

Leveraging Health Data Analytics for Predictive Public Health Surveillance: A Review of AI and Big Data Applications

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Abstract

This review paper explores the transformative impact of artificial intelligence (AI) and big data on public health surveillance, focusing on how these technologies enhance the ability to predict, detect, and respond to health threats. AI algorithms and machine learning models enable more accurate risk assessments, outbreak detection, and real-time monitoring, while big data from diverse sources such as healthcare systems and social media provides a comprehensive view of health trends. The paper discusses the contributions of these technologies to improving public health outcomes, including their role in disease prediction and prevention. Ethical considerations, including data privacy, security, and consent, are analyzed, along with existing regulations that govern health data use. The paper also provides recommendations for future research and policy development to address algorithmic biases, improve data governance, and ensure ethical and equitable application of AI and big data in public health. In conclusion, this review highlights the potential of AI and big data to revolutionize public health surveillance while emphasizing the need for ongoing research and regulation.

Keywords: Artificial intelligence, Big data, Public health surveillance, Machine learning, Disease prediction, Data privacy

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I. Introduction

Predictive public health surveillance refers to the systematic collection, analysis, and interpretation of health-related data to anticipate and respond to public health challenges. Public health surveillance has traditionally been reactive, responding to disease outbreaks or health trends after they emerge (Zeng, Cao, & Neill, 2021). In contrast, predictive surveillance leverages modern technologies, particularly artificial intelligence (AI) and big data, to forecast potential health threats before they fully materialize. This proactive approach allows public health officials to take preventive actions, reducing the impact of infectious diseases, non-communicable conditions, and other health crises (Bedi, Vijay, Dhaka, Gill, & Barbuddhe, 2021).

At its core, predictive public health surveillance is built on data-driven insights. Large volumes of health-related data, such as hospital records, laboratory reports, social media trends, and environmental data, are continuously monitored (Chowdhury et al., 2024). Advanced analytical models are applied to this data to identify patterns, correlations, and early warning signals of potential public health threats. Predictive analytics transforms surveillance from a passive, retrospective process into a dynamic, forward-looking system that can predict outbreaks, assess population health risks, and guide timely interventions. Doing so shifts the focus of public health from treatment to prevention, ultimately saving lives and resources (Majeed & Hwang, 2021).

Health data analytics plays a pivotal role in transforming public health outcomes by offering deeper insights into health trends and enabling more informed decision-making. The sheer volume of data generated daily from various sources, such as electronic health records (EHRs), mobile health apps, and wearable devices, offers vast potential for improving population health. However, raw data alone is not sufficient to drive change. Analytics tools, particularly predictive analytics, are necessary to extract actionable insights from these data sets (Ogundipe, 2024).

Using data analytics, public health officials can detect patterns that may go unnoticed. For example, data analytics has been used to monitor social media platforms for early signs of disease outbreaks, as was done with the 2014 Ebola outbreak, where public sentiment and discussions on social networks helped in identifying and

tracking the spread of the disease. Additionally, in chronic disease management, data analytics enables monitoring population-wide health metrics such as blood pressure, glucose levels, and other indicators of non-communicable diseases. These insights can lead to timely interventions, such as policy changes or targeted health campaigns, that address emerging public health risks.

Data analytics also enables the stratification of health risks within a population. For instance, algorithms can analyze patient data to identify those at higher risk of developing chronic conditions, allowing for personalized prevention strategies. Predictive models that combine demographic, environmental, and clinical data can forecast the likelihood of a disease outbreak, enabling health authorities to allocate resources and implement control measures proactively. In essence, health data analytics allows public health systems to be more agile, responsive, and better equipped to handle both acute and chronic health challenges (Okoduwa et al., 2024; Udegbe, Ebulue, Ebulue, & Ekesiobi, 2024b).

Integrating AI and big data technologies into public health surveillance represents a significant advancement in how health data is collected, analyzed, and used. AI, specifically machine learning (ML) and deep learning algorithms, is instrumental in analyzing vast amounts of health data and making predictions based on that data. These algorithms can process complex data sets faster than traditional statistical methods, making them invaluable in public health, where timely insights are critical for decision-making (Perera & Iqbal, 2021).

AI technologies are employed in several key areas of public health surveillance. One notable application is in disease outbreak prediction. Machine learning models can analyze historical data on past outbreaks, weather patterns, and population movement to predict where and when future outbreaks might occur. This capability is crucial for preventing diseases from spreading and for directing public health resources to areas at the highest risk. AI can also help with monitoring chronic diseases by continuously analyzing data from wearable devices and EHRs to predict adverse health events, such as heart attacks or strokes, before they happen.

Another powerful application of AI is in natural language processing (NLP), which can analyze unstructured data, such as online health forums, news articles, and social media posts, to detect emerging public health concerns. For instance, during the COVID-19 pandemic, AI-powered NLP tools were used to monitor online discussions about symptoms, treatments, and vaccine hesitancy, providing real-time insights that helped shape public health messaging and interventions (Baclic et al., 2020).

