Chapter 13
Public Health Applications

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After reading this chapter, you should know the answers to these questions:
- What aspects of public health functions have determined if they are amenable to the application of AI? What are the functions that have been the most transformed?
- How have public health surveillance systems used AI methods to detect infectious disease outbreaks? What are some example systems?
- What biases should be considered when using AI to develop prediction models in population and public health?
- Which public health functions have the greatest potential to be transformed by AI applications in the future?

Public Health and AI

Public Health, Essential Public Health Functions, and Public Health Informatics

Public health is the science and the art of preventing disease, prolonging life, and promoting health through organized community efforts [1]. With a focus on health promotion and disease prevention in populations, public health is complementary to clinical medicine, which is focused on diagnosis and treatment of disease in individual patients. Although they have distinct perspectives, public health and clinical systems should act in a coordinated manner to advance individual and population

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health. Ideally, this coordination should occur at both strategic and operational levels, ensuring, for example, the exchange of data about reportable diseases and **social determinants of health**.

The systematic application of information and computer science and technology to public health practice, research, and learning is the domain of **public health informatics** (see Box 13.1 for definitions) [2], which was first identified as a subdiscipline of biomedical informatics in 1995 [3]. A public health informatics perspective is critical for the effective application of AI in public health for at least two reasons. First, AI methods are generally implemented within software and introduced into public health settings in the same manner as other digital tools and interventions. For these tools to be effective, careful consideration must be given to the context in which they will be used and public health informatics takes a comprehensive view of this challenge. In addition to the information technology and data management aspects of this context, evidence has shown that cognitive [4] and organizational aspects [5] are important determinants of adoption and effective use. Second, AI-based software tools in public health often depend on data and knowledge contained in systems outside of public health. AI-based tools must therefore be implemented with careful consideration of data standards and **interoperability** to ensure the availability and quality of these inputs. For example, during the COVID-19 pandemic, the most common barrier to hospitals sharing electronic data with public health departments in the US was the lack of capacity within public health agencies to electronically receive data [6].

From an applied perspective, the essential public health functions describe the nature and scope of activities in public health [7]. Consequently, these functions also determine the information requirements of public health practitioners [8]. The essential functions, which were most recently updated in a US context in 2020, can be grouped under the three themes of assessment, policy development, and assurance (Box 13.2). These functions are not performed by a single monolithic system, but rather through a system of systems [9], with different public health entities operating at local, regional, national and international levels. These different systems interact with one another and systems outside of public health (e.g., clinical care, social services, urban planning) through a variety of formal and informal mechanisms.

Box 13.1: Public Health and Public Health Informatics

- *"Public Health is the science and the art of preventing disease, prolonging life, and promoting physical health and efficiency through organized community efforts"* [1]
- *"Public health informatics is the systematic application of information and computer science and technology to public health practice, research, and learning"* [2]

The Nature of Essential Public Health Functions and the Application of AI

Each of the ten essential public health functions has unique objectives, approaches, and available resources, including information systems, data and knowledge. Consequently, AI methods are more or less applicable to the different public health functions. In this chapter, the main AI methods considered are knowledge-based systems (Chap. 4), machine learning (ML, see Chap. 6), and natural language processing (NLP, see Chap. 7). The potential applicability of these AI methods to public health is considered below and examples of the application of these methods to specific public health functions are presented later in this chapter (see the section on "Examples of AI Applications to Public Health Functions").

Assessment functions, such as public health surveillance, rely extensively on the collection and analysis of data to monitor population health status and to manage population health hazards. These data are increasingly accessed from information systems used primarily in social and clinical settings and then transferred to public health organizations for secondary use. As such, the data available for assessment often have a volume sufficient for the application of machine learning methods. In primary or source systems, such as in electronic health records, many data are captured as free text, so natural language processing methods are used to extract from the free text structured data of relevance to public health (e.g., smoking status, occupation).

Functions under the *policy development* theme include communication, advocacy and coordination with stakeholders. These activities do not tend to be driven by quantitative data analysis to the same extent as the assessment functions. Consequently, data-intensive methods such as machine learning have not been used extensively to support these functions, but knowledge-based systems have been used to support the organization and application of evidence to these functions (e.g., evidence to guide implementation of chronic disease prevention programs). One exception to this general trend is the communication function, where machine learning and natural language processing methods have been used with digital media platforms to support the delivery and evaluation of public health communication campaigns.

