World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(REVIEW ARTICLE)

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Data science in public health: A review of predictive analytics for disease control in the USA and Africa

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World Journal of Advanced Research and Reviews, 2024, 21(01), 2753–2769

Publication history: Received on 21 December 2023; revised on 27 January 2024; accepted on 30 January 2024

Article DOI: https://doi.org/10.30574/wjarr.2024.21.1.0383

Abstract

This scholarly paper delves into the realm of data science in public health, with a specific focus on the transformative role of predictive analytics in disease control across the United States and Africa. Set against a backdrop of rapidly evolving healthcare challenges, the study aims to dissect and synthesize the advancements, applications, and hurdles associated with data-driven health strategies in these diverse geographical contexts.

Employing a qualitative analysis of peer-reviewed literature, the paper meticulously examines the evolution of predictive analytics, comparing public health structures, and scrutinizing key diseases and health challenges prevalent in both regions. The scope of the study extends to exploring the ethical considerations and technological advancements in health data utilization, offering a panoramic view of the current and potential landscape of data science in public health.

The findings reveal a significant surge in the application of predictive analytics, particularly in the USA for chronic disease management and in Africa for infectious disease control. The study highlights the successes and challenges in implementing data-driven health policies, emphasizing the need for a balanced approach that addresses technological, ethical, and cultural barriers. The future of AI and machine learning in disease control is identified as a promising domain, with potential for further innovation and integration into healthcare and public policy.

Conclusively, the paper recommends continued investment in data science applications in public health, advocating for collaborative efforts to overcome implementation challenges and ethical considerations. The study underscores the transformative potential of data science in enhancing healthcare delivery, advocating for more effective, efficient, and equitable healthcare systems globally.

Keywords: Predictive Analytics; Public Health; Data Science; AI in Healthcare; Cross-Continental; Health Strategies

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1. Introduction

1.1. Overview of Data Science in Public Health Initiatives

The integration of data science into public health initiatives marks a transformative shift in how healthcare systems approach disease surveillance and control. Zhang et al. (2024) underscore the importance of a cohesive, multidisciplinary approach in public health, highlighting the role of data science in advancing disease surveillance. This approach is increasingly relevant in a world where public health challenges are complex and multifaceted, requiring the collaboration of experts from various fields including data scientists, computer engineers, and social scientists.

The application of data science in public health is not just about the collection and analysis of data; it's about the integration of this data into actionable insights that can guide public health policies and interventions. Zhang et al. (2024) emphasizes the need for combining relevant data sources in innovative ways, utilizing advanced technologies for early diagnosis, and refining analytic methods to maintain high specificity in event identification. This multi-tiered approach, grounded in the One Health perspective, is economically feasible and sustainable, offering a blueprint for future public health initiatives.

Molldrem, Smith, and McClelland (2023) delve into the ethical dimensions of data science applications in public health, particularly in the context of HIV surveillance. Their work highlights the emergent ethical problems and risks associated with classifying individuals in public health systems, the new ways of combining and sharing health data, and the challenges these practices pose to existing regulatory paradigms. This commentary is crucial in understanding the turn towards predictive modeling in public health and the need for reform-oriented conversations about the regulatory frameworks and ethical norms governing data re-uses.

The potential and adoption of data science in healthcare analytics are further explored by Linh et al. (2021), who discuss the creation and validation of clinical practice predictive models. They emphasize that the adoption of healthcare analytics can occur at various levels, including medical error tracking, data integration, and personalized modelling. The authors highlight the substantial advancements made from the perspective of data science, while also acknowledging the challenges and opportunities that remain. This includes the need for organization, introduction, and assessment of health information systems, patient information representation, and the analysis and interpretation of underlying signals and data.

The intersection of data science and public health is particularly evident in the realm of disease prediction and prevention. Predictive analytics, a key component of data science, enables health professionals to anticipate outbreaks, identify risk factors, and implement targeted interventions. This proactive approach to public health is a departure from traditional reactive methods, offering a more efficient and effective means of disease control.

However, the application of data science in public health is not without its challenges. One of the primary concerns is the ethical use of health data. As Molldrem, Smith, and McClelland (2023) point out, the use of predictive analytics in public health, particularly in sensitive areas such as HIV surveillance, raises significant ethical questions. These include concerns about privacy, consent, and the potential for stigmatization. Addressing these ethical considerations is crucial for the responsible and effective use of data science in public health.

Another challenge is the integration of data science into existing public health structures. As Zhang et al. (2024) notes, achieving early disease detection has been somewhat elusive, partly due to insufficient collaboration between multidisciplinary experts. Overcoming this challenge requires a concerted effort to foster collaboration and integrate data science seamlessly into public health initiatives.

The future of data science in public health looks promising, with the potential to revolutionize how we approach disease surveillance and control. The integration of advanced technologies, innovative data sources, and multidisciplinary collaboration can lead to more effective and efficient public health interventions. However, as we move forward, it is essential to navigate the ethical, practical, and technical challenges that come with the integration of data science into public health.

The overview of data science in public health initiatives reveals a landscape where technology, ethics, and multidisciplinary collaboration intersect. The potential of data science to transform public health is immense, offering new ways to predict, prevent, and control diseases. However, realizing this potential requires addressing the ethical considerations, fostering collaboration among various experts, and integrating data science effectively into public health structures. As we continue to explore the possibilities of data science in public health, it is imperative to do so with a keen awareness of the challenges and opportunities that lie ahead.

1.2. The Evolution of Predictive Analytics in Healthcare

The evolution of predictive analytics in healthcare represents a significant shift in the paradigm of medical care and disease management. This transformation is driven by the integration of data science, artificial intelligence, and machine learning techniques, which collectively enhance the predictive capabilities of healthcare systems.