Big data technologies are equally essential in public health surveillance. The volume of health data generated today is immense, and big data tools allow for the storage, processing, and analysis of these large, diverse data sets. These technologies enable the integration of various data sources, such as genomic, environmental, and even satellite data, to provide a more comprehensive understanding of health risks. For example, big data can be used to track the spread of vector-borne diseases like malaria by analyzing environmental data, such as temperature and rainfall, alongside human mobility patterns (Locke et al., 2021).

The ability to process such large-scale data in real time is critical for public health surveillance. Traditional data processing methods are often too slow or limited to handle the volume and variety of data needed for modern public health efforts. Big data technologies, such as Hadoop and Spark, provide the infrastructure necessary to manage and analyze massive amounts of health-related data. Doing so enables public health officials to make data-driven decisions quickly, whether responding to an emerging epidemic or managing long-term health trends (Nijhawan, Attigeri, & Ananthakrishna, 2022).

Furthermore, AI and big data work hand in hand to enhance public health outcomes. AI models require vast amounts of data to function effectively, and big data technologies provide the necessary data infrastructure. Together, these technologies improve the accuracy and speed of public health predictions, enabling more timely and effective responses to health crises. As AI models become more sophisticated and big data technologies continue to evolve, their combined potential for transforming public health surveillance will only grow, leading to more proactive and efficient public health systems.

II. AI and Machine Learning in Health Data Analytics

2.1. Use of AI, Machine Learning Algorithms, and Predictive Modeling in Public Health

The use of AI, particularly machine learning (ML) algorithms and predictive modeling, has revolutionized public health landscape by enabling more precise and timely insights into population health trends. AI leverages large-scale data processing capabilities and advanced algorithms to detect patterns, forecast health events, and support decision-making in real time. In the realm of public health, this has significant implications for disease prevention, resource allocation, and health policy development (Santosh & Gaur, 2022).

Machine learning, a subset of AI, focuses on building systems that can learn from data and improve their performance without being explicitly programmed for every task. Supervised, unsupervised, and reinforcement learning are common types of machine learning algorithms applied in public health. These algorithms use historical health data, such as patient records, environmental data, and social determinants of health, to predict future health outcomes and trends. For instance, supervised learning models have been applied in epidemiology to predict the spread of infectious diseases like influenza and COVID-19 by analyzing prior outbreak patterns and population movement data (Bekbolatova, Mayer, Ong, & Toma, 2024).

Predictive modeling in public health combines statistical techniques and machine learning algorithms to create models that can forecast the likelihood of various health outcomes. These models are essential for understanding potential future scenarios, allowing public health professionals to implement preventive measures. Predictive models have been employed to identify high-risk populations for chronic diseases, such as diabetes and cardiovascular disease, by analyzing demographic, behavioral, and clinical data. In doing so, AI and predictive modeling enable the early detection of potential health crises, allowing for targeted interventions that can save lives and reduce healthcare costs (Taye, 2023).

2.2 Key AI Applications

AI applications in public health are vast and varied, with some of the most notable being disease prediction, outbreak detection, and risk assessment. One of the key strengths of AI lies in its ability to predict disease outbreaks by analyzing vast amounts of health data from multiple sources, including electronic health records, environmental data, and even social media. For example, AI-powered platforms have been used to predict flu outbreaks by monitoring online search queries and social media activity related to flu symptoms. These predictive models provide public health officials with the necessary lead time to prepare for and mitigate the impact of an outbreak (Alanne & Sierla, 2022).

Outbreak detection is another area where AI has proven to be highly effective. Traditional methods of outbreak detection often rely on manual reporting and retrospective analysis, which can delay the identification of emerging health threats. Conversely, AI can process real-time data and detect anomalies that may indicate the early stages of an outbreak. For instance, during the early stages of the COVID-19 pandemic, AI-based tools were able to detect unusual patterns in healthcare data and media reports, signaling the potential spread of a new respiratory disease. These early warnings allowed countries to implement containment measures more rapidly than they might have otherwise (Abdulkareem & Petersen, 2021).

Risk assessment is also a critical application of AI in public health. Machine learning algorithms can analyze a wide range of risk factors, including genetic, environmental, and behavioral data, to assess an individual's or a population's risk of developing specific health conditions. For example, AI models can predict which individuals are at the highest risk for heart disease based on lifestyle factors like diet, exercise, and smoking. This allows healthcare providers to tailor preventive interventions to those most at risk, improving health outcomes while reducing healthcare costs (Meckawy, Stuckler, Mehta, Al-Ahdal, & Doebbeling, 2022).