Assurance functions are heterogenous, including public health training, research, and the evaluation of public health services. Training to enable the effective implementation and use of AI-based tools is limited in many public health programs, as is the opportunity for training in public health informatics more generally [10]. In research, there has been considerable activity to explore applications of machine learning, natural language processing, and knowledge-based systems in public health, but the translation of research on AI methods to public health practice has been challenging.

Finally, many models of essential public health functions include at their core the concept of **equity**. Consideration of equity follows naturally from a population perspective, where the distributions of health determinants and outcomes are a primary focus and often revealing of inequities. While AI methods can potentially help to identify and address inequities, there is also concern that such methods, and particularly machine learning, could reinforce or worsen inequities through mechanisms such as differential access and algorithmic bias [11].

A Vision for AI in Public Health

To realize the full potential of AI in public health, it is helpful to apply the perspective of **digital transformation** [12] to essential public health functions. Digital transformation draws upon user-centered design to re-imagine how essential functions can be improved by exploiting AI methods and other digital technologies. The goal is to move beyond the use of AI methods to automate manual data processing towards the use of AI to support effective decision-making in public health. In this context, a truly AI-enabled public health system is one where the data needed to perform essential functions are available and processes are optimized, through the appropriate use of AI methods, with the goal of supporting the effective and efficient delivery of essential public health services.

Box 13.2: Essential Public Health Functions [7]

Assessment

1. *Assess and monitor population health status, factors that influence health, and community needs and assets*
2. *Investigate, diagnose, and address health problems and hazards affecting the population*

Policy Development

1. *Communicate effectively to inform and educate people about health, factors that influence it, and how to improve it*
2. *Strengthen, support, and mobilize communities and partnerships to improve health*
3. *Create, champion, and implement policies, plans, and laws that impact health*
4. *Utilize legal and regulatory actions designed to improve and protect the public's health*

Assurance

1. *Assure an effective system that enables equitable access to the individual services and care needed to be healthy*

2. *Build and support a diverse and skilled public health workforce*
3. *Improve and innovate public health functions through ongoing evaluation, research, and continuous quality improvement*
4. *Build and maintain a strong organizational infrastructure for public health*

Applications of AI in Public Health

As discussed in the section on "The Nature of Essential Public Health Functions and the Application of AI", AI methods are more easily applied to some public health functions than others due to differences in the nature of each function. In this section, specific examples of how AI has been applied to different functions are presented and barriers and risks to the application of AI methods in public health are discussed.

Examples of AI Applications to Public Health Functions

In this section, examples of applications of AI to public health functions are presented considering both the public health functions (Box 13.2) and the AI approaches used (i.e., knowledge-based, machine learning, natural language processing). The intent is to illustrate different types of applications and not to provide a systematic or comprehensive review of all applications of AI methods to public health functions.

Assessment

The theme of assessment includes two essential public health functions, monitoring population health and surveillance of health hazards. Population health is a complex construct, which can be measured in terms of sentiment, attitudes, beliefs, and health outcomes. It is also influenced by a wide range of social, behavioral and physical determinants. Similarly, health hazards are diverse, including environmental conditions, workplace environments, and infectious diseases. The multidimensional nature of assessment lends itself well to AI methods such as machine learning and knowledge representation, which have both been applied to distill large amounts of data and information in this context. Many sources of data are unstructured and NLP has the potential to extract structured data from these sources for further analysis. While monitoring population health tends to have a longer-term focus to guide policy, surveillance can require rapid decision-making and action to control health threats.

Population health monitoring systematically collects data on health status, usually to inform longer-term planning and evaluation of programs. ML methods have been used in population health monitoring to analyze data from wearable devices, social media [13] and other high-dimensional data sources such as electronic health records [14] to predict population health. Researchers have also demonstrated the use of ML to measure associations between the built environment and health [15]. More broadly, these uses of ML methods in public health practice reflect their broader adoption in epidemiology and health outcomes research [16]. NLP has been used to monitor aspects of population health through analysis of posts and discussions in online digital media, such as identifying neighborhood characteristics associated with discussions of food on Twitter [17]. Knowledge-based systems have also been applied to exploit knowledge of causal relationships between the determinants of health to help users make sense of epidemiological indicators of chronic disease determinants and outcomes [18].