Dhamodaran and Balmoor (2019) explore the future trends of healthcare data predictive analytics, emphasizing the role of soft computing techniques in data science. They highlight the importance of artificial intelligence, machine learning, artificial neural networks, and fuzzy logic in refining patient care, chronic disease management, and hospital administration. The authors argue that healthcare can learn valuable lessons from the success of these disciplines in other industries, thereby improving the efficacy of predictive analytics in healthcare. This perspective underscores the transition from traditional healthcare practices to more data-driven, predictive approaches.

Leung et al. (2020) delve into the application of data science in healthcare predictive analytics, focusing on the use of big data. They present a data science framework with two predictive analytic algorithms for accurate prediction of cancer trends. This framework demonstrates the effectiveness of predictive algorithms in healthcare data analytics, particularly in the detection and diagnosis of illnesses such as cancer. The authors' work exemplifies the practical application of predictive analytics in healthcare, showcasing how data science can be leveraged to improve patient outcomes.

Tran et al. (2022) contribute to this evolving field by presenting a deep learning-based predictive model for healthcare analytics. Their model, which comprises an autoencoder and a predictor, is capable of learning from historical healthcare data to make binary or multi-label predictions. This approach highlights the potential of deep learning in enhancing the predictive capabilities of healthcare systems, especially in scenarios where the availability of data may be limited due to privacy concerns.

The evolution of predictive analytics in healthcare is marked by several key developments. Firstly, there has been a significant increase in the volume and variety of healthcare data available for analysis. This includes patient data, clinical trials data, and real-time health monitoring data, which provide a rich source of information for predictive modeling. Secondly, advancements in data science and machine learning algorithms have enabled more accurate and sophisticated analysis of this data. These algorithms can identify patterns and trends that may not be apparent to human analysts, thereby enhancing the predictive accuracy of healthcare models.

Another important development in this field is the increasing integration of predictive analytics into clinical practice. Predictive models are being used to support decision-making in various aspects of healthcare, including diagnosis, treatment planning, and disease management. For example, predictive models can identify patients at high risk of certain diseases, enabling early intervention and more personalized care.

However, the evolution of predictive analytics in healthcare also presents several challenges. One of the primary challenges is ensuring the accuracy and reliability of predictive models. This requires careful validation and testing of models to ensure they are based on sound scientific principles and are applicable to diverse patient populations. Additionally, there are ethical and privacy concerns related to the use of patient data in predictive analytics. Ensuring the confidentiality and security of patient data is crucial to maintaining trust in healthcare systems.

The evolution of predictive analytics in healthcare represents a significant advancement in the field of medicine. The integration of data science, artificial intelligence, and machine learning techniques has enhanced the predictive capabilities of healthcare systems, enabling more accurate diagnosis, personalized treatment, and efficient disease management. However, this evolution also presents challenges that must be addressed, including ensuring the accuracy and reliability of predictive models and addressing ethical and privacy concerns related to patient data. As the field continues to evolve, it is essential to navigate these challenges to fully realize the potential of predictive analytics in improving patient care and health outcomes.

1.3. Comparative Analysis of Public Health Structures: USA vs Africa

The comparative analysis of public health structures between the USA and Africa reveals significant differences and some similarities in approaches to healthcare management and disease control. This analysis is crucial in understanding how different regions adapt their healthcare strategies to meet their unique challenges and resources.

Within the context of the Sustainable Development Goals, it is crucial to critically review research on healthcare financing in sub-Saharan Africa (SSA) from the perspective of the universal health coverage (UHC) goals of financial protection and access to quality health services for all.

McIntyre et al. (2018) highlight the concerning reliance on direct out-of-pocket payments in many SSA countries, accounting for an average of 36% of current health expenditure compared to only 22% in the rest of the world. Contributions to health insurance schemes, whether voluntary or mandatory, contribute a small share of current health expenditure. While domestic mandatory prepayment mechanisms (tax and mandatory insurance) represent the next largest category of healthcare financing in SSA (35%), a relatively large share of funding in SSA (14% compared to <1% in the rest of the world) is attributable to, sometimes unstable, external funding sources. There is a growing recognition of the need to reduce out-of-pocket payments and increase domestic mandatory prepayment financing to move towards UHC. Many SSA countries have declared a preference for achieving this through contributory health insurance schemes, particularly for formal sector workers, with service entitlements tied to contribution."

Sotola, Pillay, and Gebreselassie (2021) discuss the early policy responses to the COVID-19 pandemic in Africa, providing insights into the continent's public health strategies. Their analysis indicates that quick and early measures, recent experience in managing health crises, and community resilience were key factors in the management of the pandemic in Africa. This contrasts with the USA's approach, which involved more robust healthcare infrastructure and advanced technological resources but faced challenges in coordination and public compliance.

Sahadew, Pillay, and Singaram (2022) focus on the public healthcare sector's response to diabetes in South Africa, offering a perspective on chronic disease management in an African context. Their study highlights the challenges of unreliable data collection, overburdened health systems, and poor infrastructure, which are common in many African countries. In contrast, the USA, with its more developed healthcare infrastructure, has more comprehensive and reliable data collection systems and better-resourced health facilities.

One of the key differences between the public health structures of the USA and Africa is the level of infrastructure development. The USA boasts advanced healthcare facilities, a high ratio of healthcare professionals to the population, and widespread access to cutting-edge medical technology. In contrast, many African countries struggle with underfunded healthcare systems, inadequate healthcare facilities, and a shortage of medical professionals.

Another significant difference is in the approach to healthcare financing. In the USA, healthcare financing is a mix of public and private funding, with a significant portion of the population covered by private health insurance. In contrast, many African countries rely heavily on public funding for healthcare, with a significant portion of the population having limited or no access to health insurance. This difference in financing models impacts the accessibility and quality of healthcare services available to the population.

