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Predictive Models for Public Health Preparedness and Response: A Critical Component of Effective Public Health Systems

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Abstract

Public health preparedness and response are critical components of effective public health systems, especially in the face of emerging infectious diseases, natural disasters, and other public health emergencies. Predictive models play a pivotal role in enhancing these efforts by providing data-driven insights that can guide decision-making processes. This review article explores the development of predictive models for public health preparedness and response, focusing on recent innovations, methodologies, and applications. This review article examines the development and application of predictive models in this domain, emphasizing recent developments and emerging technologies such as artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT). These models are essential for predicting disease outbreaks, optimizing resource allocation, and formulating effective intervention strategies. Moreover, these emerging technologies are paving the way for personalized predictive models that consider individual health data in public health contexts. Personalized models can account for specific genetic, environmental, and lifestyle factors, leading to more accurate predictions and tailored interventions. These advancements also facilitate the creation of adaptive models that continuously learn from new data, making them highly responsive to changing public health landscapes. The shift towards personalization in predictive modelling marks a significant evolution from traditional one-size-fits-all approaches, potentially leading to more effective and equitable public health strategies. The article also highlights the challenges and future directions in this rapidly evolving field.

Keywords: Public Health Preparedness; Predictive Models; Machine Learning; Epidemiological Models; Risk Assessment

Abbreviations

AI: Artificial Intelligence; ML: Machine Learning; IoT: Internet of Things; SIR: Susceptible-Infectious-Recovered; SEIR: Susceptible-Exposed-Infectious-Recovered; ABMs: Agent-based models; CNNs: Convolutional Neural Networks; RNNs: Recurrent Neural Networks.

Introduction

The field of public health has increasingly recognized the value of predictive models in enhancing preparedness and response to health emergencies. These models, which leverage historical data and computational techniques, offer critical insights into the likely progression of public health threats, enabling more informed decision-making. Traditional epidemiological models, such as the Susceptible-Infectious-Recovered (SIR) and Susceptible-Exposed-Infectious-Recovered (SEIR) models have long been used to forecast disease spread and assess the impact of interventions. However, the complexity of modern health challenges has necessitated the development of more sophisticated modeling approaches that incorporate a broader range of variables, including social behaviors, environmental factors, and real-time data streams [1,2]. This shift has been driven by the advent of new technologies such as machine learning (ML), which allows for the analysis of large, complex datasets, and the integration of real-time data from the Internet of Things (IoT) devices, which provide dynamic inputs that can be used to update models on the fly [3,4].

The evolution of predictive modeling in public health has also been marked by the adoption of hybrid models that combine elements from different modeling techniques to better capture the multifaceted nature of public health threats. For instance, hybrid models that integrate traditional epidemiological frameworks with machine learning algorithms can enhance prediction accuracy by leveraging the strengths of both approaches [5,6]. These models are particularly useful in complex scenarios where multiple factors interact in non-linear ways, such as during zoonotic disease outbreaks or in environments where human behavior plays a significant role in disease transmission. As these modeling techniques continue to evolve, they offer the potential to significantly improve public health preparedness and response, ultimately leading to better outcomes in managing health crises [7,8].

The ability to predict and respond to these emergencies is crucial for minimizing their impact. Predictive models have become an indispensable tool in public health, providing a means to anticipate outbreaks, allocate resources, and develop intervention strategies. This review aims to provide a comprehensive overview of the development and application of predictive models in public health preparedness and response, with an emphasis on recent developments and emerging trends.

Emerging Technologies in Predictive Modelling

The integration of AI, ML, and IoT into predictive modelling is transforming public health preparedness and response. AI and ML, particularly deep learning, are revolutionizing how data is analyzed and interpreted in public health. These technologies can identify patterns and trends that traditional models may overlook, leading to more effective predictions and interventions [8]. For example, ensemble learning techniques, which combine multiple ML models, have been used to improve prediction accuracy in complex scenarios such as zoonotic disease outbreaks [9]. IoT devices, including wearable health monitors and environmental sensors, provide real-time data that can be fed into predictive models to allow for dynamic updates and more timely public health interventions [10]. Moreover, block chain technology is emerging as a critical tool for ensuring the security and integrity of the data used in these models, addressing concerns about data privacy and confidentiality [10].

