

The potential roles and risks of Artificial Intelligence in public health: A scoping review

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Abstract

Background

Artificial intelligence (AI) is a broad field encompassing various techniques, which include algorithms that learn from data to perform automated tasks without explicit human programming. Public health aims to protect and improve the health of communities and populations at local, regional, national, and global level, but typically suffers from limited resources. AI may lead to improved efficiency or effectiveness of public health interventions, but there needs to be appropriate consideration of the risks of implementation. The purpose of this scoping review is to identify the potential roles and risks of AI in public health.

Methods

We searched Medline, Embase, Web of Science (Core Collection), and Scopus for relevant reports published between 01 January 2020 and 08 September 2025. Two reviewers independently screened reports. Eligible reports were primary studies, reviews, opinion pieces, commentaries, and editorials relevant to high income countries. Data were extracted by one reviewer and checked by a second. We combined substantively similar potential roles and risks by narrative theme across reports. We refined the protocol and gained feedback on initial findings from stakeholder consultation with 9 people from Health Determinants Research Collaborations, and 9 people from data science institutes, public health agencies, and national Local Government networks.

Results

We screened 1,805 records and 320 full texts, including 67 reports. These reports considered 44 potential roles of AI across eight public health contexts. Potential roles primarily included using machine learning to make predictions, analyse data, and make recommendations, and using large language models to help tailor educational content or communications. Most frequently indicated risks were bias and generalisability, confidentiality and ethical concerns, and exacerbation of inequalities. Specifically, AI could lead to perpetuation or reinforcement of health inequalities and discrimination, a reduction in public trust for public health communications and interventions, and inaccurate predictions, unintended consequences, or ineffective interventions.

Conclusion

While we did not consider how plausible or beneficial the identified potential roles of AI in public health may ultimately be, when adopting any new intervention, the intervention should be evaluated for anticipated effectiveness (and cost-effectiveness), with careful consideration of the risks. Future research needs to evaluate the effectiveness of AI interventions across the range of public health domains, with a focus on assessing the potential of inequity generating impacts and harms. There needs to be meaningful community engagement and co-production with diverse and underrepresented people to help mitigate against inequity (and improve trust) when adopting AI tools. Stakeholders emphasised

the importance of examining how interventions can be optimally diffused and implemented within public health systems to maximise the likelihood of any realising any positive effects.

Background

Artificial intelligence (AI) is a broad field encompassing various techniques, including machine learning, natural language processing, and generative AI (1). AI, learns from data to perform automated tasks without explicit human programming using algorithms integrated into systems and tools (2–4). While the theoretical groundwork for machine learning was laid in the 1980s, recent advancements in computing power and the development of large language models (LLMs), like OpenAI's ChatGPT and Google's Gemini have sparked renewed interest in AI (5). These models, with more user-friendly interfaces and general-purpose applications, offer the potential to tackle a wide range of problems (6).

Public health is an area where AI is increasing being used, largely with a view to harnessing potential improvements in efficiency and effectiveness. We found several examples of chatbots, machine learning, and other AI-assisted interventions aiming to reduce engagement with alcohol drinking, smoking, and physical activity in our recent reviews (7, 8), and some limited uses of chatbots, machine learning, and generative AI in current public health system practices (9). Other reviews have identified existing uses of AI in public health, both in clinical public health, such as disease screening, diagnosis, prognosis, and clinical decision support, as well as non-clinical public health, such as disease surveillance, emergency response, and health communication (10, 11). Amidst this increase in uptake, there are emergent concerns about the advancement of AI and whether it can be delivered in an equitable, responsible, trustworthy, and ethical manner. Globally there has been a rapid expansion in regulatory frameworks for usage (12), alongside critical debate about the gaps where innovative and legislation is needed (13). However, much of this work is concentrated on the development, evaluation and post-market surveillance of medical devices. Most recently the UK Faculty of Public Health Artificial & Digital Public Health Special Interest Group has expressed concerns that the regulatory focus on monitoring clinical harms, which has meant the potential for AI to amplify inequalities may have been largely overlooked (14). As such, it is essential to understand not only where AI may offer future value but also how its implementation could introduce a range of unintended harms, lest ineffective or biased AI interventions lose trust in public health (15).

