on the societal and ethical changes brought about by AI. Similar to AI, public health research spans a wide range of themes, including pandemic control and prevention, the design and implementation of public health policy, and health education. The use of broad rather than specific search terms ensured the unbiased and comprehensive coverage of literature relevant to the goal of this study. A general search using these terms returned 4273 papers. The search was restricted to the years 2021 to 2025. We restricted our search to these years because the use of AI surged after the release of generative AI tools, such as ChatGPT, in 2022. Papers published before this time were not relevant to our study. A copy of the search terms used is provided in Multimedia Appendix 1. The search resulted in 2122 papers. After discarding 51 papers that were not relevant to our study, we were left with 2071 papers.

In the arranging stage, we restricted the WoS categories to those listed in the search query provided in Multimedia Appendix 1. The search included all papers published until the end of August 2025. The search query resulted in 2071 relevant papers.

In the assessing stage, we first conducted a performance analysis to identify trends in health care and AI research, based on the number of publications and citations of research papers in this area. Furthermore, we ranked authors, institutions, and countries based on their research productivity using the number of papers published under their names. During the performance analysis, we also identified the major research areas in this domain, which encompass the majority of the papers in our dataset.

We used VOSviewer (Leiden University's Centre for Science and Technology Studies) to analyze papers and to construct a co-occurrence network of keywords. This analysis involves creating a keyword co-occurrence network 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 co-occurrence map visualization shows how keywords cluster into thematic groups based on their co-occurrence frequency across all WoS records.

The network structure reveals patterns, connections, and the text's underlying knowledge framework [41]. This technique is commonly used in SLRs and bibliometric analyses. The co-occurrence map also reveals major clusters, which are represented by keywords that frequently appear together in the health care and AI literatures. The identification and interpretation of these clusters help us understand the major research themes of the health care and AI research domain.

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

Results

Analytical Results

AI is a rapidly evolving field that has garnered significant interest, as evidenced by the rising volume of research publications. Figure 1 provides an overview of the SLR and bibliometric analysis. 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.

Figure 1. Overview of the systematic literature review (SLR) and bibliometric analysis. The Systematic Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) [37] protocol with details of this study.

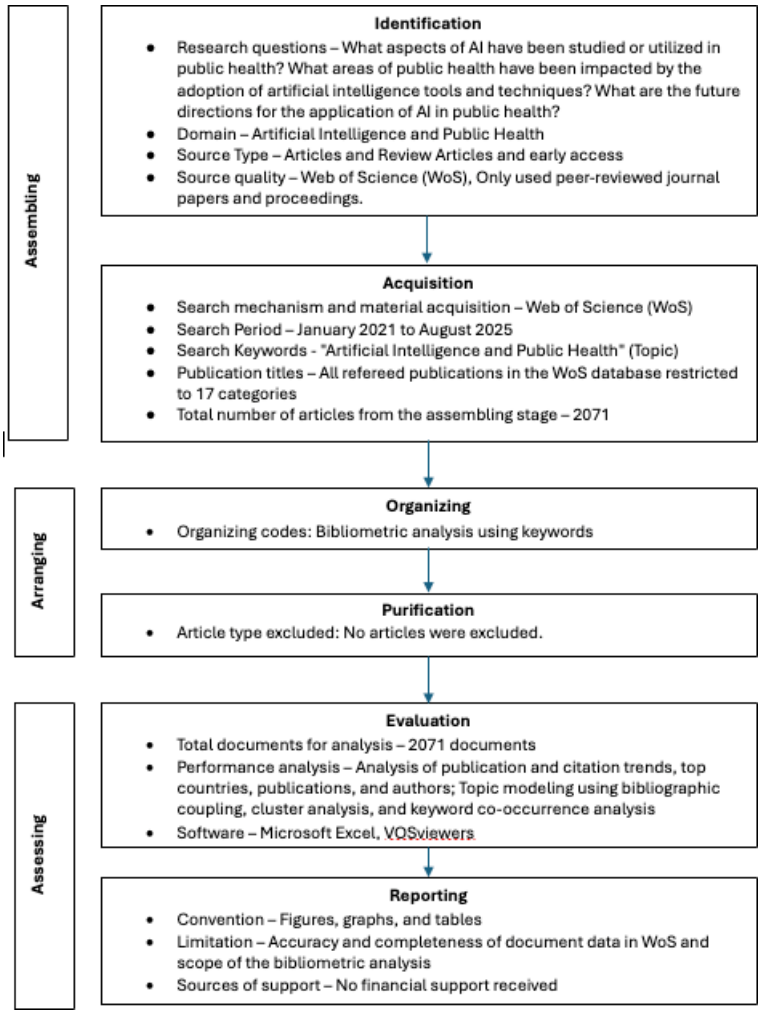
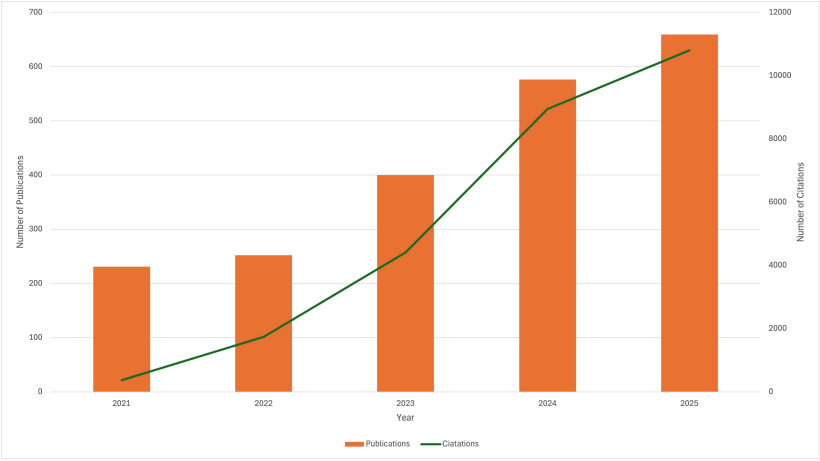


Figure 2. Number of publications and citations.