Despite these differences, there are some similarities in the public health challenges faced by the USA and Africa. Both regions grapple with the burden of chronic diseases, such as diabetes and heart disease, and face the challenge of managing infectious diseases. The COVID-19 pandemic has further highlighted these challenges, with both regions having to adapt their public health strategies to manage the outbreak.

In conclusion, the comparative analysis of public health structures between the USA and Africa reveals significant disparities in healthcare infrastructure, financing, and management strategies. While the USA benefits from advanced healthcare facilities and a mix of public and private financing, many African countries face challenges of underfunded healthcare systems and inadequate infrastructure. However, both regions share common public health challenges, including the management of chronic and infectious diseases. Understanding these differences and similarities is crucial for developing effective public health strategies that are tailored to the unique needs and resources of each region. As the global health landscape continues to evolve, it is essential to learn from these comparative analyses to improve healthcare outcomes worldwide.

1.4. Key Diseases and Public Health Challenges in Both Regions

The public health landscapes of the USA and Africa are marked by distinct challenges and key diseases, shaped by diverse socio-economic, environmental, and healthcare factors. A comparative analysis of these regions provides insights into the global health dynamics and the need for tailored health strategies.

Talisuna et al. (2020) highlight the significant burden of infectious diseases in Africa, with epidemics and disasters posing a continuous challenge to the continent's health systems. Between 2016 and 2018, over 260 events, including outbreaks of cholera, measles, viral hemorrhagic diseases, malaria, and meningitis, were identified. These diseases, often exacerbated by limited healthcare infrastructure and socio-economic constraints, underline the critical public health challenges in Africa. In contrast, the USA, with its advanced healthcare system, faces different challenges, such as managing chronic diseases like heart disease, diabetes, and obesity, alongside infectious diseases like influenza and, more recently, COVID-19.

Okoroafor et al. (2022) discuss the preparation of the health workforce in Africa for future public health emergencies. The study underscores the region's health systems' fragility, characterized by weak health governance, inadequate infrastructure, and limited financing capacity. The increasing frequency of infectious disease outbreaks in Africa, coupled with workforce challenges, contrasts sharply with the USA's healthcare scenario, where a more robust infrastructure and a larger health workforce are in place. However, both regions face the challenge of ensuring their health workforce is adequately prepared and equipped to handle public health emergencies, a fact highlighted by the COVID-19 pandemic.

Mfuh, Abanda, and Titanji (2023) emphasize the importance of strengthening diagnostic capacity in Africa as a key aspect of public health and pandemic preparedness. The anticipated doubling of Africa's population by 2050, along with climate change and increased human-animal interactions, is likely to lead to more outbreaks of emerging diseases. This need for enhanced diagnostic capacity is a stark contrast to the USA, where diagnostic capabilities are more advanced, but the challenge lies in ensuring equitable access to these services across diverse and often underserved populations.

In Africa, the public health challenges are further compounded by factors such as poverty, inadequate sanitation, and limited access to clean water, which contribute to the spread of infectious diseases. In addition, the high burden of HIV/AIDS in many African countries presents a unique public health challenge, requiring sustained efforts in prevention, treatment, and care. The USA, while dealing with its own set of public health issues, including the opioid crisis and mental health disorders, has a more established infrastructure to address these challenges.

The management of public health emergencies also differs significantly between the two regions. In Africa, the response to outbreaks like Ebola and Marburg virus has been hampered by limited resources and infrastructure. In contrast, the USA has the capacity to mobilize substantial resources and technology in response to health emergencies, although issues such as healthcare inequality and access remain challenges.

Preventive healthcare is another area where the two regions differ. In Africa, preventive measures often focus on vaccination campaigns and vector control to combat diseases like malaria and yellow fever. In the USA, preventive healthcare encompasses a broader range of services, including regular health screenings, lifestyle interventions, and vaccination programs.

The key diseases and public health challenges in the USA and Africa reflect these regions' diverse healthcare needs and capacities. While Africa grapples with infectious diseases, limited healthcare infrastructure, and socio-economic challenges, the USA faces issues related to chronic diseases, healthcare access, and emergency preparedness. Understanding these differences is crucial for developing effective health policies and interventions tailored to the specific needs of each region. As global health continues to evolve, lessons learned from both regions can inform a more integrated and responsive approach to public health challenges worldwide.

1.5. Role of Big Data in Disease Prediction and Prevention

The advent of big data has revolutionized the field of public health, particularly in disease prediction and prevention. The integration of large datasets, advanced analytics, and computational technologies has enabled healthcare professionals to gain deeper insights into disease patterns, risk factors, and effective intervention strategies.

Hu, Chen, and Li (2023) discuss the application of big data in developing early warning and prediction models for public health emergencies. Their research highlights the use of regression analysis, spatiotemporal models, and neural networks combined with geographic information systems for early disease detection. This approach underscores the potential of big data in transforming traditional public health models by providing more accurate and timely predictions, thereby enhancing the ability to respond to health emergencies effectively.

Kikuchi et al. (2022) explore the use of anonymized medical and healthcare big data for disease prediction. Their study demonstrates the feasibility of using big data to analyze disease risk by employing logistic regression and machine learning models. This research is particularly significant in the context of epidemiology, where big data can be used to predict disease trends and identify at-risk populations. The ability to analyse large datasets anonymously also addresses privacy concerns, making it a viable option for large-scale health data analysis.

Asri and Jarir (2023) delve into the integration of big data analytics and the Internet of Things (IoT) for real-time disease prediction, with a focus on miscarriage prediction. Their work involves collecting data from sensors, mobile phones, and patient inputs, processed using advanced algorithms to predict health outcomes. This approach exemplifies the role of big data in creating smart health systems that are proactive, patient-centred, and capable of providing real-time insights into health risks.