Public health surveillance is the systematic, ongoing collection and analysis of data to detect and guide actions to control hazards such as infectious disease outbreaks. It includes indicator-based surveillance (IBS) and event-based surveillance (EBS). IBS entails the systematic collection, analysis and interpretation of data about individuals, such as infectious disease reports, while EBS routinely analyzes online media to detect events of public health interest, such as disease outbreaks (Fig. 13.1). NLP methods have been applied in IBS to extract information from medical charts for case detection in areas such as syndromic surveillance [19], communicable disease surveillance [20], and occupational health surveillance [21]. To facilitate this type of surveillance, researchers have developed automated systems such as RiskScape [22] for public health surveillance using electronic health records. Machine learning methods have also been used to forecast the incidence of infectious disease [23] and to detect aberrations in epidemiological indicators [24]. Knowledge-based methods have been used to develop systems for syndromic surveillance, such as BioSTORM [25], and have also been used to develop a Population Health Record [26] for integrating indicators of chronic disease using knowledge of the determinants of health [18].

While IBS can be facilitated by AI methods, EBS is critically dependent on AI methods, in particular NLP methods for recognizing and extracting entities from large amounts of online media [27]. Notable systems in this space include the ontology-based BioCaster [28], HealthMap [29], which uses ML to automate many tasks, and GPHIN [30, 31], which uses AI methods to support human analysts. Related approaches, such as probabilistic topic modelling, have also been used in EBS to monitor diseases [32] and interventions [33]. Finally, given the wide range of relevant knowledge (i.e., spatial, temporal, and semantic aspects of disease outbreaks and other public health events) and the small number of global events detected by EBS, knowledge-based systems have also been applied to interpret the information extracted by NLP from online media [28].

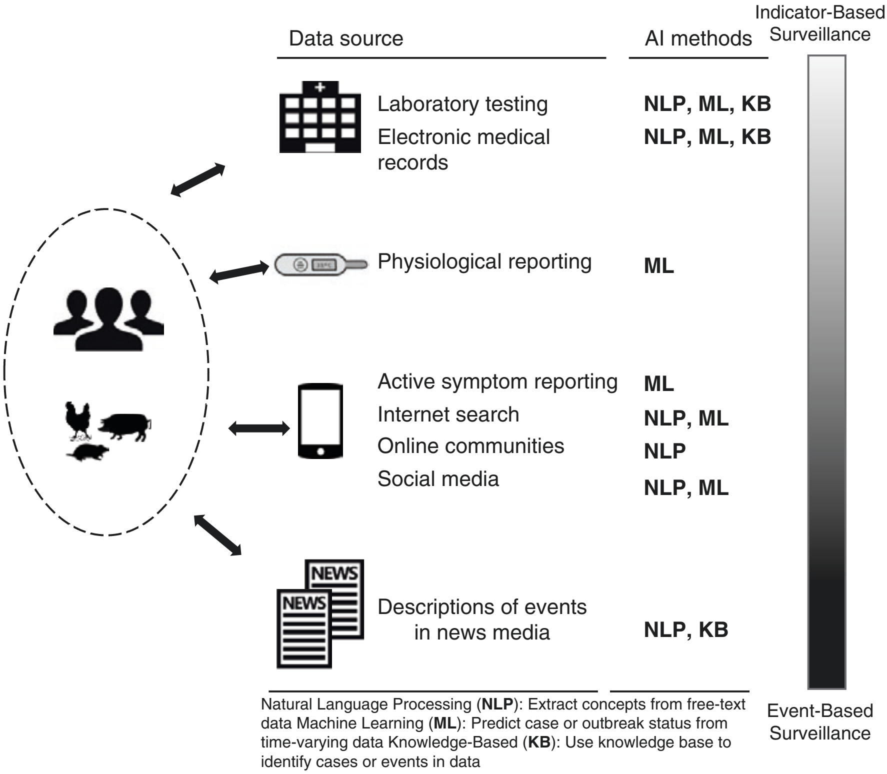

Fig. 13.1 Applications of artificial intelligence methods to infectious disease surveillance. Human and animal populations can be monitored for infectious disease outbreaks using a range of data sources. Data such as laboratory results and electronic medical records allow measurement of cases of disease (i.e., indicator-based surveillance), while other sources, such as news media allow detection of events, without measuring individual cases (i.e., event-based surveillance). Regardless of the data source, many approaches to surveillance rely on artificial intelligence methods to extract concepts from free-text, predict cases or outbreaks from time-varying data, or to reason about data using existing knowledge

Policy Development

The theme of policy development includes the functions of communication, mobilizing communities and partnerships to improve health, creating and implementing policy, and taking legal and regulatory actions to protect health. A task common to many of the functions in this theme is the extraction and synthesis of evidence from the literature about public health interventions. Machine learning and NLP methods have been used for this task in biomedicine [34], but adaptations are necessary for application in public health. For example, existing approaches to representing knowledge about interventions require adaptation [35] to accommodate the different nature of interventions in public health, where individuals and populations are targeted through a range of mechanisms [36]. Another example is the need to consider different types of evidence as randomized controlled trials are not possible for many types of public health interventions [37].