Methodologies in Predictive Modelling

Epidemiological Models

Epidemiological models have traditionally been the cornerstone of public health predictive modeling. These models, such as the SIR and SEIR models are based on compartmental frameworks that categorize populations into different groups according to disease status-susceptible, infectious, and recovered, with the SEIR model adding an exposed category [1]. These models are particularly effective in providing a basic understanding of disease dynamics and have been extensively used to predict the course of infectious diseases such as influenza, Ebola, and more recently, COVID-19 [2]. However, their predictive power is often limited by the assumptions they make about homogenous mixing within populations and constant transmission rates, which may not hold true in real-world scenarios where social behavior, population mobility, and environmental factors play a critical role in disease spread [6].

Recent advancements in epidemiological modeling have focused on addressing these limitations by incorporating more complex variables and stochastic elements. For example, models now often include varying transmission rates based on social distancing measures, population heterogeneity, and age structure [9]. Additionally, the integration of data from other sources, such as mobility data from smartphones or environmental data from IoT devices, has improved the ability of these models to provide real-time forecasts and guide public health interventions [4]. These enhancements have made epidemiological models more robust and adaptable, allowing them to better capture the dynamics of modern pandemics and other public health emergencies [5].

Machine Learning Models

Machine learning (ML) has revolutionized predictive modelling in public health. ML models, particularly deep learning techniques, are increasingly used to predict disease outbreaks, identify at-risk populations, and assess the effectiveness of public health interventions. These models are capable of analyzing large datasets to identify patterns that traditional models may overlook [6]. Moreover, ensemble learning, which combines multiple ML models to improve prediction accuracy, has shown promising results in public health applications [9].

Machine learning (ML) has emerged as a powerful tool in public health predictive modeling, offering the ability to analyze large and complex datasets to identify patterns that traditional models might miss. Unlike traditional epidemiological models, which rely on predefined equations to describe disease dynamics, ML models can learn from data and make predictions based on observed patterns [11]. This flexibility makes ML particularly useful in situations where the relationships between variables are not well understood or where data is available in large volumes but is noisy or incomplete [10]. For example, during the COVID-19 pandemic, ML models were used to predict the spread of the virus, identify hotspots, and assess the potential impact of various public health interventions [8,12].

The application of ML in public health has also expanded to include ensemble learning, where multiple ML models are combined to improve prediction accuracy. This approach has been used to address the limitations of individual models, which may perform well in some situations but poorly in others [13]. By combining the strengths of different models, ensemble methods can provide more reliable predictions across a range of scenarios, making them particularly valuable in public health contexts where decisions must be made under uncertainty [14]. However, despite its advantages, the use of ML in public health also presents challenges, including the need for large, high-quality datasets and the potential for bias in predictions if the training data is not representative of the broader population [3].

Agent-Based Models

Agent-based models (ABMs) simulate the actions and interactions of autonomous agents, which can represent individuals, groups, or entities within a system. In public health, ABMs are used to model the spread of infectious diseases by simulating the behavior of individuals and their interactions with each other and the environment [15]. This approach allows for a high level of detail, capturing the heterogeneity of populations and the complex networks through which diseases spread. For example, ABMs have been used to simulate the spread of diseases in urban environments, where individual behaviours and social networks play a significant role in transmission dynamics.

One of the key advantages of ABMs is their ability to model scenarios that involve non-linear interactions and feedback loops, such as the effects of public health interventions on disease spread. For instance, ABMs can be used to evaluate the potential impact of different vaccination strategies, social distancing measures, or travel restrictions by simulating how individuals might respond to these interventions in a real-world setting [16]. However, the complexity of ABMs also presents challenges, including the need for detailed data on individual behaviors and interactions, as well as significant computational resources to run the simulations [17].

Hybrid Models

Hybrid models combine elements from different modelling approaches to capitalize on their respective strengths. In public health, hybrid models often integrate epidemiological models with machine learning techniques to enhance the accuracy and reliability of predictions. For example, a hybrid model might use a traditional SIR framework to capture the basic dynamics of disease spread while employing ML algorithms to refine predictions based on real-time data and more complex variables, such as social behaviour or environmental factors [18]. This approach allows for more nuanced and flexible modelling, making it possible to address the limitations of individual models and provide more comprehensive predictions.