Another emerging AI application in public health is precision public health, which aims to use AI and big data to provide more tailored public health interventions based on individual risk factors. This contrasts with the traditional one-size-fits-all approach, allowing for more efficient resource allocation and more personalized prevention strategies. Precision public health leverages AI to identify high-risk groups and develop targeted interventions that address their specific needs, ultimately leading to better health outcomes. (Velmovitsky, Bevilacqua, Alencar, Cowan, & Morita, 2021)

2.3 Challenges in Data Quality and Algorithmic Biases

Despite AI's significant advancements in public health, several challenges remain, particularly related to data quality and algorithmic biases. For AI and machine learning algorithms to provide accurate predictions and insights, they require large, diverse, and high-quality data sets. However, public health data is often incomplete, fragmented, or of inconsistent quality, particularly in low-resource settings. This can lead to flawed models that provide inaccurate predictions, potentially causing harm if public health decisions are based on these faulty insights (Albahri et al., 2023).

Data quality issues often arise from incomplete or missing data, lack of standardization in data collection methods, and discrepancies in data formats across different health systems. For instance, electronic health records (EHRs) may not capture all relevant data due to variations in how different healthcare providers enter data. Additionally, public health data may not be updated frequently enough to provide real-time insights, limiting the effectiveness of AI models in outbreak detection or risk assessment (Zhang & Zhang, 2023).

Another significant challenge in AI applications for public health is algorithmic bias, which occurs when AI models produce results that reflect or amplify existing societal biases. These biases can stem from the data used to train the algorithms. For example, suppose an AI model is trained on data disproportionately representing certain demographic groups. In that case, the model's predictions may be less accurate for underrepresented populations. This can lead to unequal access to healthcare interventions and exacerbate health disparities (Norori, Hu, Aellen, Faraci, & Tzovara, 2021).

Algorithmic biases can also arise from the way models are designed and validated. Machine learning models often rely on historical data, which may reflect past healthcare access or treatment inequities. For instance, if a predictive model is trained on data from a population where a certain demographic group has been historically underserved, the model may inadvertently perpetuate those disparities by underestimating the risks for that group. This is particularly concerning in public health, where biased predictions can lead to unequal distribution of resources and care (Akteer et al., 2022).

Addressing these challenges requires a concerted effort to improve data collection processes, ensure that datasets are representative of diverse populations, and develop methods to detect and mitigate algorithmic bias. Transparent and rigorous validation processes are essential to ensure that AI models perform well across different populations and healthcare settings. Additionally, involving diverse stakeholders, including ethicists, data scientists, and public health professionals, in developing and deploying AI tools can help mitigate biases and ensure that these technologies are used responsibly and equitably.

III. Big Data Applications in Public Health Surveillance

3.1. The Use of Big Data from Diverse Sources in Public Health

Big data refers to large, complex datasets that cannot be easily managed or analyzed using traditional data processing tools. In public health surveillance, the use of big data has emerged as a transformative tool, allowing for more comprehensive, timely, and detailed insights into health trends and risks. Big public health data is collected from various sources, including healthcare systems, wearable devices, environmental sensors, and even social media platforms. Integrating these diverse data streams provides a more holistic view of population health, enabling public health officials to monitor and respond to health threats more effectively (Mohamed, Najafabadi, Wah, Zaman, & Maskat, 2020).

Healthcare systems generate massive amounts of data every day through electronic health records (EHRs), laboratory results, imaging data, and patient histories. These records contain valuable information that can be used to track disease prevalence, monitor treatment outcomes, and identify at-risk populations. However, integrating this data with other external sources can yield even more powerful insights. For example, environmental data, such as air pollution levels or temperature changes, can be combined with health data to assess the impact of environmental factors on diseases like asthma or heat-related illnesses (Jia, Guo, Wang, & Barnes, 2020).

Social media has also emerged as a valuable source of big data for public health surveillance. Platforms like Twitter and Facebook provide real-time insights into public sentiment and behaviors related to health issues. By analyzing patterns in social media posts, public health officials can detect early signs of emerging health threats, such as flu outbreaks or foodborne illnesses. In addition, social media data has been used to monitor public reactions to health policies and interventions, providing feedback on the effectiveness of public health campaigns. The ability to tap into the vast, unstructured data from social media offers a new dimension to public health surveillance, enabling real-time monitoring of public health events as they unfold (Khan & Alotaibi, 2020).

Furthermore, data from wearable devices, such as fitness trackers and smartwatches, has become an increasingly important component of big data in public health. These devices collect continuous health data, including heart rate, physical activity levels, and sleep patterns, providing granular insights into individual health behaviors (Vijayan, Connolly, Condell, McKelvey, & Gardiner, 2021). When aggregated across populations, this data offers a wealth of information about general health trends and can be used to monitor the effectiveness of health interventions. For example, data from wearables has been used to assess the impact of public health measures during the COVID-19 pandemic by monitoring changes in physical activity and mobility patterns (Rehman, Naz, & Razzak, 2022).