The role of big data in disease prediction and prevention can be seen in various aspects:

1.5.1. Enhanced Disease Surveillance

Big data enables the collection and analysis of vast amounts of health-related data from multiple sources, including electronic health records, social media, and wearable devices. This comprehensive surveillance helps in early detection of disease outbreaks and tracking disease spread in real-time.

1.5.2. Predictive Modelling

By applying machine learning algorithms to big data, healthcare professionals can develop predictive models that identify individuals at high risk of certain diseases. These models can forecast outbreaks and inform targeted interventions, thereby preventing the spread of diseases.

1.5.3. Personalized Medicine

Big data analytics facilitate personalized medicine by allowing for the analysis of patient-specific data. This leads to tailored treatment plans based on individual risk factors and health histories, improving patient outcomes and reducing healthcare costs.

1.5.4. Public Health Research

Big data provides a rich resource for public health research, enabling scientists to uncover patterns and associations that were previously undetectable. This research can lead to new insights into disease aetiology, risk factors, and effective prevention strategies.

1.5.5. Resource Allocation

In public health management, big data analytics can inform more efficient resource allocation. By predicting disease hotspots and identifying populations at risk, health authorities can allocate resources more effectively, ensuring that interventions are directed where they are most needed.

1.5.6. Policy Development

Big data can inform public health policy by providing evidence-based insights into the effectiveness of health interventions and policies. Policymakers can use these insights to develop strategies that address the most pressing health challenges.

The role of big data in disease prediction and prevention is multifaceted, offering significant benefits for public health. The ability to analyse large datasets provides unprecedented opportunities for early disease detection, targeted interventions, and personalized healthcare. However, challenges such as data privacy, the need for robust data infrastructure, and the integration of big data insights into clinical practice must be addressed to fully realize the potential of big data in public health. As technology continues to advance, the role of big data in transforming healthcare is expected to grow, leading to more effective disease prevention and improved health outcomes.

1.6. Technological Advancements and Their Impact on Health Analytics

The intersection of technological advancements and health analytics has brought about a transformative shift in the healthcare sector. The integration of innovative technologies has not only streamlined healthcare delivery but also enhanced the precision and effectiveness of medical interventions. Marino and Lorenzoni (2019) delve into the complexities of assessing the impact of technology on healthcare expenditure. Their study underscores that technological advancements are intricately linked with various determinants such as income, population health status, and the broader institutional context. This interplay of factors determines the extent to which technology is utilized in healthcare, influencing both the cost and quality of healthcare services. The authors emphasize that while technological progress brings about quality improvements, it also incurs monetary costs and benefits, making the assessment of its impact a challenging yet crucial task.

Wilson, Steele, and Adeli (2022) explore the revolutionary changes in laboratory medicine driven by technological innovations. They highlight how advancements in laboratory automation, genomics, spectroscopy, mass spectrometry, and microfluidics have transformed modern laboratory medicine, enhancing its role in healthcare and clinical decision-making. The integration of these technologies with microtechnology and point-of-care testing has improved patient outcomes and facilitated a more patient-centered approach to healthcare. However, the authors note that to fully capitalize on these advancements, new tools such as artificial intelligence and data mining are needed to harness the potential of medical big data derived from these novel techniques.

Zetino and Mendoza (2019) discuss the utility of big data in social work, drawing insights from its impact in business and healthcare. They illustrate how advanced data analytics and the big data revolution have driven innovation in disease diagnosis, care coordination, and health outcomes, leading to cost savings. The technological advancements in data storage, merging, and analysis have revolutionized both the business and healthcare sectors, enabling various forms of data analyses. These new tools have the potential to transform how social workers develop and implement strategies to address complex social challenges.

1.7. Ethical Considerations in Health Data Utilization

The ethical considerations in health data utilization have become increasingly prominent with the integration of digital data into public health research and policy. Garett and Young (2022) examine the ethical perspectives of participants on sharing digital data, including social media and wearable device data, with health researchers. Their study reveals a nuanced landscape where participants express comfort in sharing electronic health data for personalized healthcare and altruistic purposes but exhibit significant discomfort with sharing location and text message data. The primary concerns center around the loss of privacy and the potential disclosure of private information. This dichotomy underscores the ethical challenges in balancing the benefits of data sharing for public health against the risks of privacy infringement.

Lee (2019) delves into the evolving ethical considerations in public health surveillance. Traditional concerns related to infectious disease surveillance, such as privacy, confidentiality, and consent, have expanded to include considerations for noncommunicable conditions, encompassing self-determination, justice, and the provision of benefit. Lee emphasizes that the advent of technology and data science in public health surveillance necessitates a comprehensive integration of ethical considerations throughout the development and implementation of surveillance systems. This approach is vital to anticipate, address, and potentially avoid ethical conflicts in public health practice.

Ngan and Kelmenson (2021) explore the ethical implications of using big data tools to analyse digital footprints during the COVID-19 pandemic. They highlight how technology applications, such as real-time location data and geofencing technology, are employed in novel ways to track movement patterns and stem viral spread. The use of big data analytics, often involving involuntary and unconsented data access, raises public concerns about data protection and privacy rights. The authors discuss the ethical dilemma of using big data analytics for public health purposes, which may infringe on personal privacy in exchange for maximizing public security. They argue that demonstrating the effectiveness of public health measures is challenging due to scientific uncertainties and social complexities, necessitating a balanced approach to public health ethics.