The purpose of this scoping review is to identify the potential roles and risks of AI in public health. In doing so, the review will provide a future-focused perspective on how AI could shape public health practice, the conditions required for its responsible use, and the implications for professionals, organisations, and populations. Scoping reviews are ideally placed to map the research landscape, visualising potential areas of exploration, balanced this against the potential risks.

Methods

This scoping review systematically synthesised evidence to answer the following review question:

1. What are the potential roles and risks of AI in public health?

This review formed part of a broader programme of work evaluating the past, current, and potential uses of AI in public health (7–9). The protocol was registered on Zenodo: 15971614 (16). This review is reported with reference to the PRISMA Extension for Scoping Reviews (PRISMA-ScR) (17). All data produced in this review are contained in the manuscript and its supplementary information files. We did not use AI in any part of the review process or when writing this article.

Stakeholder engagement

We conducted stakeholder engagement across our broader programme of work across two phases of activity. The first phase involved protocol refinement and confirmation, with the aim of defining concepts related to AI and understanding comprehension of different models and platforms. The second phase gained feedback on initial synthesis findings, with consideration of how public health systems may support diffusion and delivery of AI-based interventions.

We conducted consultation meetings with two UK-based communities of practice at each phase. One community comprised nine practitioners from the NIHR funded Health Determinants Research Collaborations (HDRCs), with experience of public health service delivery. HDRCs are Local Government funded infrastructures intended to develop research capacity and capability to improve evidence-based decision-making. The second community, also comprising nine people, included strategic directors with significant leadership roles for AI in public health across data science institutes, public health agencies, and national Local Government networks.

Eligibility criteria

We included primary studies, reviews (systematic, rapid, scoping, literature), opinion pieces, commentaries, and editorials published or preprinted in English from 01 January 2020 that discussed specific ways that AI tools could be used in public health contexts relevant to high income countries (as defined by the World Bank (18)) and the associated risks. We defined public health contexts as those where the primary aim was to improve public health, typically involving local and national Government-funded public health organisations delivering interventions or making policy decisions. We excluded pandemic contexts and clinical settings, for instance reports where reports only considered roles of AI that used NHS resources. We defined AI broadly as algorithms integrated into systems and tools that can learn from data to be able to perform automated tasks without explicit human programming.

In post-hoc changes to the protocol, we refined the eligibility criteria to exclude outbreaks (including local disease modelling and prediction), given that AI use in outbreak contexts has been extensively researched already (19). To more tightly focus on population-level public health interventions, we also excluded studies primarily related to environmental monitoring (for example, air, water, and food quality, pollution, wastewater), infrastructure and safety systems (for example, transport safety), climate and weather modelling, and individual-level clinical risk prediction (for example, the risk of falls).

Search strategy

We used one AI search facet in the search strategy. This facet drew upon an unpublished filter created by members of the InterTASC (Technology Appraisal Support Collaboration) Information Specialists' Sub-Group (ISSG), as well as filters hosted on the associated ISSG Search Filter Resource (20). We combined the AI search facet with public health terms and terms to capture the future of AI in public health. These terms were derived from iterative searching, with pertinent words and MeSH terms harvested from relevant papers and reference lists. We added a systematic review filter to this (21). We conducted a second, more focused, search without a study design filter to ensure key editorials and opinion pieces were retrieved. Search strategies for all databases are presented in **Supplementary Information A**.

Information sources

We conducted searches in four bibliographic databases: Medline (Ovid); Embase (Ovid); Web of Science (Core Collection); and Scopus. Searches were deduplicated with DOI matching using Stata 19 (22). Searches were conducted up to 08 September 2025.

Selection of sources of evidence

Two reviewers (SH and GJMT) independently screened titles and abstracts in Rayyan (23), and two reviewers (SH and CT) independently screened full texts in a standardised Excel sheet. Titles and abstracts included by at least one reviewer on eligibility assessment progressed to full-text screening. Conflicts in assessment of full texts were resolved through discussion, with no necessity to involve a third party.

Data charting process and items

One reviewer (SH) completed all data extraction, which was checked by a second reviewer (GJMT). For each included report, we extracted information into a standardised Excel sheet about the public health context in which AI could be used, the type of report (review, commentary, or primary study), the type of AI, how it could be used in that context, and any associated risks.