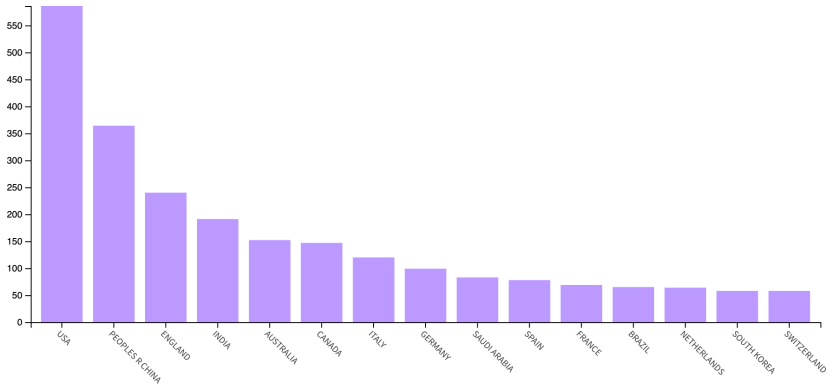


While the number of papers has increased, so has the number of citations. As seen in Figure 2, the number of citations has increased dramatically since 2023. This also reflects the growing interest in AI.

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 3 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 (17.3%) publications, 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 6 countries represent 79% of all publications during the 5-year period analyzed in this study. The countries that have the highest

numbers are the Western developed nations, such as the United States, England, Australia, and Canada, and the countries that are strong in emerging computer and information technologies, such as China and India. Additionally, publications related to AI and public health can be found globally. Figure 3 displays the number of publications by country.

Figure 3. 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. A tree chart was created using the tools provided within the WoS software. Figure 4 shows the top 10 institutions with the most publications in this field.

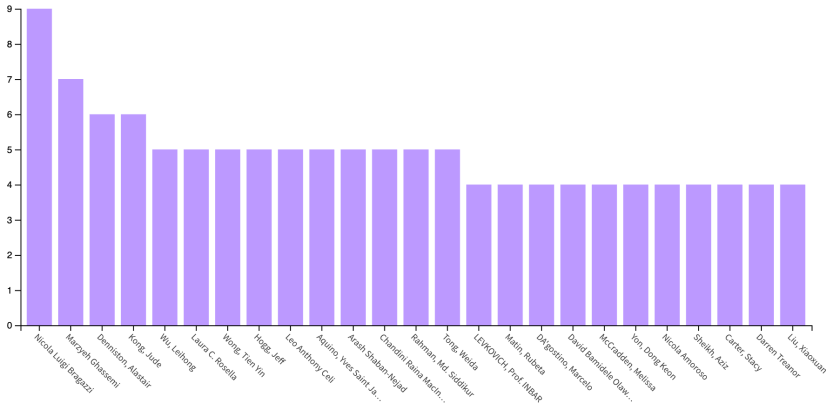
Figure 4. Publications by institution (tree chart).



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 reported 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 with 33 publications each.

Now that we have examined the research output of institutions in the area of AI and public health, we can review the most prolific researchers in the field. The list of researchers and the number of academic publications are provided in Figure 5. Since this is a new, evolving field, the number of papers published by our leading author is 9.

Figure 5. Publications by authors.



Next, we examine the common research areas in the field of AI and public health. As illustrated in Figure 6, studies have primarily focused on 5 key areas: health care sciences and services, public environmental and occupational health, medical informatics, general internal medicine, and science and technology. These research domains account for 1900 of the 2071 papers included in our study.

Figure 6. Research areas by tree map chart.



In this section, we presented the results of our performance analysis of AI in public health research. We reviewed the annual number of publications over the past 5 years, the increasing number of citations, publications by country, publications by leading authors in the field, and the main topics of study. In the next section, we present a co-occurrence network analysis of keywords.

Co-Occurrence Network Analysis of Keywords

As mentioned in the previous sections, we used a dataset of 2071 papers for this analysis. We applied 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 the keyword co-occurrence network analysis because we had a large number of papers 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 7 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 8, presented in the next section, illustrates the evolution of these themes over time. For instance, trending topics such as large language models (LLMs), ChatGPT, and governance are relatively new. Together, these maps highlight both the existing themes and the direction in which the field is evolving.

The co-occurrence analysis of keywords from the WoS records revealed 5 major thematic clusters in the application of AI to public health. These clusters are identified using different colors in Figure 7, and they are listed in Table 1.

Figure 7. Co-occurrence analysis of keywords.