1.7.1. Identifying Research Gaps in Ethical Health Data Use

The ethical use of health data in research is a rapidly evolving field, marked by significant advancements and emerging challenges. Johnson and Smith (2021) address the ethical implications of data-driven software development, particularly in the context of machine learning technologies. Their work highlights the need for ongoing research to understand and address the ethical challenges posed by these technologies. The authors identify gaps in our understanding of ethical software development practices, emphasizing the importance of validating these practices for effectiveness in real-world scenarios. This focus on ethical computing is crucial in an era where automated decision-making is becoming increasingly prevalent, and the potential for unexpected, undesirable outcomes is a growing concern.

Samuel, Chubb, and Derrick (2021) explore the boundaries between research ethics and ethical research use in the context of artificial intelligence (AI) health research. Their study, using AI population health research in the United Kingdom and Canada as a case study, reveals a separation between the ethical responsibility of researchers and the societal impact of their research. The authors argue that researchers often do not fully incorporate the ethical dimensions associated with the societal impact of their research into their agendas. This gap highlights the need for a more integrated approach to ethical considerations in AI health research, where the societal implications of research are given equal importance as the ethical responsibility of conducting the research itself.

Bak et al. (2023) contribute to the discussion by advocating for a trust-based governance model in health data research. Their empirically informed ethical analysis focuses on the implementation of the General Data Protection Regulation (GDPR) within a European research consortium. The authors observe that strictly formalized data protection requirements may lead to routinization among researchers rather than substantive ethical reflection and may crowd out trust between actors in the health data research ecosystem. They argue that the concept of trust provides an escape from the privacy-solidarity debate in health data research. The paper details three aspects of trust that can help create a responsible research environment: trust as a multi-agent concept, trust as a rational and democratic value, and trust as a method for priority setting.

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1.8. Objectives and Scope of the Current Review

The current review is designed to provide a comprehensive analysis of the role of data science in public health, particularly focusing on predictive analytics for disease control in the USA and Africa. The primary objective is to explore and compare the advancements, challenges, and impacts of data science applications in these two diverse regions. This includes examining the evolution of predictive analytics in healthcare, the structure of public health systems, key diseases and health challenges, and the ethical considerations in health data utilization.

The scope of this review extends to various dimensions of data science in public health. It begins with an overview of data science initiatives in public health, tracing the evolution of predictive analytics in healthcare and comparing public health structures in the USA and Africa. The review then delves into the key diseases and public health challenges faced by both regions, highlighting the role of big data in disease prediction and prevention.

Technological advancements and their impact on health analytics form a crucial part of the discussion, underscoring how innovations are reshaping disease control strategies. Ethical considerations, particularly in the utilization of health data, are critically examined to identify research gaps and propose future directions.

By encompassing these diverse yet interconnected topics, the review aims to provide a holistic understanding of the current state and potential future of data science in public health. The ultimate goal is to offer insights that can inform policy, practice, and research in the field, contributing to more effective and ethical public health strategies in both the USA and Africa.

2. Methods

2.1. Selection Criteria for Studies in Qualitative Analysis

The selection criteria for studies in qualitative analysis are crucial for ensuring the validity and reliability of research outcomes. Nong and Ho (2019) highlight the importance of context-specific criteria in their study on supplier selection in the textile and apparel industry in Vietnam. They emphasize the need for a comprehensive understanding of industry-specific factors and the integration of both qualitative and quantitative approaches in the selection process. Panwar, Tripathi, and Jha (2019) develop a qualitative framework for selecting optimization algorithms in construction projects, demonstrating the importance of aligning selection criteria with specific project objectives and performance parameters. Nguyen et al. (2022) propose an integrated approach combining Data Envelopment Analysis and Spherical Fuzzy MCDM for sustainable supplier selection in the steel industry, illustrating the need for multi-criteria decision-making tools in qualitative analysis.

2.2. Analytical Approaches in Qualitative Analysis

Analytical approaches in qualitative analysis involve interpreting and making sense of the collected data. Assarroudi et al. (2018) describe a directed qualitative content analysis method, providing a detailed description of analytical steps for qualitative researchers. This method increases the rigor of qualitative data analysis and allows for the comparison of findings across different studies. Bryda and Costa (2023) discuss the impact of digital technologies on qualitative research practices, highlighting the importance of adapting analytical methods to the digital era. They emphasize the need for collaborative thinking and the development of new analytical, digital, and IT skills. Pratama and Jumadi (2023) analyse the implementation of the ethnoscience approach in science learning, demonstrating the effectiveness of qualitative analysis in educational research.

The selection criteria for studies and analytical approaches in qualitative analysis are critical components of research design. The research objectives, theoretical framework, and the specific characteristics of the data should guide the choice of criteria and approaches. As qualitative analysis continues to evolve, particularly in fields such as education, industry, and digital research, the importance of rigorous selection criteria and innovative analytical approaches cannot be overstated.

3. Results of the Study

3.1. Trends in Predictive Analytics Applications in the USA

The application of predictive analytics in the United States has seen a significant surge across various sectors, driven by the increasing availability of data and advancements in analytical techniques. Olaniyi et al. (2023) provide a comprehensive review of the techniques and applications of predictive analytics, emphasizing its transformative potential in converting raw data into actionable insights. The study highlights how predictive analytics is being utilized across diverse industries, including healthcare, finance, marketing, and government, to shape strategies, optimize operations, and enhance user experiences. This trend underscores the growing recognition of predictive analytics as a strategic asset for organizations seeking to anticipate future trends, optimize resource allocation, and mitigate risks effectively.

In the healthcare sector, Trivedi (2023) discuss the transformative impact of predictive analytics using machine learning. Their overview of the applications in healthcare reveals how machine learning algorithms are being employed to analyze vast amounts of patient data, identify trends, and predict future health outcomes. This approach is revolutionizing patient care through personalized treatment plans and disease management, optimizing healthcare operations, and contributing to the development of new drugs and therapies. The study also addresses concerns regarding patient data privacy, algorithmic bias, and the necessity for educated interpretation of results, highlighting the ethical dimensions of predictive analytics in healthcare.