Synthesis of results

We narratively summarised the evidence by public health context. In this review, public health contexts were more closely aligned to the roles within public health, such as public health communication and interventions, rather than public health domains (health improvement, health protection, and healthcare public health), as in our review of current uses of AI in public health (9). Within each public health context, we summarised potential uses and potential risks, combining substantively similar potential roles and risks by narrative themes across reports.

All data generated or analysed during this review are included in this published article and its supplementary information files.

Ethical approval

for this review was not required. We consulted with stakeholder groups in accordance with any ethical requirements stipulated by the organisations and research studies that recruited participating members.

Results

Figure 1 shows the PRISMA diagrams for the flow of references. **Supplementary Information B** contains full text screening results and data extractions for reports.

We screened 1,805 titles and abstracts, 320 full texts, and ultimately included 67 reports. These reports considered potential roles of AI across eight public health contexts (some reports considered potential roles in multiple contexts): 18 for public health communication (15, 24–40), three for public health education (24, 27, 41), 10 for public health emergencies (excluding disease outbreaks) (28, 42–50), eight for evidence reviews (26, 51–57), 12 for forecasting of population-level public health concerns (58–69), 19 for public health interventions (11, 24, 27, 31, 33, 70–83), 12 for public health organisations generally (15, 26, 27, 30, 31, 65, 74, 77, 78, 84–86), and two for public health surveillance (87, 88).

Multiple types of AI were considered in the reports, including machine learning, deep learning, natural language processing, and various algorithms, chatbots, large language models and generative AI. However, 17 reports did not specify the type of AI for any proposed potential roles (24, 27, 28, 31, 41, 43, 45, 50, 73–75, 77, 78, 81, 83–85).

The potential roles and risks of AI in public health

The 44 potential roles of AI we identified from included reports are detailed in Table 1, categorised by their public health context. Almost all the potential roles were specific to a particular public health context, for example, automating citation searching and removing duplicate articles and extracting data from included articles using generative AI are specific to evidence synthesis. Generally, though, potential roles included using machine and deep learning to make predictions, analyse data, or make recommendations, or involved using large language models to help tailor educational content or communication, as well as automating tasks.

The potential risks of AI we identified from included reports are detailed in Table 2. In contrast to the potential roles of AI, most of the risks of AI were shared across contexts; the few risks that were more specific to certain contexts are highlighted as such. The most widely cited and generalisable risk was bias and generalisability, meaning AI interventions could be ineffective or even harmful, at least for certain groups.

Table 1
Potential roles of AI in public health

Communication - how AI (particularly machine and deep learning, natural language processing, generative AI, and chatbots) could be used to improve public health communication (15, 24–40):

- creating targeted messaging for public health communication interventions, for example by considering demographics, culture, and literacy levels (15, 30, 31, 35, 37, 39)
- generating images to assist in public health communication (15)
- improving clarity of communication (15, 31, 39)
- improving engagement with public health communication (35), for instance by using chatbots and generative AI to give the public better access to, and engagement with, public health information online (15, 26, 27, 30, 31, 33)
- monitoring of public health indicators in real-time to help develop strategies to address emerging health concerns (35), for example using machine learning, deep learning, natural language processing, or generative AI to assess topical trends, or public concerns or sentiment, and adapting communication as necessary (25, 26, 29, 30, 32, 36, 38, 40) or debunking rumours or misinformation (28, 30, 34, 38)
- translating public health information (15, 24, 35, 39)

Education - how AI (particularly machine learning) could be used improve education of public health professionals (24, 27, 41):

- assessing, evaluating, and providing feedback for student assignments (24)
- moving in-person education to online programs and the creation of dynamic (tailored and multimodal) learning modules (24)
- providing personalised learning through tailored content and interactive or simulated training, adjusting to learning pace, comprehension levels, and preferred teaching style of students (24, 27, 41)

Emergencies - how AI (particularly machine learning, including ant colony algorithms) could be used to improve the effectiveness and efficiency of emergency public health response and improve communication and collaboration between stakeholders (28, 42–50):

- allocating resources, such as hospital beds and personnel (42–44, 46, 50)
- communicating effectively, including translating during emergencies (44)
- gathering and analysing data from diverse sources, recommending courses of action and helping to make decisions, including where to target interventions and guiding recovery after an emergency (42–46)
- managing logistics, including emergency evacuations of people (42, 46) and vehicle routing to provide and distribute resources (45, 47, 49, 50)
- planning, capacity building, creating early warning systems, and training (28, 42–45)
- triaging victims (46, 48)