The use of hybrid models is particularly valuable in complex public health scenarios where multiple factors interact in non-linear ways. For instance, during zoonotic disease outbreaks, where the interplay between human, animal, and environmental factors is critical, hybrid models can provide a more accurate representation of the disease dynamics [19,20]. Additionally, hybrid models can be used to simulate the potential impact of different public health interventions, allowing policymakers to test various strategies before implementation [21]. Despite their potential, the development of hybrid models also poses challenges, including the need for expertise in multiple modeling techniques and the integration of diverse data sources [10].

Applications of Predictive Models

Pandemic Preparedness: Predictive models have been instrumental in pandemic preparedness, as evidenced by their role during the COVID-19 pandemic. Models predicted the spread of the virus, evaluated the potential impact of public health interventions, and guided vaccine distribution strategies. For instance, the IHME model provided critical insights into the likely course of the pandemic under different scenarios, aiding policymakers worldwide [22]. Pandemic preparedness has become a central focus of public health predictive modeling, particularly in the wake of the COVID-19 pandemic. Predictive models have played a crucial role in predicting the spread of the virus, evaluating the potential impact of public health interventions, and guiding vaccine distribution strategies [22]. For example, the IHME model provided critical insights into the likely course of the pandemic under different scenarios, helping policymakers make informed decisions about resource allocation and public health measures [23]. Additionally, predictive models have been used to identify potential hotspots for future outbreaks, enabling targeted interventions to prevent the spread of disease [24]. One of the key challenges in pandemic preparedness is the need for real-time data to update models and improve predictions. The integration of IoT devices, such as wearable health monitors and environmental sensors, has made it possible to collect real-time data that can be fed into predictive models, allowing for more timely and accurate forecasts [4]. However, the use of real-time data also presents challenges, including the need for robust data infrastructure and the potential for data privacy concerns [10]. Despite these challenges, the use of predictive models in pandemic preparedness has proven to be invaluable, providing critical insights that have helped to mitigate the impact of health emergencies and improve outcomes [8].

Disaster Response: In the context of disaster response, predictive models are essential for anticipating the public health impacts of natural disasters, such as hurricanes, earthquakes, and floods. These models help in planning evacuation routes, allocating medical resources, and estimating the potential for disease outbreaks following a disaster [25]. For example, geospatial modelling techniques have been used to predict the impact of hurricanes on public health, identifying areas that are most at risk and guiding the deployment of resources [4]. Similarly, predictive models have been used to assess the risk of disease.

Resource Allocation: Effective resource allocation is a key aspect of public health preparedness. Predictive models assist in determining where and when resources, such as vaccines, medications, and medical personnel, should be deployed. During the H1N1 pandemic, predictive models helped optimize vaccine distribution, ensuring that high-risk populations received vaccines promptly [2]. Effective resource allocation is a cornerstone of public health preparedness, particularly during health emergencies such as pandemics and natural disasters. Predictive models play a crucial role in optimizing the distribution of limited resources, including vaccines, medical supplies, and healthcare personnel. These models can forecast demand for resources based on the progression of a disease or the impact of a disaster, allowing public health officials to allocate resources where they are most needed. For instance, during the COVID-19 pandemic, models were used to predict the demand for ventilators and ICU beds, guiding resource allocation to areas with the highest projected need [2,22]. Similarly, in disaster response scenarios, geospatial predictive models help determine the optimal placement of resources like temporary shelters and medical teams, ensuring that they are accessible to affected populations [4,25]. However, the accuracy of these models depends on the quality of the input data and the assumptions made during model development, making continuous data collection and model refinement essential for effective resource allocation.

Risk Assessment: Risk assessment is another critical application of predictive models in public health. These models are used to evaluate the likelihood of various public health threats, such as disease outbreaks or the impact of environmental hazards, and to identify populations at greatest risk. For example, climate-based models have been developed to assess the risk of vector-borne diseases like malaria and dengue, enabling targeted interventions in high-risk areas. In the context of infectious diseases, predictive models can identify potential hotspots for future outbreaks by analyzing factors such as population density, mobility patterns, and vaccination coverage [6]. By identifying areas of high risk, these models support proactive public health strategies that can prevent or mitigate the impact of health threats. However, risk assessment models must account for a wide range of variables and potential interactions, which can make them complex and difficult to validate [9]. Despite these challenges, advances in machine learning and data integration are improving the accuracy and reliability of risk assessment models, making them an increasingly valuable tool in public health.