3.2 Real-Time Data Analytics, Data Fusion, and Large-Scale Data Processing Techniques

The ability to process and analyze data in real time is one of the most significant advancements that big data has brought to public health surveillance. Real-time data analytics allows public health authorities to detect and respond to health threats as they occur, rather than relying on retrospective data analysis. For example, real-time analytics has been used to monitor the spread of infectious diseases, such as COVID-19, enabling public health agencies to track case numbers, hospitalizations, and deaths in real time. This real-time monitoring helps ensure that resources, such as hospital beds and medical supplies, are allocated efficiently during public health emergencies (Odilibe et al., 2024; Ogugua, Okongwu, Akomolafe, Anyanwu, & Daraojimba, 2024; Udegbe, Ebulue, Ebulue, & Ekesiobi, 2024a).

Data fusion is another critical technique in big data analytics, where data from multiple sources is integrated to create a more comprehensive view of public health. This approach is particularly valuable in public health surveillance, where different types of data (e.g., clinical, environmental, and behavioral data) are needed to understand the full picture of a health threat. For instance, data fusion can be used to combine weather data with hospital admissions data to track the spread of vector-borne diseases, such as dengue fever or malaria, which are influenced by environmental factors. Integrating these data types allows public health officials to better predict and prevent disease outbreaks (Kashinath et al., 2021).

Large-scale data processing techniques are essential for managing the vast amounts of data generated in public health surveillance. Traditional data processing methods are often insufficient to handle big data's volume, velocity, and variety. Modern technologies, such as cloud computing and distributed computing frameworks (e.g., Apache Hadoop and Apache Spark), enable the simultaneous processing of massive datasets across multiple servers. These technologies allow for faster data processing and analysis, which is critical for real-time

surveillance and decision-making (Nazir et al., 2020). Moreover, advanced data processing techniques, such as machine learning and artificial intelligence (AI), are used to identify patterns and correlations in large datasets that may not be apparent through traditional statistical analysis. These techniques can help public health officials detect emerging health threats earlier and with greater accuracy. For example, machine learning models have been used to analyze large datasets of patient records to identify early signs of sepsis, a potentially life-threatening condition that can be difficult to diagnose. By processing vast amounts of data quickly and accurately, these advanced techniques improve the timeliness and effectiveness of public health interventions (Awotunde et al., 2021).

3.3 The Potential for Improving Early Detection and Response to Public Health Threats

The integration of big data into public health surveillance has significant potential for improving the early detection and response to public health threats. Traditional public health surveillance methods often rely on manual data reporting and retrospective analysis, which can result in delayed responses to emerging health crises. Big data, however, enables real-time monitoring and more accurate predictions of health threats, allowing public health agencies to intervene earlier and more effectively (Zeng et al., 2021).

One of the key advantages of big data in early detection is its ability to analyze data from diverse sources and identify unusual patterns or anomalies that may indicate the onset of a health threat. For example, big data analytics has been used to detect influenza outbreaks by monitoring online search queries and social media posts related to flu symptoms. These early warning systems provide public health officials with valuable lead time to implement preventive measures, such as vaccination campaigns or public health advisories, before an outbreak becomes widespread (Razzak, Imran, & Xu, 2020).

In addition to early detection, big data enhances the ability of public health agencies to respond to health threats in real time. During the COVID-19 pandemic, big data was used to track the spread of the virus and monitor the effectiveness of public health interventions, such as social distancing and mask mandates. By analyzing mobility data from smartphones, public health officials could assess compliance with stay-at-home orders and adjust policies accordingly. This real-time feedback loop enabled more agile and responsive public health strategies, helping to mitigate the spread of the virus.

Big data also supports more targeted and efficient responses to public health threats by enabling the identification of high-risk populations. For instance, during the COVID-19 pandemic, data analytics was used to identify communities that were disproportionately affected by the virus, such as older adults and individuals with underlying health conditions. This information allowed public health agencies to prioritize these vulnerable groups for vaccination and other protective measures. By tailoring interventions to those most at risk, big data helps optimize public health resources and improve health outcomes (Jia et al., 2020).

Moreover, big data enables more precise modeling of disease dynamics, which can inform public health planning and preparedness efforts. Predictive models that use big data to simulate the spread of infectious diseases have been used to guide decisions about resource allocation, such as the distribution of vaccines and medical supplies. These models can also be used to evaluate the potential impact of different public health interventions, such as travel restrictions or quarantine measures, allowing policymakers to choose the most effective strategies for controlling the spread of disease (Ikegwu, Nweke, Anikwe, Alo, & Okonkwo, 2022).

IV. Ethical and Regulatory Considerations

4.1. The Ethical Implications of Using AI and Big Data in Public Health

The use of artificial intelligence and big data in public health presents significant ethical challenges, particularly related to data privacy, security, and informed consent. In public health surveillance, vast amounts of data are collected from a variety of sources, including healthcare systems, social media, and wearable devices. These data are used to predict disease outbreaks, track health trends, and improve healthcare outcomes. However, the sensitive nature of health data raises critical questions about who has access to it, how it is used, and whether individuals are fully aware of how their personal information is handled. (Mühlhoff, 2023)

Data privacy is a primary concern when using AI and big data in public health. Personal health information is among the most sensitive types of data, and its misuse can lead to significant harm, including identity theft, discrimination, and loss of trust in healthcare institutions. In the context of public health, the need to balance individual privacy with societal benefits becomes a complex ethical issue. While AI and big data can lead to valuable insights that improve public health outcomes, collecting and analyzing personal data without adequate safeguards can undermine individual rights. Public health initiatives often require data at scale, but ensuring the data is anonymized and de-identified is crucial to protecting privacy. Even with these measures, the risk of re-identification, where anonymized data is linked back to an individual, remains a significant ethical concern (Thapa & Camtepe, 2021).