Evidence reviews - how AI (particularly machine and deep learning, natural language processing, and generative AI) could be used to improve the efficiency of public health evidence reviews (26, 51–57):

- analysing data, writing of the final report, recommending journals, and helping create ancillary documents required for submission, such as cover letters, using generative AI (56)
- automating citation searching and removing duplicate articles (57)
- automating risk of bias assessments or critical appraisals using natural language processing or generative AI (55–57)
- creating search strategies (56)
- determining the review question, for example by using generative AI to search for previous reviews on the topic and refining the question to be addressed (56)
- extracting data from included articles using generative AI (56, 57)
- reducing screening burden, for example by using machine learning with natural language processing to semi-automate or automate article title and abstract screening through prioritisation (51, 53, 54, 57), by using generative AI to screen article titles and abstracts (56) or full texts (57), or by predicting the usefulness of articles (52)
- registering and writing the review proposal, and defining the eligibility criteria, using generative AI (56)
- summarising evidence (26)

Forecasting - how AI (particularly large language models and machine learning, such as autoregressive integrated moving average, long-short term memory, gated recurrent units, random forest, vector autoregression model, and extreme gradient boosting) could improve the accuracy of forecasting models for population-level public health concerns (58–69). All included reports were primary studies, except one commentary about primary studies (65) and one scoping review (62), and all reports looked at forecasting for different population-level outcomes:

- alcohol consumption (66) and alcohol-related liver disease mortality (58)
- cardiovascular mortality (64)
- colorectal cancer prevalence (68)
- dementia prevalence (69) and dementia-related mortality (65)
- diabetes prevalence (63) and the consumptions of diabetic drugs (62)
- mosquito abundance (67)
- obesity prevalence (61), prognosis (60), and mortality (59)

Interventions - how AI (particularly machine learning, chatbots, and virtual and augmented reality) could be used to improve public health interventions (11, 24, 27, 31, 33, 70–83):

- developing and tailoring population-level interventions, such as for health promotion (11, 24, 27, 31, 73–75, 77, 78)
- interventions aimed at healthy aging, through improving mental and physical health, physical activity, social participation, wellbeing, and digital inclusion, using AI-assisted interventions (81, 83), including using robots (72)
- predicting the effects of policy changes (71)
- predicting who would be most likely to respond in a volunteer first responder intervention for opioid overdose emergencies (79)

- screening for and reducing behavioural risks for poor health, such as obesity (70, 73), physical inactivity (11, 82), poor diet (71), hypertension (80), opioid overdoses (76), and unprotected sex (33)

Public health organisations - how AI (particularly machine learning and generative AI) could be used to improve the performance of public health organisations as a whole (15, 26, 27, 30, 31, 35, 65, 74, 77, 78, 83–86):

- analysing large datasets from multiple sources to provide more comprehensive information about individuals or populations and therefore make more informed public health decisions (30)
- developing public health policies, strategies and community-based programmes targeting older adults (83)
- identifying promising public health interventions (26)
- organising and analysing data (15), for example qualitative analyses of interviews (86) or examining determinants of health in the population (27, 65, 78, 85), which can aid in making decisions and recommendations, allocating resources, and planning health programs and campaigns (26, 31, 74, 77, 84)
- summarising and automating routine tasks, reducing clerical burden (15, 31, 35)
- writing grant applications, policies, and reports (15)

Surveillance: how AI could be used in public health surveillance (87, 88)

- monitoring mask wearing, for example through deep learning with image classification (88)
- monitoring social distancing, for example through deep learning with object detection models on unmanned aerial vehicles (87)