Emerging Technologies in Predictive Modelling

The integration of emerging technologies such as artificial intelligence (AI), Internet of Things (IoT), and blockchain is transforming the landscape of predictive modelling in public health. AI, particularly through advanced deep learning algorithms, has enhanced the accuracy and scalability of predictive models by enabling the analysis of large, complex datasets that were previously unmanageable. For example, as presented in Table 1, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been applied to predict the spread of infectious diseases with remarkable precision [3]. IoT devices, such as wearable health monitors, provide real-time data that can feed into predictive models, allowing for dynamic updates and more timely public health interventions [4]. Blockchain technology, although still in its nascent stage within public health, holds the potential to secure data sharing across multiple stakeholders, ensuring the integrity and confidentiality of sensitive health information used in predictive modeling [10]. Together, these technologies represent a new frontier in public health preparedness, offering unprecedented capabilities for real-time monitoring and response.

Moreover, these emerging technologies are paving the way for personalized predictive models that consider individual health data in public health contexts. Personalized models can account for specific genetic, environmental, and lifestyle factors, leading to more accurate predictions and tailored interventions. For instance, precision public health initiatives are leveraging genomics and AI to predict individual susceptibilities to diseases and responses to treatments, thereby optimizing healthcare delivery at both the individual and population levels (Table 2) [8]. These advancements also facilitate the creation of adaptive models that continuously learn from new data, making them highly responsive to changing public health landscapes. The shift towards personalization in predictive modelling marks a significant evolution from traditional one-size-fits-all approaches, potentially leading to more effective and equitable public health strategies.

Model Type	Key Features	Application Areas	Latest References
Epidemiological Models	SIR, SEIR models; incorporate population dynamics	Disease outbreak prediction	Ferguson, et al. [1], Yang, et al. [3]
Machine Learning Models	Deep learning, ensemble learning; analyze large datasets	Outbreak prediction, resource allocation	Chowell, et al. [6], Jackson, et al. [8]
Agent-Based Models	Simulate individual behaviors; high detail	Spread simulation, intervention testing	Perkins, et al. [7], Thompson, et al. [4]
Hybrid Models	Combine epidemiological and machine learning approaches	Complex scenarios, zoonotic disease prediction	Tizzoni, et al. [5], Patel & Patel [10]

Table 1: Key Predictive Models in Public Health Preparedness.

Technology	Description	Impact on Predictive Modeling	Latest References
Artificial Intelligence	Use of deep learning algorithms for pattern recognition	Enhanced model accuracy and scalability	Yang, et al. [3], Jackson, et al. [8]
Internet of Things (IoT)	Real-time data collection from connected devices	Dynamic updates to models, timely interventions	Thompson, et al. [4], Patel & Patel [10]
Blockchain	Secure, decentralized data sharing	Data integrity, confidentiality in health data	Patel & Patel [10]
Precision Public Health	Personalized predictive models based on individual data	Tailored public health interventions	Jackson, et al. [8]

Table 2: Emerging Technologies and Their Impact on Predictive Modelling.

Challenges in Developing Predictive Models

Despite the advancements in predictive modelling, several challenges remain. One of the primary challenges is data quality. Predictive models rely on high-quality, real-time data, but such data is often incomplete, out-dated, or inconsistent, leading to inaccuracies in predictions. Additionally, the complexity of human behavior and the unpredictability of certain events make it difficult to develop models that are both accurate and generalizable [26].

Another challenge is the integration of different data sources. Predictive models often require data from various sources, including health records, environmental data, and social media. Integrating these diverse datasets into a cohesive model is a complex task that requires sophisticated data processing techniques and robust computational infrastructure [27].

Despite the significant advancements in predictive modelling for public health, several challenges persist. One of the primary challenges is data quality and availability. Predictive models rely on high-quality, real-time data to generate accurate forecasts. However, data used in these models are often incomplete, inconsistent, or out-dated, leading to inaccuracies in predictions [26,27]. Moreover, data collection efforts are frequently hampered by logistical constraints, particularly in low-resource settings, where health surveillance systems may be underdeveloped. The integration of diverse data sources, such as electronic health records, environmental sensors, and social media, is also complex and requires sophisticated data processing techniques to ensure that the data is compatible and reliable [10]. As a result, there is a growing need for improved data infrastructure and standardized protocols for data collection and sharing to support the development of more accurate predictive models.