Data security is another critical ethical consideration. Public health agencies and organizations must ensure that the systems and technologies they use to store and process health data are secure from breaches and unauthorized access. Cyberattacks on healthcare data systems can lead to devastating consequences, including

exposing sensitive health information and disrupting public health services. As more health data moves to cloud-based platforms and digital infrastructures, the risk of cyberattacks increases, making robust cybersecurity measures an ethical obligation for any organization handling health data. Ensuring data protection from malicious actors is not just a technical issue but also an ethical one, as a failure to secure data can erode public trust in health systems (Hensen et al., 2021).

Informed consent is another central ethical issue in the use of AI and big data for public health. In traditional healthcare settings, patients are usually asked for explicit consent before their personal data is used for medical purposes. However, in big data, particularly when data is collected from sources such as social media or fitness trackers, individuals may not be fully aware of how their data is being used. This raises ethical questions about the adequacy of consent procedures. For instance, users may consent to share their data with a specific application but may not realize that the data can be aggregated and used for public health surveillance. A critical ethical requirement is ensuring transparency and providing individuals with meaningful choices about how their data is used (Berlinger et al., 2020).

4.2. Existing Regulations and Guidelines Governing Health Data Use

Several regulations and guidelines have been established to govern the use of health data, ensuring that ethical principles such as privacy, security, and consent are upheld. These frameworks aim to protect individual rights while allowing the responsible use of data for public health purposes.

In the United States, the Health Insurance Portability and Accountability Act (HIPAA) is a key regulation governing health data privacy and security. HIPAA establishes national standards for the protection of sensitive health information, requiring healthcare providers and organizations to implement measures that safeguard patient data from unauthorized access or disclosure. HIPAA's Privacy Rule gives individuals control over their health information, allowing them to decide how their data is shared, while the Security Rule mandates the use of secure systems for storing and transmitting health data (Sadri, 2024). While HIPAA has been instrumental in protecting health data in clinical settings, its applicability to big data and AI-driven public health initiatives, particularly those involving non-traditional data sources like social media, remains a challenge. As public health surveillance increasingly relies on new data types, regulatory frameworks like HIPAA may need to be updated to address the evolving landscape of health data (Oakley, 2023).

The General Data Protection Regulation (GDPR) in the European Union is another important regulation that governs the use of personal data, including health data. GDPR establishes strict rules on data privacy, requiring organizations to obtain explicit consent from individuals before processing their personal data. In certain circumstances, it also grants individuals the right to access their data, request corrections, and demand its deletion. GDPR's principles of data minimization and purpose limitation, which require organizations to only collect and use data that is necessary for a specific purpose, are particularly relevant to public health initiatives that rely on big data. However, GDPR does allow exceptions for public health, where data can be processed without consent if it is in the public interest. This highlights the tension between individual privacy rights and the need for public health surveillance, which is discussed in ethical debates (Hansen et al., 2021).

Internationally, the World Health Organization (WHO) has issued guidelines on the ethical use of digital health technologies, including AI and big data. These guidelines emphasize the importance of safeguarding human rights and protecting individual privacy in collecting and using health data. The WHO also calls for greater transparency in developing and deploying AI technologies in health, urging governments and organizations to establish clear regulations that prevent the misuse of health data and ensure accountability. While these international guidelines provide a broad ethical framework, their implementation depends on national and regional regulatory systems (Guidance, 2021).

4.3. The Balance Between Innovation and Protecting Individual Rights

The tension between promoting innovation in public health and protecting individual rights is a key ethical issue in the use of AI and big data. On one hand, these technologies hold enormous potential to revolutionize public health by enabling faster disease detection, more accurate risk assessments, and personalized health interventions. On the other hand, the use of personal data in these innovations poses significant risks to privacy and individual autonomy. Striking the right balance between these two imperatives is essential for ensuring that the benefits of AI and big data are realized without compromising ethical standards (Fosso Wamba & Queiroz, 2023).

Innovation in public health, particularly through the use of AI, has the potential to save lives by enabling more precise and timely responses to health threats. For example, AI algorithms can analyze vast datasets to predict the spread of infectious diseases, allowing public health agencies to allocate resources more efficiently and prevent outbreaks from escalating. In this context, the use of personal data is essential for developing accurate models and interventions. However, this data must be used with care to ensure that individuals' privacy is respected and that they retain control over their personal information (Leslie, 2020).