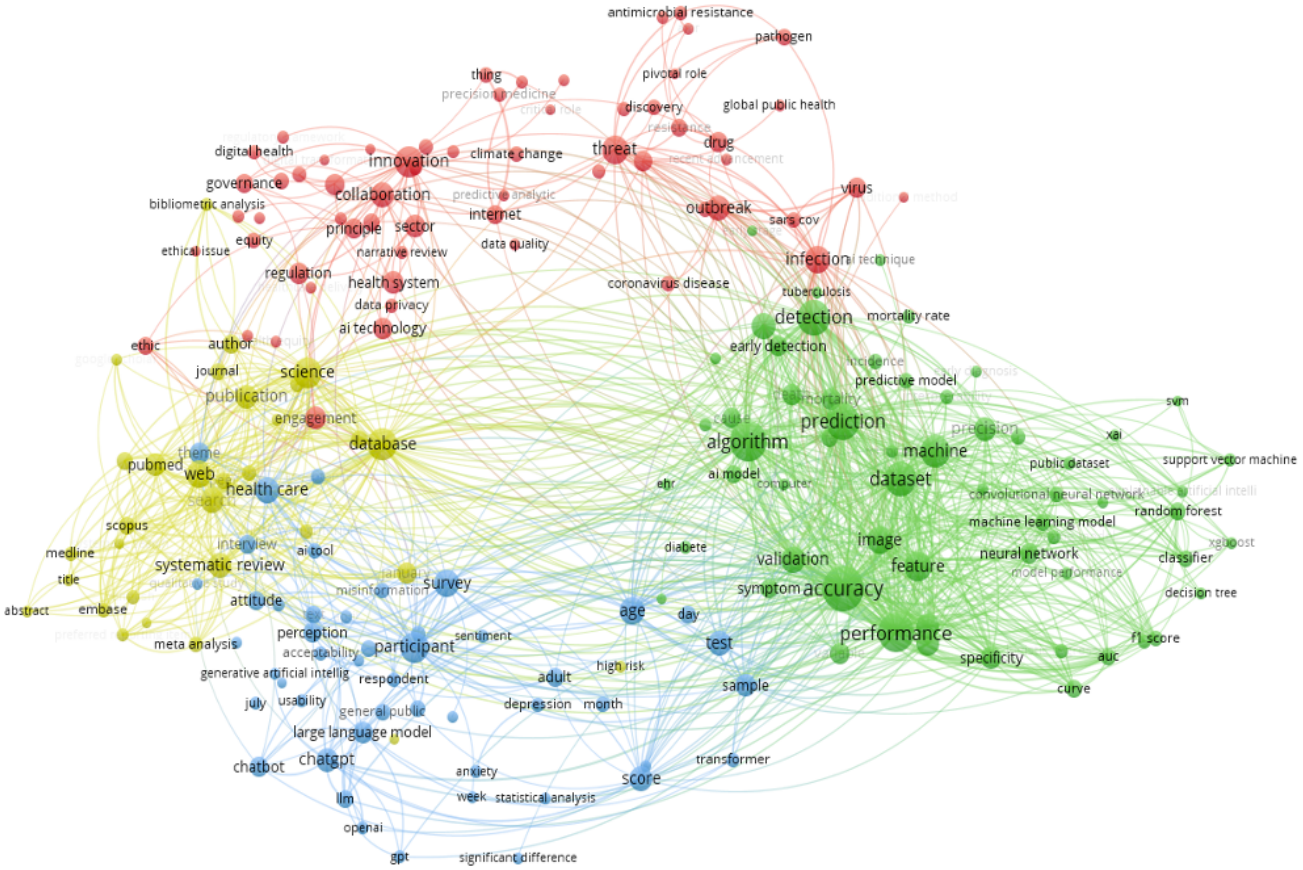


Figure 8. Overlay visualization.

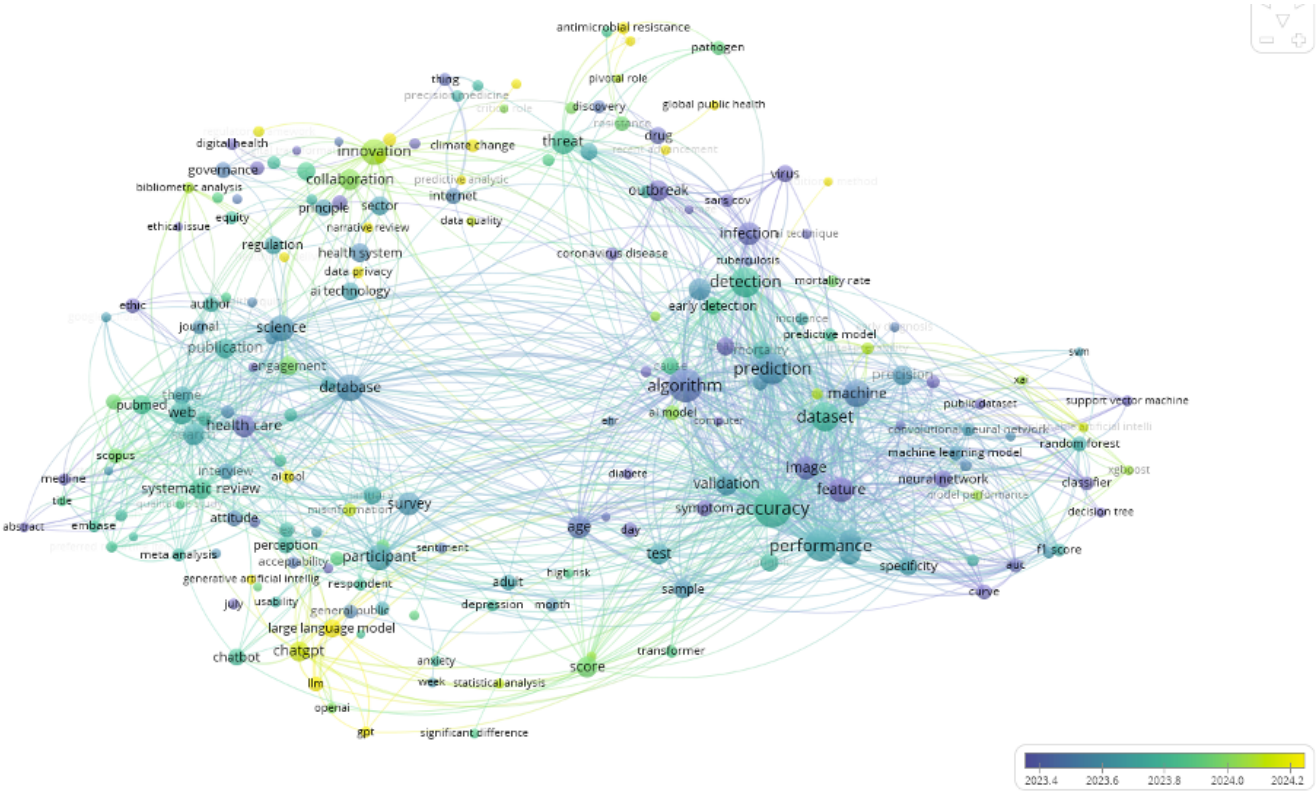


Table 1. Main thematic clusters after co-occurrence analysis.