Aggarwal,Bali and Mittal (2019) offer insights into various predictive analytics techniques, including Decision Tree, Regression Analysis, and Neural Network. Their paper illustrates how these methods are used across industries to reduce risk, optimize operations, and increase revenue. The study provides a clear understanding of how predictive models are developed using known results to predict values for different or new data. This insight is crucial for industries such as banking and finance, retail, healthcare, manufacturing, and government, where predictive analytics plays a key role in decision-making processes.

The trends in predictive analytics applications in the USA reflect a broader shift towards data-driven decision-making. Organizations are increasingly leveraging predictive analytics to gain a competitive edge, improve efficiency, and enhance customer experiences. The healthcare sector, in particular, has been a significant beneficiary of predictive analytics, with applications ranging from patient outcome prediction to operational optimization. However, the adoption of predictive analytics also brings challenges, including ensuring data privacy, addressing algorithmic biases, and maintaining the accuracy and reliability of predictive models.

The trends in predictive analytics applications in the USA demonstrate the technology's growing importance across various sectors. As organizations continue to harness the power of predictive analytics, it is essential to address the accompanying challenges and ethical considerations. The future of predictive analytics in the USA looks promising, with potential for further innovation and integration into various aspects of business and public life.

3.2. Case Studies: Predictive Analytics in African Public Health

The application of predictive analytics in African public health has been instrumental in addressing various health challenges, particularly in the context of pandemics and chronic diseases. Adekemi and Sheriff (2022) examine the effectiveness of predictive analytics in precision public health, particularly in strengthening health systems for future pandemics. Their study highlights how predictive analytics, supported by artificial intelligence and machine learning, can be used to gather demographic, environmental, social, and socio-economic data to improve decision-making and policy formulation. This approach has been crucial in managing communicable and non-communicable diseases, prescription overdoses and underdoses, neonatal conditions, health disparities, substance abuse, and motor vehicle injuries.

Molldrem, Smith, and McClelland (2023) explore the ethical challenges of using predictive analytics in HIV surveillance. Their study focuses on the potential harms related to classifying people living with HIV in public health systems, new ways of combining and sharing individuals' health data, and the challenges these practices pose to existing regulatory paradigms. The authors argue for reform-oriented conversations about the regulatory frameworks and ethical norms governing data re-uses in public health, emphasizing the need for new approaches to data ethics, rights, and regulation.

Farhat, Dumbuya, and McNabb (2018) present a collection of case studies in African public health, providing insights into various health initiatives and their outcomes. These case studies illustrate the diverse applications of predictive analytics in public health, from managing infectious diseases to addressing socio-economic factors that influence health outcomes. The compilation serves as a valuable resource for understanding the practical implications of predictive analytics in the African context.

Kreienbrinck, Zeeb, and Becher (2021) investigate the influence of socioeconomic and public health indicators on the COVID-19 case-fatality rate in sub-Saharan African countries. Their ecological study uses publicly available COVID-19 data to analyze the association between various indicators and the case-fatality rate. The findings reveal that factors such as human development index, political stability index, number of hospital beds, and population density have a significant impact on the case-fatality rate. This study underscores the importance of considering socioeconomic and public health factors in predictive analytics to understand and address the drivers of health outcomes at the population level.

The case studies in African public health demonstrate the significant role of predictive analytics in addressing a wide range of health challenges. From managing pandemics to understanding the impact of socio-economic factors on health outcomes, predictive analytics offers valuable insights that can inform decision-making and policy formulation. However, the application of these techniques also raises ethical considerations, particularly in the context of data privacy, consent, and the potential for stigmatization. As predictive analytics continues to evolve, it is essential to navigate these challenges to fully realize its potential in improving public health outcomes in Africa.

3.3. Comparative Effectiveness of Predictive Models in Disease Control

The comparative effectiveness of predictive models in disease control is a critical area of research, particularly in the context of public health challenges such as infectious diseases and chronic conditions. Yuying et al. (2023) conducted a study to create risk predictive models for healthcare-seeking delay among imported malaria patients in Jiangsu Province using machine learning algorithms. Their research utilized a variety of models, including back propagation neural network, logistic regression, random forest, and Bayesian models, to analyze factors influencing healthcare-seeking behaviour. This study demonstrates the effectiveness of machine learning in predicting healthcare-seeking delays, which is crucial for early identification and management of imported malaria cases.

Youssef and Hassan (2022) present a comparative study of mathematical models for epidemic diseases, focusing on the SIR model's application to strategic management. They estimated the model parameters from recorded data and used them to predict values in subsequent periods, illustrating the model's effectiveness in controlling the spread of disease. The study highlights the importance of lockdown and social distancing in managing epidemics and provides insights into the mathematical properties and initial conditions within the estimated parameter values. This research underscores the value of mathematical models in understanding and managing epidemic diseases.

Reddy, Kiran, and Xavier (2022) conducted a comparative analysis of liver disease detection using various machine learning techniques. Their research employed multiple machine learning models, including Logistic Regression, Random Forest, Support Vector Machine, K-Nearest Neighbours, and Artificial Neural Networks, to analyze and predict liver disease in its early stages using patient blood report datasets. The study found that the Random Forest technique achieved better performance in terms of accuracy and precision compared to other techniques. This comparative analysis highlights the potential of machine learning in early diagnosis and prognosis of liver disease, contributing to rapid treatment and reduction in serious health consequences.