Table 2
Risks of AI in public health

- Bias and generalisability, which could lead to perpetuation or reinforcement of health inequalities and discrimination, a reduction in public trust for public health communications and interventions, and inaccurate or unreliable predictions, unintended consequences, or ineffective interventions (15, 26, 27, 30, 31, 33–35, 37–39, 41, 46, 52, 57, 65–68, 71, 73–76, 78, 83, 85, 86, 88)
- Concerns that AI lacked transparency, had concerns around data management, privacy, security, and confidentiality, or had ethical, legal, and regulatory concerns (15, 26, 27, 30, 31, 34, 35, 38, 41, 44, 45, 48, 56, 57, 65, 71–74, 76–78, 81, 83–86)
- Existing health inequalities could be exacerbated by a lack of workforce capacity, training, infrastructure, equipment, or resources (15, 24, 27, 48, 63, 72–74, 76, 77, 81, 85, 88)
- Inaccurate or incorrect content created by generative AI (27, 34, 55–57, 65)
- Barriers to AI technology adoption in the public, which could lead to digital exclusion of vulnerable populations (27, 72, 81)
- Concerns about the interpretability of AI outputs (63, 81, 83)
- Technical challenges of using AI, such as data accessibility and integration issues, system interoperability, and algorithmic complexity (35, 63)
- Issues with plagiarism when using generative AI (34)
- Deskilling and overconfidence of public health professionals when using generative AI, potentially leading to harmful public health decisions (27)
- *More specific to communication:* Inaccuracy, inauthenticity, misinterpretation, or misuse of AI-generated communications, potentially leading to a reduction in trust in public health communications (15, 30, 32, 34, 35, 37–39)
- *More specific to education:* Students could use AI to generate assignments, sabotaging their own learning (24)
- *More specific to evidence reviews:* Potentially missing relevant articles when using AI for screening (51, 53, 54)
- *More specific to evidence reviews:* Potential restrictions on use of AI due to the copyright restrictions of articles (57)

Discussion

This scoping review summarised evidence for the potential roles of AI in public health contexts along with associated risks. This review is vital in a current policy and practice environment that is trying to carefully balance a permissive and innovative system of AI generation with robust regulation and mitigation of harms (89). We identified a total of 44 potential roles of AI across eight public health contexts, including using machine learning to make predictions, analyse data, or make recommendations, and using large language models to help tailor educational content and communication.

Many included reports were vague when discussing the potential roles of AI. It is possible that some authors were using “AI” as shorthand for “generative AI”, as the two have become more synonymous after the release and proliferation of ChatGPT. However, it may also be possible that the authors did not know which type of AI would be most appropriate for the stated roles, and so were proposing use of AI without fully understanding how the technology could potentially be used. While this lack of specificity might be understandable given the nature of the publication types included, it does speak to a wider issue around the reporting of AI interventions, as seen in the broader programme of work we’ve conducted evaluating the past, current, and potential uses of AI in public health (7–9). Although focussed on more clinical settings, AI-specific reporting guidelines, such as SPIRIT-AI (90), CONSORT-AI (91) and DECIDE-AI (92), may be useful in prompting more informative and standardised descriptions of interventions that incorporate AI in public health.

The UK Faculty of Public Health have suggested that the use of AI in public health should be trustworthy, equitable, ethical, responsible, while based in methodological rigour (14). Our review has indicated that there are potential risks to these principles being realised.

First, there are concerns about a lack of trust in tools, which can arise from a lack of methodological rigour. From our accompany reviews, we found little evidence for past or current uses of AI tools in public health practice, and evidence for either effectiveness or usefulness was mixed (7–9). As such, new evidence should be generated, establishing a clear evidence base for which AI tools could be beneficial to adopt, if any. Evidence generation, however, can be slow, and our stakeholders highlighted the issue with universities not keeping pace with industry and applied practice and called for deeper collaboration and study designs that can support the pace of change. Pragmatic randomised controlled trials, and Plan-Do-Study-Act research cycles (93), living systematic reviews, preprints, and grey literature repositories such as the Local Government Authority AI case study bank in the UK (94) may facilitate quicker evidence generation while maintaining methodological rigour. There is also a need to ensure sufficient regulatory frameworks to ensure this rigour is achieved and maintained.

While clinical settings have a comprehensive programme of regulatory compliance for AI interventions (12), public health does not. For example, the Food and Drug Administration (FDA) has regulatory frameworks for medical devices in the US (95) and the Medicines & Healthcare Products Regulatory Agency (MHRA) has the Software and AI as a Medical Device Change Programme in the UK (96). The European Union’s AI act harmonises rules and regulations on AI for a wider range of systems and technologies, but this is not specific to public health (89). Given the potential risks involved and the increase in trust such regulation would bring to approved interventions, there should be public health specific regulatory compliance for AI interventions that centres public health values. Regulation even has popular support: when the Health Foundation surveyed the UK public about AI use in healthcare, 71% of respondents preferred strict rules and regulations in place around AI to encouragement for companies to develop AI in the UK (97).