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, F_1-score, and specificity	Development and evaluation of AI[a]/machine-learning models for diagnostics, classification, and health-related predictions
2	Red—public health threats and outbreaks	Outbreak, threat, virus, SARS-CoV, coronavirus disease, detection, tuberculosis, antimicrobial resistance, pathogen, drug discovery, and global public health	Application of AI in epidemiology and infectious disease surveillance, outbreak detection, and global health threats
3	Yellow—systematic reviews, databases, and evidence	Systematic review, meta-analysis, health care, PubMed, Scopus, Medline, Embase, publication, Science, and journal	Evidence-based research foundations, systematic reviews, bibliometrics, and meta-analyses of AI in health care
4	Blue—social and ethical issues in public health	Participant, survey, perception, acceptability, chatbot, ChatGPT, large language model, LLM[b], GPT, OpenAI, usability, respondent, general public, anxiety, and 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, and digital health	Ethical, legal, and social implications of AI in health care, emphasizing governance, equity, privacy, and innovation

[a]AI: artificial intelligence.
[b]LLM: large language models.

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.

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. Cluster 3, represented by the yellow cluster, includes 29 keywords. This cluster focuses on systematic reviews, databases, and bibliometric evidence, linking health care applications with large scientific databases such as PubMed, Scopus, Medline, and Embase, as well as meta-analytic approaches.

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, LLMs, and usability. Finally, a red-yellow intersection cluster (cluster 5) emphasizes governance, policy, and innovation, with terms such as governance, equity, regulation, and digital health. 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 health care.

The bibliometric co-occurrence network revealed 4 distinct thematic clusters and 1 intersection cluster in research on AI and public health. The following is a summary of each cluster (with representative keywords), followed by a narrative synthesis.

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

Overlay Visualization

The overlay visualization 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.

Discussion

Summary of Findings

In our research, we conducted an SLR on AI in public health. We employed this methodology to address all 3 research questions presented earlier in this study. We identified aspects of AI that have been studied or utilized in public health, examined the public health areas that have influenced the adoption of AI, and proposed areas where additional research is needed.

We identified that research in the area falls into 5 thematic clusters, as shown in Table 1.

Cluster 1 focused on AI-related research. Some papers in this cluster explored hybrid models for the prevention and monitoring of infectious diseases [39], predicted COVID-19 infections using machine learning [40], and developed a novel machine-learning model to predict multiple unplanned hospitalizations [41]. The papers in this cluster share a common theme of developing innovative AI models and algorithms for public health predictions. Several trends have been observed in the literature within this cluster. First, AI models require high standards for data accessibility, integrity, and privacy. Due to their high demands for data quality and quantity, AI algorithms are often used in combination with data collection, storage, and analysis technologies such as Internet of Things, Blockchain, Cloud, and BDA [39]. Additionally, AI models that integrate the features of multiple algorithms are often applied to public health care–related predictions due to the high complexity and multifactor nature of the problems in this domain [42,43]. These algorithms encompass both deep learning models, such as long short-term memory and convolutional neural networks, and traditional algorithms, including decision trees and random forest algorithms. Previous studies suggest that AI-based models are better than traditional statistical models in general in terms of performance measures such as precision, recall, and F_1-score in public health–related predictions [40].

Public health challenges are inherently multifactorial, involving demographic, behavioral, environmental, and biological variables. As a result, researchers increasingly adopt hybrid and ensemble approaches that combine multiple algorithms (eg, convolutional neural networks, long short-term memory, random forests, and support vector machines) to improve generalizability and robustness. This reflects an important methodological shift from single-model experimentation toward integrated model architectures capable of capturing nonlinear relationships across heterogeneous datasets.

However, this cluster also highlights critical infrastructural dependencies. AI models require high-quality, interoperable, and large-scale datasets. Consequently, AI research in public health often intersects with enabling technologies such as the Internet of Things for real-time data capture, cloud computing for scalable processing, blockchain for secure data sharing, and BDA platforms for storage and integration. This indicates that AI adoption is not merely a methodological decision but an ecosystem-level transformation requiring investment in digital infrastructure.

Cluster 2 addressed public health threats and outbreaks. This cluster illustrates how AI has been used in epidemiological monitoring and infectious disease detection. Several representative papers within this cluster address public health threats and outbreaks. For instance, Grant and Booth [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]. This cluster reveals AI's strategic value in real-time decision-making under uncertainty. During public health emergencies, traditional surveillance systems often suffer from reporting delays and fragmented data. AI systems, especially those leveraging mobility data, social media analytics, and syndromic surveillance, offer the potential for earlier detection and rapid situational awareness. The integration of LLMs and tools, such as ChatGPT, into outbreak response represents a further evolution. These systems support the dissemination of medical knowledge, the summarization of clinical guidance, and even risk communication. However, this raises concerns about reliability, misinformation, and accountability during high-stakes public health events.

Cluster 3 consisted of papers related to SLRs. Several studies are present within this cluster. The SLR methodology is used to explore topics such as the impact of AI on income-related health disparities [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 AI and public health research, nor does it provide answers to our research questions.

Cluster 3 forms the epistemological backbone of AI in public health. Although this cluster does not directly develop new AI applications, it plays a critical role in validating, synthesizing, and structuring knowledge in the domain. SLRs, meta-analyses, and bibliometric studies help identify trends, gaps, and methodological weaknesses.

