AIM INTERNATIONAL JOURNAL Publisher
Journal of Next-Gen Engineering Systems, 2024;1(01): 69-88

DATA ANALYTICS FOR HEALTHCARE IMPROVEMENT: DEVELOP SYSTEMS FOR ANALYZING LARGE HEALTH DATA SETS TO IMPROVE PATIENT OUTCOMES, MANAGE PANDEMICS, AND OPTIMIZE HEALTHCARE DELIVERY

Anisur Rahman[1]
[1]Master in Management Information System, International American University, Los Angeles, USA
Corresponding Email: anisurrahman.du.bd@gmail.com

Md Ashrafuzzaman[2]
[2]Master in Management Information System, International American University, Los Angeles, USA
Email: md.ashrafuzzamanuk@gmail.com

A B M Ashraf Mridha[3]
[3]Master of Business Administration in Management Information System, International American University, Los Angeles, USA
Email: shuvomridha36@gmail.com

Md Saidul Islam Papel[4]
[4]Master of Business Administration in Management Information System, International American University, Los Angeles, USA
Email: mdpapeldu@gmail.com

Keywords

Data Analytics
Healthcare Optimization
Patient Outcomes
Pandemic Management
Big Data in Healthcare

ABSTRACT

The integration of data analytics into healthcare systems has revolutionized the management, delivery, and quality of healthcare services. This study systematically reviews and synthesizes findings from 105 peer-reviewed articles to explore the transformative role of data analytics in enhancing diagnostic accuracy, improving operational efficiency, managing public health crises, and addressing health disparities. Machine learning and artificial intelligence emerged as significant tools in supporting early diagnosis of chronic and acute diseases, improving clinical decision-making, and streamlining hospital workflows. Real-time analytics systems have been instrumental in managing healthcare resources, monitoring hospital capacities, and responding effectively to pandemics such as COVID-19. The integration of big data analytics with electronic health records (EHRs) has optimized resource allocation, reduced redundant processes, and lowered operational costs. Additionally, emerging technologies such as blockchain and Internet of Things (IoT) devices have addressed challenges related to secure data sharing, interoperability, and real-time health monitoring. Despite these advancements, the review identifies critical gaps, including the lack of long-term evaluations of analytics systems and scalability challenges in low-resource settings. These findings emphasize the need for robust infrastructure, ethical frameworks, and scalable solutions to ensure the widespread adoption and equitable use of healthcare analytics.

1 INTRODUCTION

Data analytics has become a cornerstone of modern healthcare systems, revolutionizing the way health data is utilized to enhance patient outcomes, streamline healthcare delivery, and address large-scale health crises such as pandemics (Scobie & Castle-Clarke, 2019). With the exponential growth in healthcare data, estimated to double every 73 days (Flynn, 2019), healthcare organizations face both opportunities and challenges in managing and analyzing this vast information. Advanced analytics techniques, including machine learning, predictive modeling, and real-time data processing, enable the extraction of actionable insights from diverse and complex datasets (Islam et al.,

Received: 28th October, 2024 **Accepted**: 21st December,2024 **Published**: 24th December,2024