Public health communication provides information to individuals and communities with the aim of improving health outcomes [36]. In targeting communication to individuals, the incorporation of AI into health communication tools can make the communication more engaging, increasing immediacy [38]. There have been many applications of ML and NLP methods to detect changes in health status and to gather information and provide guidance for self-management or additional support of mental and physical health, but the evidence for their effectiveness is limited [39]. A related application of AI methods is the widespread use of social media and machine translation to target communities. For example, NLP methods have been applied to social media content to detect and analyze discourse on topics such as vaccine hesitancy [40], misinformation [41], and foodborne illness [42, 43]. This type of analysis can help to develop targeted messaging campaigns, such as those that apply AI methods to social media platforms to prevent foodborne illness due to restaurant dining (Fig. 13.2).

The application of AI and informatics more generally to policy creation and program planning in public health has led to proposals to update the determinants of health model to account for how information technologies can be used to influence

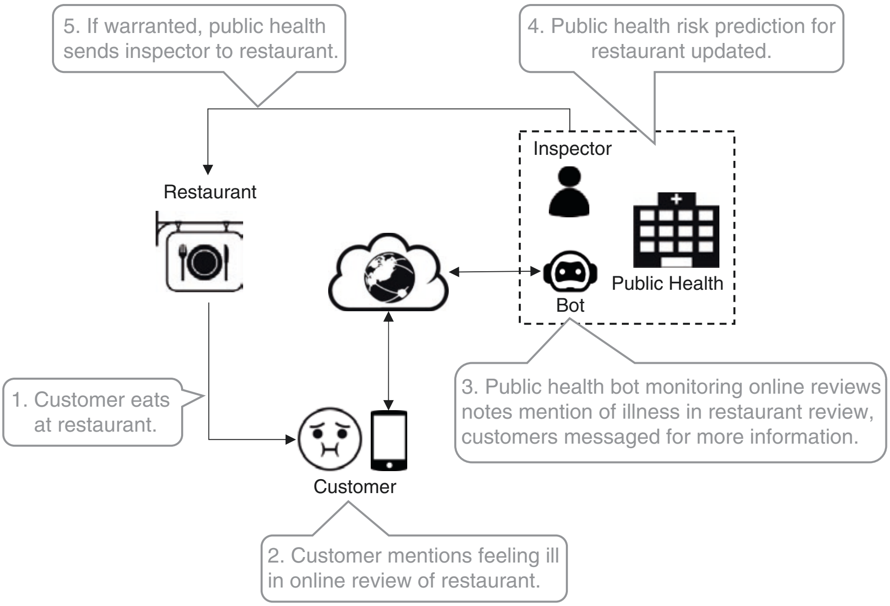

Fig. 13.2 An example of how artificial intelligence methods can be used to monitor comments on social media and generate information to guide public health interventions. Here, a bot developed by a public health organization detects a comment that may indicate foodborne illness due to a restaurant meal. This information is used to update the risk assessment of the restaurant and possibly trigger an in-person inspection (See [43] for more information)

health [36]. Precision public health provides another perspective on the use of AI for program planning [44]. As with precision medicine, the intent is to precisely match interventions to subjects, but in public health the subject is a population, not an individual. Measurement in the public health context entails high-resolution surveillance data for a population [45] and matching interventions requires transferring evidence from studies in other settings to that population in a causal reasoning framework [35, 46]. However, this application of AI has raised concerns about the effect on equity of employing targeted interventions at the expense of efforts to address the broader determinants of health [47], such as social position, which can be challenging to measure accurately [48].

Assurance

The theme of assurance groups together functions that assure equity, a diverse and skilled workforce, research and continuous quality improvement, and a strong organizational infrastructure. The application of AI methods to assurance functions has been more limited than in other themes. An exception is public health research, which has seen the exploration of AI methods to support many public health functions, as noted throughout this section and particularly for monitoring and surveillance.