The presence of this cluster suggests that the field is transitioning from exploratory innovation to consolidation and reflection. As AI applications proliferate, systematic synthesis becomes necessary to evaluate methodological rigor, reproducibility, bias, and equity implications. Moreover, this cluster underscores the importance of transparency in reporting AI research. Public health decisions rely heavily on evidence-based practices. Therefore, systematic reviews serve as quality control mechanisms that assess dataset representativeness, algorithm fairness, and external validity.

Although Cluster 3 does not directly answer the research questions, it plays a foundational role in shaping them. Without rigorous synthesis, fragmented AI studies risk overclaiming effectiveness. Future research should promote the use of standardized reporting frameworks (eg, TRIPOD+AI [Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis + Artificial Intelligence] and CONSORT-AI [Consolidated Standards of Reporting Trials–Artificial Intelligence]) to enhance reproducibility and cross-study comparability.

Cluster 4 encompassed research on social and ethical issues in public health. 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 et al [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.

This cluster shifts the focus from algorithmic performance to human-centered evaluation. Questions of informed consent, data privacy, algorithmic bias, mental health impact, and equity in access are central themes. For instance, AI-driven mental health monitoring tools may improve early detection but simultaneously raise concerns about surveillance and autonomy.

The increasing presence of LLMs and generative AI in this cluster indicates a shift toward conversational and interactive AI systems in public health contexts. These tools have the potential to enhance health literacy, patient engagement, and self-management. However, issues of misinformation, hallucinated outputs, and uneven digital literacy create ethical dilemmas.

The growth of this cluster suggests that AI adoption in public health is entering a sociotechnical phase, where acceptance depends on transparency, explainability, and fairness. Future research should integrate participatory design approaches, involving patients and public stakeholders in AI system development to enhance legitimacy and trust.

Cluster 5 was the intersection of governance, policy, and innovation. This cluster shows how ethical, legal, and policy issues intersect with the 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 demonstrate that AI in public health is an emerging field. However, there are issues of governance, equity, and regulation that still need to be resolved. More importantly, the field is evolving faster than governance and regulation can keep up with.

This intersectional cluster is particularly significant because it connects technical innovation (cluster 1) and outbreak applications (cluster 2) with societal concerns (cluster 4). It reflects the recognition that AI in public health is not solely a technological innovation but also a policy and institutional challenge. The presence of innovation and collaboration keywords indicates that AI adoption requires multistakeholder engagement across government agencies, health care providers, technology companies, and research institutions. Governance must balance innovation incentives with safeguards for privacy, fairness, and accountability.

This cluster also highlights the global dimension of AI in public health. Governance challenges are amplified in resource-constrained settings, where digital infrastructure, regulatory capacity, and technical expertise may be limited. Future research should examine scalable governance models and adaptive regulatory frameworks that can evolve alongside AI technologies.

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

- Technical methods (green, cluster 1) are strongly connected to disease- and outbreak-related applications (red, cluster 2). This demonstrates the important role of AI in public health surveillance and diagnostics.
- Systematic reviews and evidence synthesis (yellow, cluster 3) form the foundation for validating knowledge 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.

We also used an overlay visualization to show trends in publications over time. 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 [5,61,62].

In the next section, we present our conclusions, where we identify the challenges, research gaps, and future directions.

Conclusions

In this study, we examined the existing literature on 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 analyzed gaps in the research and highlighted areas for future research.

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 are 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 [5,62]. 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 health care infrastructures. AI tools must comply with medical device regulations, fit seamlessly into clinical workflows, and ensure compatibility with current systems [5,61]. Finally, 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 [5,62].

Research Gaps and Future Directions

While the literature strongly emphasizes the 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 responses (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, leaving human factors, implementation constraints, and contextual realities to inform only 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 health care 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 and 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 health care realize its full potential as a policy-relevant, trustworthy, and just tool.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Boolean search query used for literature review.
[DOCX File (Microsoft Word File), 14 KB-Multimedia Appendix 1]

References

1. Gil de Zúñiga H, Goyanes M, Durotoye T. A scholarly definition of artificial intelligence (AI): advancing AI as a conceptual framework in communication research. Polit Commun. Mar 3, 2024;41(2):317-334. [doi: 10.1080/10584609.2023.2290497]
2. Dahlke J. A.I. go by many names: towards a sociotechnical definition of artificial intelligence. arXiv. Preprint posted online on Oct 17, 2024. [doi: 10.48550/arXiv.2410.13452]
3. Winslow CEA. The untilled fields of public health. Science. Jan 9, 1920;51(1306):23-33. [doi: 10.1126/science.51.1306.23] [Medline: 17838891]
4. Artificial intelligence (AI) in health care. Congressional Research Service; 2024. URL: https://www.congress.gov/crs-product/R48319 [Accessed 2026-06-16]
5. Panteli D, Adib K, Buttigieg S, et al. Artificial intelligence in public health: promises, challenges, and an agenda for policy makers and public health institutions. Lancet Public Health. May 2025;10(5):e428-e432. [doi: 10.1016/S2468-2667(25)00036-2] [Medline: 40031938]
6. Giansanti D. Artificial intelligence in public health: current trends and future possibilities. Int J Environ Res Public Health. Sep 21, 2022;19(19):11907. [doi: 10.3390/ijerph191911907] [Medline: 36231208]
7. Benke K, Benke G. Artificial intelligence and big data in public health. Int J Environ Res Public Health. Dec 10, 2018;15(12):2796. [doi: 10.3390/ijerph15122796] [Medline: 30544648]
8. MacIntyre CR, Chen X, Kunasekaran M, et al. Artificial intelligence in public health: the potential of epidemic early warning systems. J Int Med Res. Mar 2023;51(3):3000605231159335. [doi: 10.1177/03000605231159335] [Medline: 36967669]