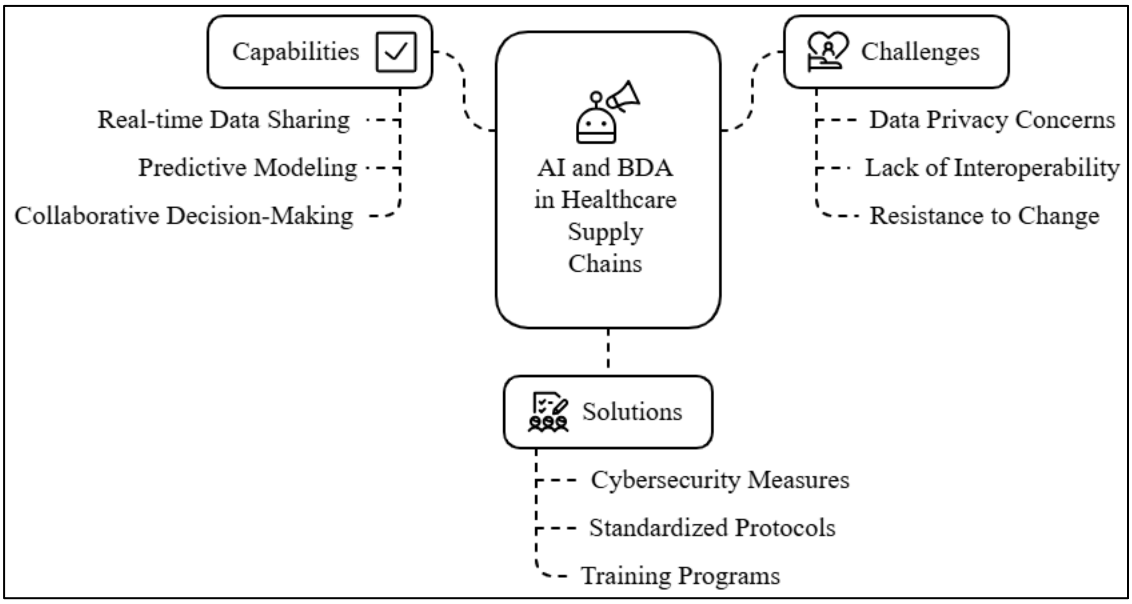
2015). For example, predictive analytics has been employed to forecast patient readmissions, optimize hospital resources, and improve overall care quality (Enticott et al., 2020). These applications underscore the transformative potential of data analytics systems in healthcare, yet also highlight the need for sophisticated tools and strategies to address their inherent complexities. Moreover, the integration of artificial intelligence (AI) and machine learning into healthcare analytics has significantly enhanced the ability to process and interpret large datasets, fostering improved diagnostics and treatment planning (Noritz et al., 2018). Machine learning algorithms excel at identifying patterns in data that might otherwise go unnoticed, enabling earlier detection of diseases such as cancer, diabetes, and cardiovascular conditions (McLinden et al., 2019). Moreover, AI-based predictive models have played a critical role in pandemic management by assisting in the surveillance of infection rates, modeling the spread of diseases, and optimizing the distribution of critical resources (Zhao et al., 2016). For instance, during the COVID-19 pandemic, AI-driven analytics helped track real-time case counts and assess the impact of public health measures. However, despite these advancements, challenges such as algorithmic bias, lack of interoperability between systems, and privacy concerns pose significant barriers to widespread adoption (Budrionis & Bellika, 2016). Addressing these issues is essential for ensuring the equitable and ethical deployment of AI in healthcare. Moreover, big data analytics also plays a pivotal role in operational and financial optimization within healthcare institutions. Hospitals and clinics utilize analytics to improve patient flow, reduce wait times, and enhance resource allocation, ultimately increasing efficiency and reducing costs (Sondhi et al., 2012). The incorporation of electronic health records (EHRs) into analytics platforms has further facilitated personalized care delivery by enabling healthcare providers to tailor treatment plans based on historical patient data, genetic predispositions, and other relevant factors ((Wade et al., 2015). However, the potential of EHR data is often constrained by issues such as data quality, fragmentation, and security risks, as noted by Gramlich et al. (2017). These limitations highlight the importance of developing robust data governance frameworks and advanced analytical tools to maximize the benefits of big data in healthcare.