There is a recognized need to educate the public health workforce about AI methods to enable the development and use of effective AI-enabled tools [12]. As discussed earlier, it would be ideal if pedagogical content about AI could be incorporated into public health informatics training, thereby providing practitioners with an appreciation of AI methods within the broader context of data and information management and analysis in public health. However, despite the widely recognized importance of training in public health informatics, and examples of effective programs [49], significant gaps in data and informatics skills persist in the public health workforce [10]. While there are likely many reasons for this continued lack of capacity, it may be attributable in part to the underinvestment in public health more generally and the challenges of applying computer-based innovations in this context.

The public health system is recognized as being critical for a nation's health [50] and measurement and optimization of the operations of public health systems is one area where AI methods have considerable potential [51]. However, progress in the application of AI methods has been limited by challenges in conceptualizing [52] and measuring public health activities and interventions [53].

Barriers and Risks to AI Applications in Public Health

The previous section highlighted how the current state of AI applications in public health has been shaped to a large extent by the availability of novel data sources and innovations in algorithms. In addition to demonstrating the potential of AI, the research and practice efforts to date have also identified barriers and risks to implementing AI in public health. To enable the future application of AI, it is helpful to consider the barriers and risks to applying AI methods in public health and how they might be addressed.

Barriers to implementing AI in public health include a limited understanding among public health professions of the applications to which AI methods are best suited, a limited capacity for implementing and using AI in many public health settings, and a lack of data and knowledge in some contexts [54]. A limited understanding of AI among public health professionals can be addressed through training, including continuing education. (Chap. 16) As noted in the previous section, however, challenges in enhancing training in public health informatics more generally suggest that this barrier may take time to address. The limited capacity for implementing and using AI results from the lack of skilled human and information technology resources in many public health settings, which has been noted as a barrier to digital transformation in public health more generally [12].

Risks to implementing AI in public health include algorithmic biases that may disadvantage specific groups [44] (see Chap. 18), the potential to exacerbate health inequalities by limiting access to interventions such as language-based models [55], and unrealistic expectations that may make it difficult to scale-up translational research. As an example of a bias, a widely used algorithm for making referrals to a chronic disease management programs was found to be biased against Black patients [56]. The bias was introduced through the problem formulation, because the model was developed to predict costs, which reflect barriers to accessing health care. A solution in this case would be to use another outcome, such as a measure of illness. Table 13.1 presents different types of bias that should be considered when using machine learning to develop prediction models in population and public health.

While the barriers and risks are real, they can be addressed through measures such as guidelines [59] and enhanced training opportunities targeting different stages of the public health career trajectory. For example, recognizing and avoiding bias in training and applying ML algorithms can be taught within MPH programs and continuing education programs can support practitioners in developing a realistic assessment of the potential contributions of AI in public health.

Table 13.1 Types of biases to be considered when developing machine learning models for prediction in population and public health. For further discussion of these biases, see [44]

Type of Bias	Description
Sampling Bias	The proportion of subjects or records sampled differs systematically across subpopulations. For example, a model is trained with input from mainly adult, but intended to be applied to people of all ages
Information Bias	The quality or amount of data differs systematically by subpopulations. For example, electronic health records tend to provide a more complete history of people with higher as opposed to lower socioeconomic status ([57]; [58])
Random Error	The number of subjects or records for a subpopulation is too small to achieve an acceptable precision when making predictions
Objective Specification	The outcome of the prediction model is misaligned with its intended use and may reinforce existing inequities. For example, developing a chronic disease program referral model based on health care costs as opposed to illness [56]

Future Applications of AI in Public Health

The previous sections have considered the potential for AI methods to be applied to public health functions and have highlighted examples of current AI applications in public health. In this section, progress towards the vision presented earlier (see the section on “A Vision for AI in Public Health”) is considered, and the potential for AI methods to transform public health in the future is examined.

Progress Towards the Vision

While in many respects the breadth of application of AI methods to public health functions is impressive, the examples reviewed in the section on “The Nature of Essential Public Health Functions and the Application of AI” suggest that it will take time to reach the vision presented. Notably, many applications of AI in public health have focused on automating manual tasks related to the functions of population health monitoring, surveillance, and communication. Moreover, many research advances, such as in the application of ML methods to aberration detection [24], have seen a slow and uneven translation into practice.

The reasons for the limited progress include the lack of high-quality evidence supporting the use of AI methods along with the barriers identified earlier, namely limitations in training, resources, and data access in some public health settings. The lack of high-quality evidence reflects in part the challenge in evaluating public health interventions more generally, but there is also a similar lack of high-quality evidence supporting the application of AI methods in clinical domains [60]. Minimal reporting guidelines have been developed for clinical applications of AI [61] and similar guidelines should be advanced in public health.