The comparative effectiveness of predictive models in disease control is evident in their ability to analyse complex health data and provide actionable insights for disease management. Whether it is predicting healthcare-seeking behaviour in malaria patients, understanding the spread of epidemic diseases, or detecting liver disease in its early stages, predictive models offer valuable tools for public health practitioners. The integration of machine learning and mathematical modelling in disease control underscores the potential of these technologies in enhancing public health strategies and outcomes. As predictive modelling continues to evolve, it is essential to navigate the challenges of data privacy, algorithmic bias, and model accuracy to fully realize its potential in improving disease control and public health.

3.4. Data-Driven Policy Making: Successes and Failures

The integration of big data analytics into public policy decisions marks a significant shift towards smart governance. Hossin et al. (2023) explore the potential of big data analytics (BDA) for public policy systems, providing a linkage for the transformation toward digital and smart governance. Their study employs a systematic review approach to interpret the application of BDA at each step of the public policy system. The research reveals that BDA can be used effectively in policy formulation, planning, design, service delivery, and evaluation. The study argues that BDA has the potential to transform traditional governance systems into digital and smart governance, ensuring accurate, prompt, and context-oriented public policy systems.

Lee (2020) discusses the opportunities and challenges of big data strategies for government, society, and policy-making. The paper presents practical examples from various parts of the world, where public-service delivery has seen transformation through the use of big data analytics. These examples include governments of the United States, China, the United Kingdom, and India, and their application in public services such as fraud detection, healthcare, education, and environmental protection. Lee's study makes recommendations on how big data strategies can transform government and public services to become more citizen-centric, responsive, accountable, and transparent.

Liu, Han, and DeBello (2018) examine the successes and failures of business analytics in decision-making. The paper highlights that the successful use of business analytics is a crucial element of a company's success, enabling analysts and managers to engage in an IT-driven sense-making process. However, not all organizations apply business analytics successfully to decision-making. The study presents cases of organizations that implemented data analytics programs both successfully and unsuccessfully, discussing the implications for each organization. The paper emphasizes that the actionable intelligence gained from a business analytics program can be utilized to improve strategic decision-making, while a failure to utilize business analytics information appropriately can lead to suboptimal decision-making.

Data-driven policy making has shown both successes and failures. The integration of big data analytics into public policy decisions offers the potential to transform governance systems, making them more efficient, responsive, and citizen-centric. However, the successful application of these strategies requires careful consideration of the challenges, including data privacy, algorithmic bias, and the need for educated interpretation of results. As big data analytics continues to evolve, it is essential to navigate these challenges to fully realize its potential in improving policy-making and public governance.

3.5. Cross-Continental Collaborations and Their Impact

Cross-continental collaborations have emerged as a pivotal force in addressing global health challenges, particularly in the wake of the COVID-19 pandemic. Nguyen et al. (2021) emphasize the need for scaling up research collaborations to address the pandemic's global impact. Their commentary suggests that the unprecedented nature of the COVID-19 crisis calls for researchers to extend beyond traditional boundaries and engage in global collaborations. The paper highlights the mental health and economic consequences of the pandemic, illustrating the extent to which these issues cross national borders. The authors urge researchers, especially those from higher-income economies, to share resources and increase international collaborative research efforts, advocating for a global approach to solve global problems.

Khan et al. (2022) explore the future of cross-continental telemedicine in managing complicated endocrine patients, presenting a case report from Nigeria. The study demonstrates how telemedicine, which gained traction during the COVID-19 pandemic, can facilitate international collaboration in healthcare. The case report showcases a patient diagnosed with a pituitary tumor through telemedicine, who subsequently underwent successful surgery. This example highlights the potential for cross-continental collaboration in healthcare, enabling health professionals to work with developing countries to improve patient care.

Randall, White, and Dennis (2023) discuss a collaborative primary healthcare model for children and young people in rural Australia, focusing on cross-sectoral leader action. Their study uses a descriptive qualitative design to collect data from executive and senior managers across three organizations. The findings reveal strategies for managing change and designing a primary healthcare model in a remote community. The study underscores the importance of cross-sectoral collaborations in addressing health, social, and educational outcomes for marginalized and disadvantaged populations. The authors conclude that strong management of change principles could make a service model designed for one remote community transferable to other communities.

Cross-continental collaborations play a crucial role in addressing global health challenges. The COVID-19 pandemic has underscored the need for such collaborations, as global problems require global solutions. Telemedicine has emerged as a key tool in facilitating international healthcare collaboration, offering opportunities for healthcare professionals to work beyond borders. Additionally, cross-sectoral collaborations in healthcare, as demonstrated in the Australian context, highlight the importance of integrated approaches in addressing complex health and social issues. As the world continues to face global health challenges, the role of cross-continental collaborations will be increasingly vital in shaping effective and sustainable health solutions.

4. Discussion of the Results

4.1. Interpretation of Predictive Analytics Outcomes

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Data-driven policy making has shown both successes and failures. The integration of big data analytics into public policy decisions offers the potential to transform governance systems, making them more efficient, responsive, and citizen-centric. However, the successful application of these strategies requires careful consideration of the challenges, including data privacy, algorithmic bias, and the need for educated interpretation of results. As big data analytics continues to evolve, it is essential to navigate these challenges to fully realize its potential in improving policy-making and public governance.

4.2. Challenges in Implementing Data-Driven Health Policies

The implementation of data-driven health policies presents a range of challenges, from technological hurdles to ethical considerations. Dorr, Cohen, and Adler-Milstein (2018) explore the successes and challenges in three large-scale innovative delivery models, including accountable care organizations, advanced primary care practice, and EvidenceNOW. Their study reveals that while the implementation of technological components like electronic health records has occurred, core functions needed to use data effectively are lacking. These include challenges in extracting and aggregating data, gaps in data sharing, and difficulties in adopting advanced data functions, particularly those related to timely performance data reporting. The unexpectedly high costs and burdens incurred during implementation have limited organizations' ability to address these deficits, highlighting the need for more efficient and cost-effective solutions.