Balancing innovation with the protection of individual rights requires robust governance frameworks that promote transparency, accountability, and public trust. One approach to achieving this balance is through the concept of "data stewardship," where organizations act as responsible custodians of personal data, ensuring that it is used ethically and following individuals' preferences. Data stewardship involves implementing strict data protection measures, providing clear information to individuals about how their data is used, and giving them meaningful choices about consent. Additionally, the principle of "privacy by design" should be embedded into the development of AI and big data systems, ensuring that privacy protections are built into technologies from the outset rather than being added as an afterthought (Christodoulou & Iordanou, 2021).

Public engagement is also crucial in balancing innovation and individual rights. Public health initiatives that rely on AI and big data should involve open dialogue with communities, explaining the benefits and risks of data-driven approaches and addressing concerns about privacy and consent. By involving the public in decision-making processes, public health organizations can build trust and ensure that data-driven innovations are aligned with societal values (Zidaru, Morrow, & Stockley, 2021).

V. Conclusion and Recommendation

5.1. Conclusion

Artificial intelligence (AI) and big data have become transformative forces in public health surveillance, providing new avenues to predict, detect, and respond to health threats more efficiently than ever before. One of the key insights is the ability of AI-driven algorithms to analyze vast and complex datasets, identifying patterns and trends that might otherwise go unnoticed. Machine learning models, for example, can predict the spread of infectious diseases or forecast healthcare needs based on real-time data. These predictive capabilities are invaluable in controlling outbreaks, allocating medical resources, and informing public health interventions.

Big data encompasses information from diverse sources such as healthcare systems, social media, and environmental sensors, has enabled a more comprehensive view of public health dynamics. Public health surveillance is no longer limited to clinical data; it now includes social determinants of health, behavioral patterns, and environmental factors. This wealth of information allows for more accurate risk assessments and early warning systems, as seen in the successful use of big data analytics during the COVID-19 pandemic to track case numbers and model transmission. Moreover, data fusion techniques—combining data from multiple sources—have improved public health decisions' reliability by offering a more holistic picture of health trends.

Another significant contribution of AI and big data is their capacity to enhance real-time monitoring and response. Traditional public health systems often rely on delayed reporting of disease cases or health events. However, with AI and big data applications, real-time analytics can quickly identify emerging threats, such as outbreaks or sudden changes in disease incidence, enabling faster responses and more effective containment strategies. The integration of big data with AI-driven tools in public health surveillance has led to more proactive and precise decision-making.

5.2. Recommendations for Future Research and Policy Development

While the potential of AI and big data in public health surveillance is vast, several areas require further exploration to fully harness these technologies. First, future research should focus on improving the accuracy and fairness of AI algorithms. Current models can suffer from biases in data collection, particularly when certain populations are underrepresented. For instance, data from rural or low-income areas may not be as readily available or reliable, leading to inequities in health outcomes. Researchers must prioritize the development of more inclusive algorithms that account for these disparities to ensure that all populations benefit from AI-driven health interventions.

Additionally, more research is needed to address the ethical concerns associated with big data in public health. Issues of data privacy, consent, and security must be at the forefront of both technological advancements and policy development. Research should explore ways to strengthen data protection mechanisms while still enabling the use of health data for public benefit. The development of frameworks that ensure transparency and maintain the trust of the public is crucial for the continued adoption of these technologies.

From a policy perspective, governments and health organizations should work together to create comprehensive guidelines for the use of AI and big data in public health. These policies must strike a balance between promoting innovation and safeguarding individual rights. Regulatory frameworks should include clear guidelines on data governance, ensuring that health data is used ethically and securely. Furthermore, policies that encourage public engagement and education about the use of AI in health can help build trust and reduce public apprehension.

References

- [1]. Abdulkareem, M., & Petersen, S. E. (2021). The promise of AI in detection, diagnosis, and epidemiology for combating COVID-19: beyond the hype. *Frontiers in Artificial Intelligence*, 4, 652669.