Population health management is another area where data analytics has shown remarkable potential, particularly in addressing healthcare disparities and improving access to care (Budrionis & Bellika, 2016). Analytics tools can analyze social determinants of health, such as income levels, education, and geographic location, to identify underserved populations and design targeted intervention programs (Kavakiotis et al., 2017). For example, predictive models have been successfully used to identify individuals at high risk for chronic illnesses, enabling early intervention and preventive care (Services, 2010). This proactive approach not only improves individual health outcomes but also reduces the financial burden on healthcare systems by minimizing hospital admissions and long-term care costs (Richardson et al., 2010). These advancements underscore the critical role of data-driven strategies in achieving health equity and improving population health. Furthermore, real-time data analytics has become indispensable in responding to public health emergencies and pandemics. During the COVID-19 pandemic, real-time analytics systems were leveraged to monitor hospital capacity, track vaccine distribution, and evaluate the effectiveness of public health interventions (Toh et al., 2017). By providing actionable insights in near real-time, these systems enabled healthcare providers and policymakers to make informed decisions in rapidly changing circumstances. However, the deployment of such analytics systems raises important questions about data security, ethical use, and scalability (Miah et al., 2017; Psek et al., 2015). Ensuring that these systems adhere to rigorous privacy standards while maintaining their efficacy in emergency scenarios is a critical challenge for the future of healthcare analytics (Serena et al., 2017). As the field continues to evolve, the development of scalable, secure, and interoperable data analytics systems will be crucial for advancing global healthcare initiatives (Wallace et al., 2014). The primary objective of this study is to explore the development and application of data analytics systems in healthcare to enhance patient outcomes, manage pandemics effectively, and optimize healthcare delivery processes. By leveraging advanced techniques such as machine learning, predictive modeling, and real-time analytics, the study aims to identify innovative methods for analyzing large-scale health data. The focus extends to addressing critical challenges, including data interoperability, privacy concerns, and algorithmic bias, to ensure ethical and

Journal of Next-Gen Engineering Systems
DoI: 10.70937/jnes.v1i01.30

effective implementation. Additionally, the study seeks to highlight the role of data-driven strategies in improving clinical decision-making, resource allocation, and personalized care delivery, while also providing insights into how analytics can reduce healthcare disparities and enhance population health management. Ultimately, this research aims to contribute to the growing body of knowledge on how data analytics can be harnessed to build resilient and efficient healthcare systems.

Figure 1: Overview of AI and BDA in Healthcare Supply Chains



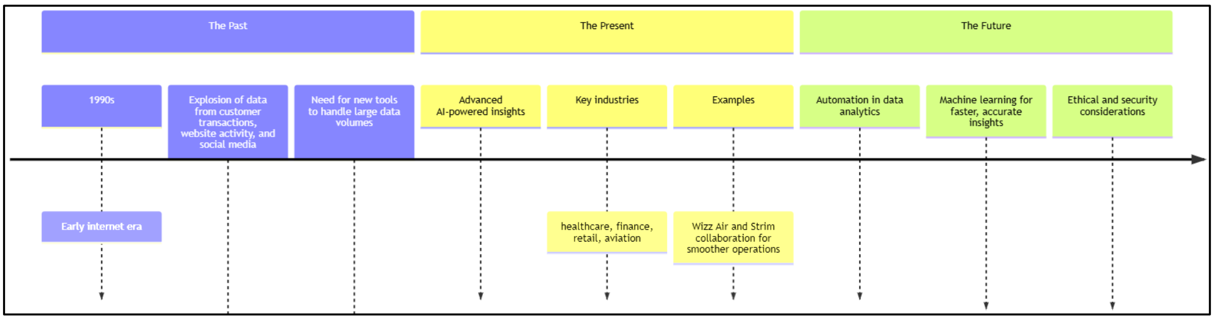
2 LITERATURE REVIEW

The application of data analytics in healthcare has garnered significant attention from researchers and practitioners due to its potential to transform patient care, healthcare delivery, and pandemic management. This section reviews the existing body of literature on data analytics systems, focusing on their development, deployment, and impact on healthcare outcomes. It synthesizes key findings from studies that highlight advancements in predictive modeling, machine learning, and real-time analytics, while addressing challenges such as data privacy, interoperability, and scalability. By organizing the literature into specific thematic areas, this section aims to provide a comprehensive understanding of the current state of research, identify gaps, and outline opportunities for future exploration.