9. Xiao Y, Watson M. Guidance on conducting a systematic literature review. J Plan Educ Res. Mar 2019;39(1):93-112. [doi: 10.1177/0739456X17723971]
10. Lame G. Systematic literature reviews: an introduction. Proc Int Conf Eng Des. Jul 2019;1(1):1633-1642. [doi: 10.1017/dsi.2019.169]
11. Nightingale A. A guide to systematic literature reviews. Surgery (Oxford). Sep 2009;27(9):381-384. [doi: 10.1016/j.mpsur.2009.07.005]
12. Olawade DB, Wada OJ, David-Olawade AC, Kunonga E, Abaire O, Ling J. Using artificial intelligence to improve public health: a narrative review. Front Public Health. 2023;11:1196397. [doi: 10.3389/fpubh.2023.1196397] [Medline: 37954052]
13. Fu Y, Han P, Wang J, Shahzad F. Digital pathways to healthcare: a systematic review for unveiling the trends and insights in online health information-seeking behavior. Front Public Health. 2025;13:1497025. [doi: 10.3389/fpubh.2025.1497025] [Medline: 40013047]
14. Gunasekeran DV, Chew A, Chandrasekar EK, et al. The impact and applications of social media platforms for public health responses before and during the COVID-19 pandemic: systematic literature review. J Med Internet Res. Apr 11, 2022;24(4):e33680. [doi: 10.2196/33680] [Medline: 35129456]
15. Li L, Novillo-Ortiz D, Azzopardi-Muscat N, Kostkova P. Digital data sources and their impact on people's health: a systematic review of systematic reviews. Front Public Health. May 5, 2021;9. [doi: 10.3389/fpubh.2021.645260]
16. Wang P, Ai X, Zhang X, Ma F, Zhuang Y, Wang S. Evaluating virtual reality technology in psychotherapy: impacts on anxiety, depression, and ADHD. Front Psychiatry. 2024;15:1480788. [doi: 10.3389/fpsyt.2024.1480788] [Medline: 39744548]
17. Shergill M, Durant S, Birdi S, et al. Machine learning used to study risk factors for chronic diseases: a scoping review. Can J Public Health. Feb 2026;117(1):125-139. [doi: 10.17269/s41997-025-01059-9] [Medline: 40498391]
18. Sha S, Loveys K, Francis I, et al. Self-disclosure and relational agents for mental health: a scoping review protocol. BMJ Open. Aug 24, 2025;15(8):e100613. [doi: 10.1136/bmjopen-2025-100613] [Medline: 40850916]
19. Tiwari A, Kumar A, Jain S, et al. Implications of ChatGPT in public health dentistry: a systematic review. Cureus. Jun 2023;15(6):e40367. [doi: 10.7759/cureus.40367] [Medline: 37456464]
20. Kitchenham B, Pearl Brereton O, Budgen D, Turner M, Bailey J, Linkman S. Systematic literature reviews in software engineering—a systematic literature review. Inf Softw Technol. Jan 2009;51(1):7-15. [doi: 10.1016/j.infsof.2008.09.009]
21. Snyder H. Literature review as a research methodology: an overview and guidelines. J Bus Res. Nov 2019;104:333-339. [doi: 10.1016/j.jbusres.2019.07.039]
22. Boell SK, Cecez-Kecmanovic D. On being 'systematic' in literature reviews in IS. J Inf Technol. Jun 2015;30(2):161-173. [doi: 10.1057/jit.2014.26]
23. Fan D, Breslin D, Callahan JL, Iszatt-White M. Advancing literature review methodology through rigour, generativity, scope and transparency. Int J Manag Rev. Apr 2022;24(2):171-180. [doi: 10.1111/ijmr.12291]
24. Anderson A, Ahmad A, Chang S. Case-based learning for cybersecurity leaders: a systematic review and research agenda. Inf Manag. Nov 2024;61(7):104015. [doi: 10.1016/j.im.2024.104015]
25. vom Brocke J, Simons A, Riemer K, Niehaves B, Plattfaut R, Cleven A. Standing on the shoulders of giants: challenges and recommendations of literature search in information systems research. Commun Assoc Inf Syst. 2015;37. [doi: 10.17705/1CAIS.03709]
26. Laine J, Minkkinen M, Mäntymäki M. Ethics-based AI auditing: a systematic literature review on conceptualizations of ethical principles and knowledge contributions to stakeholders. Inf Manag. Jul 2024;61(5):103969. [doi: 10.1016/j.im.2024.103969]
27. Moher D, Liberati A, Tetzlaff J, Altman DG, PRISMA Group. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. BMJ. Jul 21, 2009;339(jul21 1):b2535. [doi: 10.1136/bmj.b2535] [Medline: 19622551]
28. Altrichter B, Benoit S. Technology discontinuance: a systematic literature review and research agenda. Eur J Inf Syst. Nov 2, 2025;34(6):1088-1112. [doi: 10.1080/0960085X.2025.2516427]
29. Palmatier RW, Houston MB, Hulland J. Review articles: purpose, process, and structure. J Acad Mark Sci. Jan 2018;46(1):1-5. [doi: 10.1007/s11747-017-0563-4]
30. Mustapha I, Khan N, Qureshi MI, Harasis AA, Van NT. Impact of industry 4.0 on healthcare: a systematic literature review (SLR) from the last decade. Int J Interact Mob Technol. Sep 20, 2021;15(18):116-128. [doi: 10.3991/ijim.v15i18.25531]
31. Khanra S, Dhir A, Islam AKMN, Mäntymäki M. Big data analytics in healthcare: a systematic literature review. Enterp Inf Syst. Aug 8, 2020;14(7):878-912. [doi: 10.1080/17517575.2020.1812005]