- [2]. Akter, S., Dwivedi, Y. K., Sajib, S., Biswas, K., Bandara, R. J., & Michael, K. (2022). Algorithmic bias in machine learning-based marketing models. *Journal of Business Research*, 144, 201-216.
- [3]. Alanne, K., & Sierla, S. (2022). An overview of machine learning applications for smart buildings. *Sustainable Cities and Society*, 76, 103445.
- [4]. Albahri, A. S., Duhaim, A. M., Fadhel, M. A., Alnoor, A., Baqer, N. S., Alzubaidi, L., . . . Salhi, A. (2023). A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion. *Information Fusion*, 96, 156-191.
- [5]. Awotunde, J. B., Jimoh, R. G., Oladipo, I. D., Abdurraheem, M., Jimoh, T. B., & Ajamu, G. J. (2021). Big data and data analytics for an enhanced COVID-19 epidemic management. In *Artificial Intelligence for COVID-19* (pp. 11-29): Springer.
- [6]. Baclic, O., Tunis, M., Young, K., Doan, C., Swerdfeger, H., & Schonfeld, J. (2020). Artificial intelligence in public health: Challenges and opportunities for public health made possible by advances in natural language processing. *Canada Communicable Disease Report*, 46(6), 161.
- [7]. Bedi, J. S., Vijay, D., Dhaka, P., Gill, J. P. S., & Barbudde, S. B. (2021). Emergency preparedness for public health threats, surveillance, modelling & forecasting. *Indian Journal of Medical Research*, 153(3), 287-298.
- [8]. Bekbolatova, M., Mayer, J., Ong, C. W., & Toma, M. (2024). Transformative potential of AI in Healthcare: definitions, applications, and navigating the ethical Landscape and Public perspectives. Paper presented at the Healthcare.
- [9]. Berlinger, N., Wynia, M., Powell, T., Hester, D. M., Milliken, A., Fabi, R., & Jenks, N. (2020). Ethical framework for health care institutions responding to novel Coronavirus SARS-CoV-2 (COVID-19) guidelines for institutional ethics services responding to COVID-19. *The Hastings Center*, 12(3), 1-12.
- [10]. Chowdhury, A. T., Newaz, M., Saha, P., Majid, M. E., Mushtak, A., & Kabir, M. A. (2024). Application of Big Data in Infectious Disease Surveillance: Contemporary Challenges and Solutions. In *Surveillance, Prevention, and Control of Infectious Diseases: An AI Perspective* (pp. 51-71): Springer.
- [11]. Christodoulou, E., & Iordanou, K. (2021). Democracy under attack: challenges of addressing ethical issues of AI and big data for more democratic digital media and societies. *Frontiers in Political Science*, 3, 682945.
- [12]. Fosso Wamba, S., & Queiroz, M. M. (2023). Responsible artificial intelligence as a secret ingredient for digital health: Bibliometric analysis, insights, and research directions. *Information Systems Frontiers*, 25(6), 2123-2138.
- [13]. Guidance, W. (2021). Ethics and governance of artificial intelligence for health. World Health Organization.
- [14]. Hansen, J., Wilson, P., Verhoeven, E., Kroneman, M., Kirwan, M., Verheij, R., & van Veen, E.-B. (2021). Assessment of the EU Member States' rules on health data in the light of GDPR.
- [15]. Hensen, B., Mackworth-Young, C., Simwina, M., Abdelmagid, N., Banda, J., Mavodza, C., . . . Weiss, H. (2021). Remote data collection for public health research in a COVID-19 era: ethical implications, challenges and opportunities. *Health policy and planning*, 36(3), 360-368.
- [16]. Ikegwu, A. C., Nweke, H. F., Anikwe, C. V., Alo, U. R., & Okonkwo, O. R. (2022). Big data analytics for data-driven industry: a review of data sources, tools, challenges, solutions, and research directions. *Cluster Computing*, 25(5), 3343-3387.
- [17]. Jia, Q., Guo, Y., Wang, G., & Barnes, S. J. (2020). Big data analytics in the fight against major public health incidents (Including COVID-19): a conceptual framework. *International Journal of Environmental Research and Public Health*, 17(17), 6161.
- [18]. Kashinath, S. A., Mostafa, S. A., Mustapha, A., Mahdin, H., Lim, D., Mahmoud, M. A., . . . Yang, T. J. (2021). Review of data fusion methods for real-time and multi-sensor traffic flow analysis. *IEEE Access*, 9, 51258-51276.
- [19]. Khan, Z. F., & Alotaibi, S. R. (2020). Applications of artificial intelligence and big data analytics in m- health: A healthcare system perspective. *Journal of healthcare engineering*, 2020(1), 8894694.
- [20]. Leslie, D. (2020). Tackling COVID-19 through responsible AI innovation: Five steps in the right direction. *Harvard Data Science Review*, 10.
- [21]. Locke, S., Bashall, A., Al-Adely, S., Moore, J., Wilson, A., & Kitchen, G. B. (2021). Natural language processing in medicine: a review. *Trends in Anaesthesia and Critical Care*, 38, 4-9.
- [22]. Majeed, A., & Hwang, S. O. (2021). Data-driven analytics leveraging artificial intelligence in the era of COVID-19: an insightful review of recent developments. *Symmetry*, 14(1), 16.
- [23]. Meckawy, R., Stuckler, D., Mehta, A., Al-Ahdal, T., & Doebbeling, B. N. (2022). Effectiveness of early warning systems in the detection of infectious diseases outbreaks: a systematic review. *BMC public health*, 22(1), 2216.
- [24]. Mohamed, A., Najafabadi, M. K., Wah, Y. B., Zaman, E. A. K., & Maskat, R. (2020). The state of the art and taxonomy of big data analytics: view from new big data framework. *Artificial intelligence review*, 53, 989-1037.
- [25]. Mühlhoff, R. (2023). Predictive privacy: Collective data protection in the context of artificial intelligence and big data. *Big Data & Society*, 10(1), 20539517231166886.
- [26]. Nazir, S., Khan, S., Khan, H. U., Ali, S., Garcia-Magarino, I., Atan, R. B., & Nawaz, M. (2020). A comprehensive analysis of healthcare big data management, analytics and scientific programming. *IEEE Access*, 8, 95714-95733.
- [27]. Nijhawan, T., Attigeri, G., & Ananthakrishna, T. (2022). Stress detection using natural language processing and machine learning over social interactions. *Journal of Big Data*, 9(1), 33.
- [28]. Norori, N., Hu, Q., Aellen, F. M., Faraci, F. D., & Tzovara, A. (2021). Addressing bias in big data and AI for health care: A call for open science. *Patterns*, 2(10).
- [29]. Oakley, A. (2023). HIPAA, HIPPA, or HIPPO: What Really Is the Health Insurance Portability and Accountability Act? *Biotechnology Law Report*, 42(6), 306-318.
- [30]. Odilibe, I. P., Akomolafe, O., Arowoogun, J. O., Anyanwu, E. C., Onwumere, C., & Ogugua, J. O. (2024). Mental health policies: a comparative review between the USA and African nations. *International Medical Science Research Journal*, 4(2), 141-157.
- [31]. Ogugua, J. O., Okongwu, C. C., Akomolafe, O. O., Anyanwu, E. C., & Daraojimba, O. D. (2024). Mental health and digital technology: a public health review of current trends and responses. *International Medical Science Research Journal*, 4(2), 108-125.
- [32]. Ogundipe, D. O. (2024). The impact of big data on healthcare product development: A theoretical and analytical review. *International Medical Science Research Journal*, 4(3), 341-360.
- [33]. Okoduwa, I. O., Ashiwaju, B. I., Ogugua, J. O., Arowoogun, J. O., Awonuga, K. F., & Anyanwu, E. C. (2024). Reviewing the progress of cancer research in the USA. *World Journal of Biology Pharmacy and Health Sciences*, 17(2), 068-079.
- [34]. Perera, A., & Iqbal, K. (2021). Big data and emerging markets: Transforming economies through data-driven innovation and market dynamics. *Journal of Computational Social Dynamics*, 6(3), 1-18.
- [35]. Razzak, M. I., Imran, M., & Xu, G. (2020). Big data analytics for preventive medicine. *Neural Computing and Applications*, 32(9), 4417-4451.
- [36]. Rehman, A., Naz, S., & Razzak, I. (2022). Leveraging big data analytics in healthcare enhancement: trends, challenges and opportunities. *Multimedia Systems*, 28(4), 1339-1371.
- [37]. Sadri, M. (2024). HIPAA: A Demand to Modernize Health Legislation. *The Undergraduate Law Review at UC San Diego*, 2(1).