Second, the risk of achieving equitable AI use. This was considered in relation to the perpetuation or reinforcement of health inequalities and discrimination, both due to AI interventions potentially being biased and potentially inequitable access to any uses of AI shown to be effective. These concerns add weight to the view that understanding the potential risks of an intervention before adoption is necessary even for non-clinical interventions (98). Meaningful community engagement and co-production with diverse and underrepresented people may help mitigate against inequity (and improve trust) when adopting AI tools, though poor representation within public health datasets used to train AI tools may still inevitably result in AI tools that embed inequity.

Third, the risk of using AI in an unethical manner. Ethical concerns were often noted in the included reports, but there was no explicit mention of the broad and damaging environmental impacts of using AI tools in public health (99), the exploitation of low-paid workers (100), or the shifting of responsibility to humans-in-the-loop should an AI tool perform poorly (101). While these concerns are more indirect, in that they may not directly and negatively affect people using public health services, they may nevertheless influence decisions to adopt AI tools.

Fourth, the risk to responsible AI use, particularly in relation to how it can be integrated into the real-world practice of public health systems (particularly the potential uses of AI within public health organisations listed in Table 1). We identified many potential risks of AI applicable at the systems level, including transparency, data management, privacy, security, and confidentiality, particularly relevant when working with personal information, as well as workforce capacity, training, infrastructure, equipment, and resources. Therefore, use of AI in systems needs strategic and careful thought and planning, as without a clear strategy that includes workforce training and support, there is a risk the diffusion of innovation will happen informally, inconsistently, and without evidence of effectiveness, potentially driven more by external pressures than internal need. Implementation science, previously used to explore integration of generative AI with healthcare (102), may help in understanding how any potentially effective AI tool can be integrated within public health systems.

Limitations of this review

Despite the comprehensive search strategies, it is possible that relevant reports may have been missed from searches. Equally, despite duplication of screening, relevant reports may have been missed during screening, and relevant information may have been missed during data extraction of included reports. However, the purpose of this scoping review was primarily to discover potential roles and risks of AI in public health: the inclusion of more reports that may have been missed, or information that was missed from included reports, may not have identified more roles or risks. Equally, there are almost certainly potential roles and risks of AI that have not yet been considered.

Additionally, we did not consider how plausible or beneficial the identified potential roles of AI may ultimately be, as this was beyond the scope of the review, and there is little available evidence with which to make informed predictions. We also did not consider whether the sources of the potential roles were

credible. The identified potential roles of AI in public health should therefore be treated with caution when considering uses of AI, and balanced against the many identified risks.

Implications for research, policy, and practice

The review has several implications for research, policy, and practice, based on the culmination of potential roles and risks described.

Future research needs to evaluate the effectiveness of AI interventions across the range of public health domains to create an evidence base from which future decisions about AI tools can be made, with a focus on assessing the potential of inequity generating impacts and harms. There should also be a focus on developing AI-specific reporting guidelines for AI interventions and tools used within public health practice.

For policy, there needs to be meaningful community engagement and co-production with diverse and underrepresented people to help mitigate against inequity (and improve trust) when adopting AI tools. Additionally, public health specific regulatory compliance for AI interventions should be developed, centring public health values.

When considering adopting AI in practice, public health professionals should carefully consider the potential effectiveness and cost-effectiveness alongside any risks. AI has the potential to be used across all public health contexts, but in general, there is very little current evidence to support the use of AI in any given role. Strategic and careful thought and planning, including workforce training and support, would be useful to prevent chaotic diffusion of innovation, including the adoption of AI tools that are ineffective, embed inequity, or reduce trust in the organisation.

Additionally, it may be beneficial to adopt a structured process when considering adopting AI tools into public health practice. This may follow a similar approach to that in Gitlin (2013), with an iterative and incremental process, moving from discovery to safety, feasibility and acceptability, to effectiveness and sustainability (103). In essence, finding suitable roles of AI (if any), then testing them to ensure they are cost-effective (including community engagement), ethical, and any potential benefits outweigh the risks. Notably, there is a cost to adopting new ways of working, including using AI, that need to also be considered. The risks of increasing inequity also need to be carefully considered before any implementation of AI (104).