Cruz (2020) discusses the perils of data-driven equity in safety-net care, focusing on the challenges of addressing health inequality through big data. The study presents a case study on sexual orientation and gender identity data collection within a large public safety-net health system. It highlights three main challenges: limited understanding of the social significance of data collection by providers and staff, patient perception of the cultural insensitivity of data items, and the need to balance data requests with competing priorities within constrained time windows. These issues reflect structural challenges within safety-net care that big data alone cannot address, emphasizing the need for a more holistic approach to advancing social justice in healthcare.

Batani and Maharaj (2022) explore the opportunities and potential challenges of data-driven paediatrics in Zimbabwe. Their study reveals that despite the potential benefits of data-driven pediatrics, such as improved access, efficiency, and quality of care, there are significant challenges, including fear of medico-legal hazards, centralization of decision-making, resistance by healthcare workers, network challenges, and computer illiteracy. The study suggests that to increase the chances of success, lessons learned from the introduction of electronic health records and digital health systems like Neoteric should be considered. These include starting small, sensitizing communities first, involving line healthcare workers from the beginning, avoiding hasty training, and demystifying technology's purpose.

The challenges in implementing data-driven health policies are multifaceted and require a comprehensive approach to address. Technological, structural, and cultural barriers must be overcome to fully realize the potential of data-driven health policies. The integration of technological solutions with a deep understanding of the social and cultural context of healthcare delivery is essential. As data-driven approaches continue to evolve, it is crucial to navigate these challenges to improve healthcare outcomes and advance health equity.

4.3. The Future of AI and Machine Learning in Disease Control

The integration of Artificial Intelligence (AI) and Machine Learning (ML) in disease control has opened new frontiers in healthcare, offering innovative solutions for early disease detection, treatment, and vaccine development. Lv et al. (2021) provide an extensive survey on the application of AI and ML in combating COVID-19, focusing on drug discovery and vaccine design. Their study highlights the role of AI and ML in accelerating the discovery and optimization of new antivirals and vaccines, demonstrating the potential of these technologies in responding to global health emergencies. The authors point out the challenges and future directions associated with state-of-the-art solutions, emphasizing the need for continued research and development in this area.

Kumari and Bhatia (2022) review the application of ML techniques in the public health system, providing a scientometric analysis of AI-based technology to prevent Air-Borne Diseases (ABD). Their study discusses the ideal epidemiology study, early disease diagnosis, and progression concerning ABD. The review suggests that integrating ML advances into public health research can lead to success in controlling ABD, highlighting the importance of continued research in this field. The study also addresses the obstacles and opportunities for future research, underscoring the potential of ML in transforming public health systems.

Reddy et al. (2023) explore the revolution of ML in early disease detection for healthcare, focusing on advancements, challenges, and future prospects. The paper discusses how the integration of ML into healthcare has revolutionized early disease detection through a multidimensional approach to data analysis. Advanced algorithms, rooted in deep learning, process diverse datasets encompassing medical records, genetics, and imaging data, enabling subtle pattern detection. The study underscores the impact of ML across various medical domains and the promise it holds for the future, with enhanced data integration, interdisciplinary collaboration, explainable AI, real-time monitoring, global healthcare accessibility, ethical considerations, and continuous learning.

The future of AI and ML in disease control is promising, with these technologies playing a crucial role in transforming healthcare. The application of AI and ML in drug discovery, vaccine design, and early disease detection demonstrates their potential to address global health challenges. However, the successful implementation of these technologies requires addressing challenges such as data privacy, algorithmic bias, and the need for educated interpretation of results. As AI and ML continue to evolve, their role in reshaping healthcare for the better is undeniable, offering new opportunities for innovation and improvement in disease control and public health.

5. Conclusion

This comprehensive review has meticulously explored the dynamic intersection of data science and public health, particularly through the lens of predictive analytics in disease control within the diverse contexts of the USA and Africa. The study embarked on a journey to unravel the complexities and potentials of data-driven approaches in public health, aligning with its core objectives to synthesize, analyze, and compare the advancements and challenges in this evolving field.

Methodologically, the review adopted a qualitative analysis of relevant literature, focusing on peer-reviewed articles and case studies. This approach enabled a deep dive into various aspects of data science in public health, ranging from the evolution of predictive analytics and comparative public health structures to the ethical considerations in health data utilization. The methodology was instrumental in uncovering nuanced insights and trends, thereby fulfilling the study's aims and objectives.

Key findings from the study revealed significant advancements in the application of predictive analytics across the USA and Africa, each region adapting these technologies to their unique public health challenges. In the USA, the focus was on enhancing healthcare delivery and managing chronic diseases, while in Africa, predictive analytics played a crucial role in combating infectious diseases and managing healthcare resources. The study also highlighted the challenges in implementing data-driven health policies, emphasizing the need for a balanced approach that addresses technological, ethical, and cultural barriers.

The future of AI and machine learning in disease control emerged as a promising domain, with the potential for further innovation and integration into various healthcare and public policy aspects. However, the study also underscored the importance of addressing challenges related to data privacy, algorithmic bias, and the need for educated interpretation of results.

In conclusion, this review recommends continued investment in and exploration of data science applications in public health. It advocates for collaborative efforts to overcome implementation challenges and ethical considerations, ensuring that the benefits of predictive analytics are realized across diverse healthcare systems. The study underscores the transformative potential of data science in public health, paving the way for more effective, efficient, and equitable healthcare delivery in both developed and developing regions.

Compliance with ethical standards

Disclosure of conflict of interest

The authors have not conflict of interest to disclose.

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