32. Behera RK, Bala PK, Dhir A. The emerging role of cognitive computing in healthcare: a systematic literature review. Int J Med Inform. Sep 2019;129:154-166. [doi: 10.1016/j.ijmedinf.2019.04.024] [Medline: 31445250]
33. Tandon A, Dhir A, Islam AKMN, Mäntymäki M. Blockchain in healthcare: a systematic literature review, synthesizing framework and future research agenda. Comput Ind. Nov 2020;122:103290. [doi: 10.1016/j.compind.2020.103290]
34. Pinto R, Silva L, Valentim R, et al. Systematic review on information technology approaches to evaluate the impact of public health campaigns: real cases and possible directions. Front Public Health. 2021;9:715403. [doi: 10.3389/fpubh.2021.715403] [Medline: 35087780]
35. Kitchenham B, Charters S. Guidelines for performing systematic literature reviews in software engineering. Keele University; 2007. URL: https://legacyfileshare.elsevier.com/promis_misc/525444systematicreviewsguide.pdf [Accessed 2026-06-16]
36. Petersen K, Feldt R, Mujtaba S, Mattsson M. Systematic mapping studies in software engineering. Presented at: 12th International Conference on Evaluation and Assessment in Software Engineering (EASE); Jun 26-27, 2008; University of Bari, Italy. [doi: 10.14236/ewic/EASE2008.8]
37. Paul J, Lim WM, O'Cass A, Hao AW, Bresciani S. Scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR). Int J Consum Stud. Jul 2021;45(4). [doi: 10.1111/ijcs.12695]
38. Kitchenham B. Procedures for performing systematic reviews. Keele University; 2004. URL: https://www.researchgate.net/profile/Barbara-Kitchenham/publication/228756057_Procedures_for_Performing_Systematic_Reviews/links/618cfae961f09877207f8471/Procedures-for-Performing-Systematic-Reviews.pdf [Accessed 2026-06-16]
39. Grant MJ, Booth A. A typology of reviews: an analysis of 14 review types and associated methodologies. Health Info Libr J. Jun 2009;26(2):91-108. [doi: 10.1111/j.1471-1842.2009.00848.x]
40. Sarkis-Onofre R, Catalá-López F, Aromataris E, Lockwood C. How to properly use the PRISMA Statement. Syst Rev. Apr 19, 2021;10(1):117. [doi: 10.1186/s13643-021-01671-z] [Medline: 33875004]
41. Radhakrishnan S, Erbis S, Isaacs JA, Kamarthi S. Novel keyword co-occurrence network-based methods to foster systematic reviews of scientific literature. PLoS One. 2017;12(3):e0172778. [doi: 10.1371/journal.pone.0172778] [Medline: 28328983]
42. Olsen F, Schillaci C, Ibrahim M, Lipani A. Borough-level COVID-19 forecasting in London using deep learning techniques and a novel MSE-Moran's I loss function. Results Phys. Apr 2022;35:105374. [doi: 10.1016/j.rinp.2022.105374] [Medline: 35228988]
43. Ma R, Zheng X, Wang P, Liu H, Zhang C. The prediction and analysis of COVID-19 epidemic trend by combining LSTM and Markov method. Sci Rep. Aug 31, 2021;11(1):17421. [doi: 10.1038/s41598-021-97037-5] [Medline: 34465820]
44. Meo SA, Alotaibi M, Meo MZS, Meo MOS, Hamid M. Medical knowledge of ChatGPT in public health, infectious diseases, COVID-19 pandemic, and vaccines: multiple choice questions examination based performance. Front Public Health. 2024;12:1360597. [doi: 10.3389/fpubh.2024.1360597] [Medline: 38711764]
45. Uzun Ozsahin D, Precious Onakpojeruo E, Bartholomew Duwa B, Usman AG, Isah Abba S, Uzun B. COVID-19 prediction using black-box based pearson correlation approach. Diagnostics (Basel). Mar 27, 2023;13(7):1264. [doi: 10.3390/diagnostics13071264] [Medline: 37046482]
46. Morales HMP, Guedes M, Silva JS, Massuda A. COVID-19 in Brazil-preliminary analysis of response supported by artificial intelligence in municipalities. Front Digit Health. 2021;3:648585. [doi: 10.3389/fdgth.2021.648585] [Medline: 34713121]
47. Nabizadeh-Shahre-Babak Z, Karimi N, Khadivi P, Roshandel R, Emami A, Samavi S. Detection of COVID-19 in X-ray images by classification of bag of visual words using neural networks. Biomed Signal Process Control. Jul 2021;68:102750. [doi: 10.1016/j.bspc.2021.102750] [Medline: 34007303]
48. Pienkowska A, Ravaut M, Mammadova M, et al. Understanding COVID-19 impacts on the health workforce: AI-assisted open-source media content analysis. JMIR Form Res. Jun 13, 2024;8:e53574. [doi: 10.2196/53574] [Medline: 38869940]
49. Quiroz-Juárez MA, Torres-Gómez A, Hoyo-Ulloa I, León-Montiel RDJ, U'Ren AB. Identification of high-risk COVID-19 patients using machine learning. PLOS One. 2021;16(9):e0257234. [doi: 10.1371/journal.pone.0257234] [Medline: 34543294]
50. Ahmad HF, Khaloofi H, Azhar Z, Algosaibi A, Hussain J. An improved COVID-19 forecasting by infectious disease modelling using machine learning. Appl Sci. Dec 2021;11(23):11426. [doi: 10.3390/app112311426]
51. Yu L, Zhai X. Use of artificial intelligence to address health disparities in low- and middle-income countries: a thematic analysis of ethical issues. Public Health. Sep 2024;234:77-83. [doi: 10.1016/j.puhe.2024.05.029] [Medline: 38964129]
52. Villarreal-Zegarra D, Reategui-Rivera CM, García-Serna J, et al. Self-administered interventions based on natural language processing models for reducing depressive and anxiety symptoms: systematic review and meta-analysis. JMIR Ment Health. Aug 21, 2024;11:e59560. [doi: 10.2196/59560] [Medline: 39167795]