Conclusion

This scoping review summarised evidence for the potential roles of AI in public health. Across eight public health contexts, we identified a total of 44 potential roles of AI and many risks, some of which are substantial enough to potentially pose a threat to trust in public health itself. Moving forward, future research needs to assess the effectiveness of interventions in realising these potential roles, including any effects on relevant outcomes, their cost-effectiveness, and any harms, particularly around equity.

The public health system needs a coordinated approach to mitigate these harms, working to ensure that any use of AI is responsible, equitable, trustworthy, ethical, and based in methodological rigour. To this end, there needs to be public health specific regulatory frameworks, strategic and careful guidance on how to integrate AI into real work settings, and workforce training and support.

Declarations

Disclosure of Interests:

Author Contribution

Sean Harrison: Conception and protocol, screening, data extraction, risk of bias assessment, narrative synthesis, first draft and editing of manuscript
G.J. Melendez-Torres: Conception and protocol, data extraction, editing of manuscript
Claire Tatton: Screening, editing of manuscript
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Figures

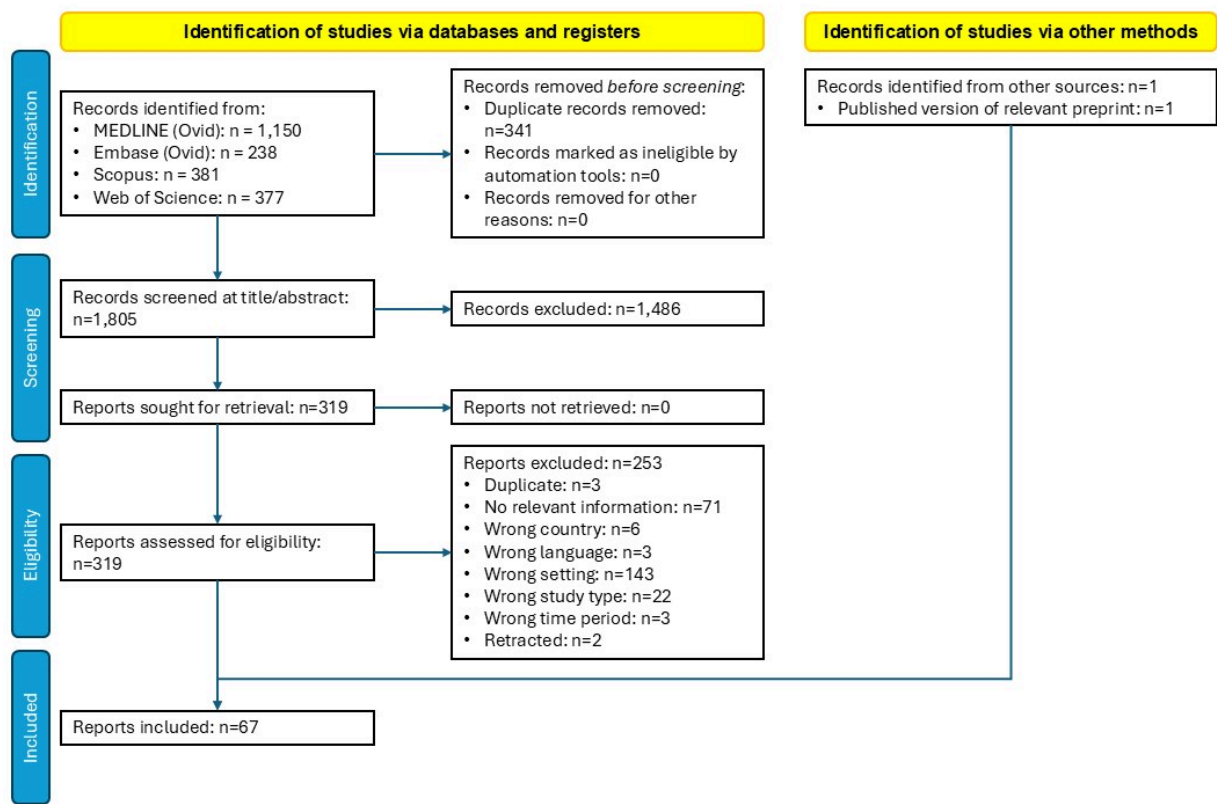


Figure 1

PRISMA diagram

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