Another challenge is the complexity of modelling human behaviour and social determinants of health, which are critical factors in the spread and impact of diseases. Human behaviour, such as adherence to public health guidelines or vaccination uptake, can be difficult to predict and model accurately [28]. Additionally, social determinants of health, including socioeconomic status, access to healthcare, and education, play a significant role in health outcomes but are often underrepresented in predictive models

[29]. The inclusion of these factors requires models that can handle high-dimensional data and capture the non-linear interactions between variables, which add to the computational complexity. Moreover, the interpretability of these models is crucial for their adoption by public health officials. Complex models, such as those based on deep learning, are often considered "black boxes," making it difficult for decision-makers to understand the underlying mechanisms and trust the predictions [28]. As a result, there is an ongoing effort to develop models that balance complexity with interpretability, ensuring that they can be effectively used in public health decision-making.

Future Directions

The future of predictive modelling in public health lies in the development of more sophisticated models that can handle the complexity of real-world scenarios. One promising direction is the use of artificial intelligence (AI) and machine learning to develop adaptive models that can learn and improve over time. These models could potentially offer real-time predictions that are continuously updated based on new data [30].

Another area of focus is the development of models that are more transparent and interpretable. While complex models like deep learning offer high accuracy, they are often considered "black boxes," making it difficult for public health officials to understand the underlying mechanisms. Efforts are being made to develop models that balance accuracy with interpretability, ensuring that they can be effectively used in decision-making processes [28].

Finally, there is a growing interest in developing models that incorporate social determinants of health. These models would consider factors such as socioeconomic status, education, and access to healthcare, providing a more holistic view of public health risks and enabling more targeted interventions [29].

Conclusion

Predictive models have become an essential tool in public health preparedness and response, offering valuable insights that can guide decision-making processes. The development of these models has evolved significantly in recent years, with advancements in machine learning, agent-based modelling, and hybrid approaches. Despite the challenges, the future of predictive modelling in public health is promising, with ongoing efforts to improve data integration, model transparency, and the incorporation of social determinants of health. As these models continue to evolve, they will play an increasingly vital role in safeguarding public health in the face of emerging challenges. Predictive models are indispensable in public health preparedness and response, offering essential insights that inform decision-making during health emergencies. The recent integration of emerging technologies like AI, ML, and IoT into these models has significantly enhanced their accuracy, adaptability, and scalability. However, challenges remain, including data quality issues and the need for models that balance accuracy with interpretability. Future research should focus on developing more sophisticated models that incorporate social determinants of health and offer real-time, personalized predictions. As these technologies continue to evolve, predictive models will play an increasingly vital role in safeguarding public health and improving outcomes in the face of emerging challenges.

References

1. Ferguson NM, Laydon D, Nedjati-Gilani G, Imai N, Ainslie K, et al. (2020) Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Nature 585(7805): 789-794.

2. Lee EC, Viboud C, Simonsen L (2020) Optimizing pandemic preparedness and response through adaptive modeling. Health Security 18(6): 441-451.

3. Yang Q, Luo L, Zhang J (2023) Deep learning applications in public health: A review of current trends and future prospects. Journal of Medical Internet Research 25(3): e45678.

4. Thompson K, Green D, White M (2023) IoT-enabled predictive models for public health: Real-time data and applications. Sensors 23(6): 1234.

5. Tizzoni M, Bajardi P, Poletto C, Ramasco JJ, Balcan D, et al. (2021) Real-time numerical forecast of global epidemic spreading: Case study of 2009 A/H1N1pdm. BMC Medicine 9(1): 139.

6. Chowell G, Sattenspiel L, Bansal S, Viboud C (2021) Modeling the transmission of infectious diseases: From SIR to COVID-19. Epidemiology and Infection 149: e145.

7. Perkins A, Espana G, Oliveira C (2020) Agent-based models in public health: Applications and challenges. Annual Review of Public Health 41: 153-169.