53. Zhao Q, Zhang C, Zhang W, Zhang S, Liu Q, Guo Y. Applications and challenges of biomarker-based predictive models in proactive health management. Front Public Health. 2025;13:1633487. [doi: 10.3389/fpubh.2025.1633487] [Medline: 40900695]
54. Mlakar I, Kampič T, Flis V, et al. Study protocol: a survey exploring patients' and healthcare professionals' expectations, attitudes and ethical acceptability regarding the integration of socially assistive humanoid robots in nursing. BMJ Open. Apr 1, 2022;12(4):e054310. [doi: 10.1136/bmjopen-2021-054310] [Medline: 35365523]
55. Shen S, Qi W, Zeng J, et al. Passive sensing for mental health monitoring using machine learning with wearables and smartphones: scoping review. J Med Internet Res. Aug 14, 2025;27:e77066. [doi: 10.2196/77066] [Medline: 40811794]
56. Wagner JK, Doerr M, Schmit CD. AI governance: a challenge for public health. JMIR Public Health Surveill. Sep 30, 2024;10:e58358. [doi: 10.2196/58358] [Medline: 39347615]
57. Toma M, Bönisch C, Löhnhardt B, et al. Research collaboration data platform ensuring general data protection. Sci Rep. May 24, 2024;14(1):11887. [doi: 10.1038/s41598-024-61912-8] [Medline: 38789442]
58. Ahmed MM, Okesanya OJ, Olaleke NO, et al. Integrating digital health innovations to achieve universal health coverage: promoting health outcomes and quality through global public health equity. Healthcare (Basel). May 5, 2025;13(9):1060. [doi: 10.3390/healthcare13091060] [Medline: 40361838]
59. Blumenberg C, Peiris D, Loret de Mola C, et al. Going digital: opportunities and barriers in the use of technology for health research. Salud Publica Mex. Jun 13, 2022;64:S22-S30. [doi: 10.21149/12977] [Medline: 36130392]
60. Chau LW, Lam RW, Minas H, Hayashi K, Nguyen VC, O'Neil J. Digital health interventions for depression and anxiety in low- and middle-income countries: rapid scoping review. JMIR Ment Health. Aug 22, 2025;12:e68296. [doi: 10.2196/68296] [Medline: 40846319]
61. Li YH, Li YL, Wei MY, Li GY. Innovation and challenges of artificial intelligence technology in personalized healthcare. Sci Rep. Aug 16, 2024;14(1):18994. [doi: 10.1038/s41598-024-70073-7] [Medline: 39152194]
62. Hattab G, Irrgang C, Körber N, Kühnert D, Ladewig K. The way forward to embrace artificial intelligence in public health. Am J Public Health. Feb 2025;115(2):123-128. [doi: 10.2105/AJPH.2024.307888] [Medline: 39571129]
63. Leslie D, Mazumder A, Peppin A, Wolters MK, Hagerty A. Does "AI" stand for augmenting inequality in the era of covid-19 healthcare? BMJ. Mar 15, 2021;372:n304. [doi: 10.1136/bmj.n304] [Medline: 33722847]
64. Burger M. The risk to population health equity posed by automated decision systems: a narrative review. arXiv. Preprint posted online on Jan 18, 2020. [doi: 10.48550/arXiv.2001.06615]
65. Markus AF, Kors JA, Rijnbeek PR. The role of explainability in creating trustworthy artificial intelligence for health care: a comprehensive survey of the terminology, design choices, and evaluation strategies. J Biomed Inform. Jan 2021;113:103655. [doi: 10.1016/j.jbi.2020.103655] [Medline: 33309898]
66. Chaddad A, Lu Q, Li J, et al. Explainable, domain-adaptive, and federated artificial intelligence in medicine. IEEE/CAA J Autom Sinica. Apr 2023;10(4):859-876. [doi: 10.1109/JAS.2023.123123]
67. Yousefi F, Dehnavieh R, Laberge M, et al. Opportunities, challenges, and requirements for artificial intelligence (AI) implementation in primary health care (PHC): a systematic review. BMC Prim Care. Jun 9, 2025;26(1):196. [doi: 10.1186/s12875-025-02785-2] [Medline: 40490689]
68. Algumaei A, Yaacob NM, Doheir M, Al-Andoli MN, Algumaie M. Symmetric therapeutic frameworks and ethical dimensions in AI-based mental health chatbots (2020–2025): a systematic review of design patterns, cultural balance, and structural symmetry. Symmetry. Jul 7, 2025;17(7):1082. [doi: 10.3390/sym17071082]
69. Baddal B, Taner F, Uzun Ozsahin D. Harnessing of artificial intelligence for the diagnosis and prevention of hospital-acquired infections: a systematic review. Diagnostics (Basel). Feb 23, 2024;14(5):484. [doi: 10.3390/diagnostics14050484] [Medline: 38472956]
70. Blaizot A, Veettil SK, Saidoung P, et al. Using artificial intelligence methods for systematic review in health sciences: a systematic review. Res Synth Methods. May 2022;13(3):353-362. [doi: 10.1002/jrsm.1553] [Medline: 35174972]
71. Vayena E, Blasimme A, Cohen IG. Machine learning in medicine: addressing ethical challenges. PLoS Med. Nov 2018;15(11):e1002689. [doi: 10.1371/journal.pmed.1002689] [Medline: 30399149]

Abbreviations

AI: artificial intelligence
BDA: big data analytics
CONSORT-AI: Consolidated Standards of Reporting Trials–Artificial Intelligence
IS: information systems
LLM: large language model
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SALSA: Search, Appraisal, Synthesis, and Analysis
SLR: systematic literature review

SPAR-4-SLR: Systematic Procedures and Rationales for Systematic Literature Reviews
TCCM: Theory, Context, Characteristics, and Methodology
TRIPOD+AI: Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis+Artificial Intelligence
WoS: Web of Science

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