Training in public health informatics and the application of AI methods more specifically are critical for progress towards the vision presented. Many efforts are underway in this regard, but the current situation remains one where awareness and knowledge of AI methods is limited in public health. Coordinated efforts by multiple stakeholders, including public health agencies, professional associations, and educational institutions are required to update public health competencies and make training available through a variety of mechanisms.

Future Applications

To close this chapter, it is helpful to consider future applications of AI that have the potential to advance the vision of AI in public health. In general, given the reliance of ML and NLP methods on large amounts of data, many future applications would be enabled by ensuring that the necessary data are generated and available for analysis (Chaps. 6, 7). For example, as discussed previously, there is great potential for ML to support the monitoring and optimization of public health services. However, data about public health activities are not currently generated and represented in a consistent manner. If public health organizations were to systematically track activities, such as the delivery of interventions, ML and other AI methods could be used to support decisions about the effective use of interventions in specific communities. This type of data generation and analysis about actions occurs routinely in clinical domains and would provide an essential foundation for a learning public health system [62].

Another foundational advance that would enable broader application of AI in public health is improved integration of individual-level and public health data. For example, tighter integration of individual-level public health data with records for clinical care and social services, such as housing support, would enable the use of machine learning to search for opportunities to improve essential services across sectors. These opportunities could emerge from the ability to better coordinate clinical and public health interventions, allowing a "person-centered" approach that integrates health promotion, disease prevention, and clinical services.

Finally, a view to the future should consider how applications of AI methods in public health are related to broader public health goals such as digital transformation and the Sustainable Development Goals [63]. Preparing public health systems for digital transformation requires attention to ensuring that enabling information technology and human resources are in place [12, 64]. This foundation can enable a broader re-imagination of how AI methods can transform public health services to achieve goals within communities, for nations, and globally.

Questions for Discussion

- What characteristics of public health functions make them amenable to the application of AI methods? Are some AI methods better suited to some public health functions than others? Explain.
- Machine learning (ML) methods have been applied in surveillance to detect individual cases and to detect outbreaks. How is the application of ML methods different for these two purposes? Are there any common challenges to applying ML methods in both contexts?
- Given what you know about knowledge-based systems, explain how they can be used most effectively in public health.
- What is the most important barrier to the application of AI in public health? Justify your choice and propose potential solutions.
- What is a risk of applying AI in public health? Explain.
- In your opinion, what future application of AI could have the greatest impact on public health?

Further Readings

Lavigne M, Mussa F, Creatore MI, Hoffman SJ, and Buckeridge DL. A population health perspective on artificial intelligence. *Healthcare Management Forum* 2019;32(4):173–177.

- This paper provides an overview of artificial intelligence in the context of population health. The field of AI and major sub-fields are introduced with examples of their application in population and public health.

Buckeridge DL. Precision, Equity, and Public Health and Epidemiology Informatics – A Scoping Review. *IMIA Yearbook of Medical Informatics* 2020;29(1):226–230.

- This paper summarizes recently published literature on two topics of central relevance to the application of AI in public health, namely precision public health (PPH) and equity in the development of prediction models. Applications of PPH are presented and debates about the concept of PPH are explored. Guidelines and barriers to promoting equity in prediction modelling are presented and discussed.

Yasnoff WA, O'Carroll PW, Koo D, Linkins RW, Kilbourne EM. Public Health Informatics: Improving and Transforming Public Health in the Information Age. *Journal of Public Health Management and Practice* 2000;6(6):67–75.

- This paper introduces the discipline of public health informatics, describing its role and the challenges it sought to address at its inception. Although not about AI directly, it provides an important context regarding the state of informatics within the domain of public health.

Hosny A, Aerts H. Artificial intelligence for global health. *Science* 2019;366(6468):955–956.

- This paper presents a framework with examples of applications of AI in resource-poor health care settings. Applications in population health are considered along with portable diagnostics and clinical decision support.

Rodriguez-Gonzalez A, Zanin M, Menasalvas-Ruiz E. Can Artificial Intelligence Help Future Global Challenges? An Overview of Antimicrobial Resistance and Impact of Climate Change in Disease Epidemiology. *IMIA Yearbook of Medical Informatics* 2019;28(1):224–231.

- This paper presents a review of AI applications in two areas of global public health importance—antimicrobial resistance and health effects of climate change. The authors summarize the recent literature highlighting where AI methods have been applied, the results, and what has been learned to guide future applications.

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