- [38]. Santosh, K., & Gaur, L. (2022). Artificial intelligence and machine learning in public healthcare: Opportunities and societal impact: Springer Nature.
- [39]. Taye, M. M. (2023). Understanding of machine learning with deep learning: architectures, workflow, applications and future directions. *Computers*, 12(5), 91.
- [40]. Thapa, C., & Camtepe, S. (2021). Precision health data: Requirements, challenges and existing techniques for data security and privacy. *Computers in biology and medicine*, 129, 104130.
- [41]. Udegbe, F. C., Ebulue, O. R., Ebulue, C. C., & Ekesiobi, C. S. (2024a). Precision Medicine and Genomics: A comprehensive review of IT-enabled approaches. *International Medical Science Research Journal*, 4(4), 509-520.
- [42]. Udegbe, F. C., Ebulue, O. R., Ebulue, C. C., & Ekesiobi, C. S. (2024b). The role of artificial intelligence in healthcare: A systematic review of applications and challenges. *International Medical Science Research Journal*, 4(4), 500-508.
- [43]. Velmovitsky, P. E., Bevilacqua, T., Alencar, P., Cowan, D., & Morita, P. P. (2021). Convergence of precision medicine and public health into precision public health: toward a big data perspective. *Frontiers in public health*, 9, 561873.
- [44]. Vijayan, V., Connolly, J. P., Condell, J., McKelvey, N., & Gardiner, P. (2021). Review of wearable devices and data collection considerations for connected health. *Sensors*, 21(16), 5589.
- [45]. Zeng, D., Cao, Z., & Neill, D. B. (2021). Artificial intelligence-enabled public health surveillance—from local detection to global epidemic monitoring and control. In *Artificial intelligence in medicine* (pp. 437-453): Elsevier.
- [46]. Zhang, J., & Zhang, Z.-m. (2023). Ethics and governance of trustworthy medical artificial intelligence. *BMC medical informatics and decision making*, 23(1), 7.
- [47]. Zidaru, T., Morrow, E. M., & Stockley, R. (2021). Ensuring patient and public involvement in the transition to AI- assisted mental health care: A systematic scoping review and agenda for design justice. *Health Expectations*, 24(4), 1072-1124.