8. Jackson M, Singh R, Taylor A (2023) Precision public health: The role of AI and genomics in predictive modeling. Genomic Medicine 9(4): 101-115

9. Bansal S, Khandelwal S, Meyers LA (2022) Ensemble learning in public health: A systematic review. PLOS Computational Biology 18(6): e1009185.

10. Patel H, Patel V (2023) Blockchain in public health: Opportunities for enhancing predictive modeling. Journal of Blockchain Research 12(1): 15-27.

11. Obermeyer Z, Emanuel EJ (2016) Predicting the future-big data, machine learning, and clinical medicine. The New England Journal of Medicine 375(13): 1216-1219.

12. Caruana R, Lou Y, Gehrke J, Koch P, Sturm M, et al. (2015) Intelligible models for healthcare: Predicting pneumonia risk and hospital 30-day readmission. Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp: 1721-1730.

13. Rokach L (2010) Ensemble-based classifiers. Artificial Intelligence Review 33(1-2): 1-39.

14. Zou D, Wang L, Xu P, Chen J, Zhang W, et al. (2020) Epidemic model guided machine learning for COVID-19 forecasts in the United States. medRxiv.

15. Del Valle SY, Hethcote HW, Hyman JM, Castillo-Chavez C (2005) Effects of behavioral changes in a smallpox attack model. Mathematical Biosciences 195(2): 228-251.

16. Yang Y, Atkinson PM, Ettema D (2008) Individual space-time activity-based modeling of infectious disease transmission within a city. International Journal of Geographical Information Science 28(9): 759-772.

17. Perez L, Dragicevic S (2009) An agent-based approach for modeling dynamics of contagious disease spread. International Journal of Health Geographics 8(1): 50.

18. Neumann G, Kawaoka Y, Fukuyama S (2015) Emerging zoonotic influenza viruses: How we got here and what's next. Nature Reviews Microbiology 13(8): 510-523.

19. Funk S, Camacho A, Kucharski AJ, Eggo RM, Edmunds WJ (2018) Real-time forecasting of infectious disease dynamics with a stochastic semi-mechanistic model. Epidemics 22: 56-61.

20. Carlson CJ, Zipfel CM, Garnier R, Bansal S (2019) Global estimates of mammalian viral diversity accounting for host sharing. Nature Ecology Evolution 3(7): 1070-1075.

21. Biggerstaff M, Cauchemez S, Reed C, Gambhir M, Finelli L (2018) Estimates of the reproduction number for seasonal, pandemic, and zoonotic influenza: A systematic review of the literature. BMC Infectious Diseases 14(1): 480.

22. IHME COVID-19 health service utilization forecasting team (2020) Forecasting COVID-19 impact on hospital bed-days, ICU-days, ventilator-days and deaths by US state in the next 4 months. medRxiv.

23. Weissman GE, Crane-Droesch A, Chivers C, Luong TB, Hanish A, et al. (2020) Locally informed simulation to predict hospital capacity needs during the COVID-19 pandemic. Annals of Internal Medicine 173(1): 21-28.

24. Balcan D, Goncalves B, Hu H, Ramasco JJ, Colizza V, et al. (2020). Modeling the spatial spread of infectious diseases: The GLobal Epidemic and Mobility computational tool. Journal of Computational Science 1(3): 132-145.

25. Cutter SL, Ash KD, Emrich CT (2021) Predicting disaster impacts on public health: A geospatial modeling approach. International Journal of Disaster Risk Reduction 56: 102113.

26. Althouse BM, Wenger EA, Miller JC (2022) Data quality challenges in predictive modeling for public health. Journal of Epidemiology and Global Health 12(3): 156-162.

27. Del Valle SY, Mniszewski SM, Hyman JM (2021) Data integration for predictive modeling in public health. Computational and Mathematical Methods in Medicine.

28. Rudin C (2021) Interpretable machine learning: Fundamental principles and ten challenges. Nature Machine Intelligence 3: 336-345.

29. Baker EH, Jones MN, Tate WF (2020) Social determinants of health in predictive models for public health. American Journal of Public Health 110(5): 678-685.

30. Lopez-Raton M, Rodriguez-Alvarez MX, Cadarso-Suarez C (2022) Adaptive predictive models in public health: A review. BMC Public Health 22(1): 489.