2.1 Data Analytics in Healthcare

The evolution of data analytics in healthcare has been marked by significant transformations over the past few decades. Initially, healthcare relied on manual record-keeping and rudimentary statistical analyses for decision-making (Kaggal et al., 2016). The introduction of electronic health records (EHRs) in the 1960s laid the groundwork for data analytics in healthcare, enabling healthcare providers to digitize patient information and improve data accessibility (Sawacha et al., 2010). Over time, advancements in computing technology facilitated the transition to more sophisticated analytical methods, allowing for the analysis of larger datasets and the identification of patterns that were previously unattainable (Boukenze et al., 2016). These developments highlighted the importance of data-driven decision-making in improving patient care and operational efficiency. However, early systems were often limited by fragmented data sources and the lack of interoperability, challenges that remain relevant today (Kumar et al., 2015). Several key milestones have shaped the development of healthcare analytics systems. The 1990s saw the widespread adoption of data warehousing and business intelligence tools, which enabled organizations to store, organize, and analyze large volumes of healthcare data (Ferris & Torchiana, 2010). During this period, predictive analytics emerged as a powerful tool for identifying trends, such as patient readmission risks and disease progression patterns (Archenaa & Anita, 2015). Another milestone was the integration of EHRs with analytics platforms, which allowed for real-time data analysis and personalized patient care (Buczak & Guven, 2016). More recently,

Figure 2: Evolution Of Data Analytics In Healthcare



the adoption of machine learning and artificial intelligence (AI) has expanded the capabilities of healthcare analytics, enabling early detection of diseases such as cancer and diabetes through advanced pattern recognition (Kavakiotis et al., 2017). These innovations underscore the pivotal role of technological advancements in the growth of healthcare analytics.

The transition from traditional data analysis to AI-driven approaches has revolutionized healthcare analytics by enhancing the precision and speed of data processing. Traditional analytics relied heavily on statistical methods and manual data handling, which were often time-consuming and error-prone (Kumar et al., 2015). In contrast, AI-driven systems leverage algorithms that can process vast datasets in real time, providing actionable insights that improve clinical decision-making and operational efficiency (Archenaa & Anita, 2015). For example, AI has been used to predict patient outcomes, optimize treatment plans, and monitor the spread of infectious diseases (Buczak & Guven, 2016). Machine learning, a subset of AI, has proven particularly effective in identifying patterns in unstructured data, such as medical images and natural language records, further enhancing diagnostic accuracy and patient care (Calyam et al., 2016). Despite these advancements, the integration of AI into healthcare systems poses challenges, including the need for robust data governance frameworks to address privacy and ethical concerns (Kaggal et al., 2016). The increasing reliance on AI-driven healthcare analytics reflects a broader shift towards leveraging data for precision medicine and population health management. Studies have demonstrated that AI algorithms can analyze genetic data, lifestyle factors, and clinical records to provide personalized treatment recommendations, improving patient outcomes while reducing healthcare costs (Boukenze et al., 2016). Additionally, AI-based predictive models have been instrumental in pandemic management, enabling real-time tracking of infection rates and efficient resource allocation during emergencies such as the COVID-19 pandemic (Ferris & Torchiana, 2010). However, these advancements are accompanied by challenges, such as addressing biases in AI models and ensuring equitable access to analytics tools across diverse healthcare settings (Buczak & Guven, 2016). As healthcare systems continue to adopt AI-driven approaches, it is evident that data analytics has become an indispensable tool in shaping the future of healthcare delivery and management.

2.2 Applications of Predictive Modeling in Healthcare

Predictive modeling has proven instrumental in the early diagnosis of chronic and acute diseases by enabling healthcare professionals to identify patterns in patient data that may signal the onset or progression of illnesses (Boukenze et al., 2016). Chronic conditions such as diabetes and cardiovascular diseases often present complex patterns of symptoms, making early detection challenging. Machine learning models, which utilize vast datasets from electronic health records (EHRs) and wearable devices, have demonstrated remarkable accuracy in predicting disease onset (Kumar et al., 2015). For example, Ng et al. (2013) found that machine learning algorithms significantly improved the early detection of skin cancer, outperforming dermatologists in identifying malignant lesions. Similarly, predictive models analyzing historical patient data have enhanced the early detection of acute diseases, such as sepsis, by identifying subtle physiological changes that often precede critical symptoms (Liu et al., 2016). These advancements underscore the role of predictive modeling in supporting proactive healthcare interventions. In addition to diagnostic applications, predictive models have been employed to forecast patient readmissions, a critical issue for healthcare systems aiming to improve

DoI: 10.70937/jnes.v1i01.30

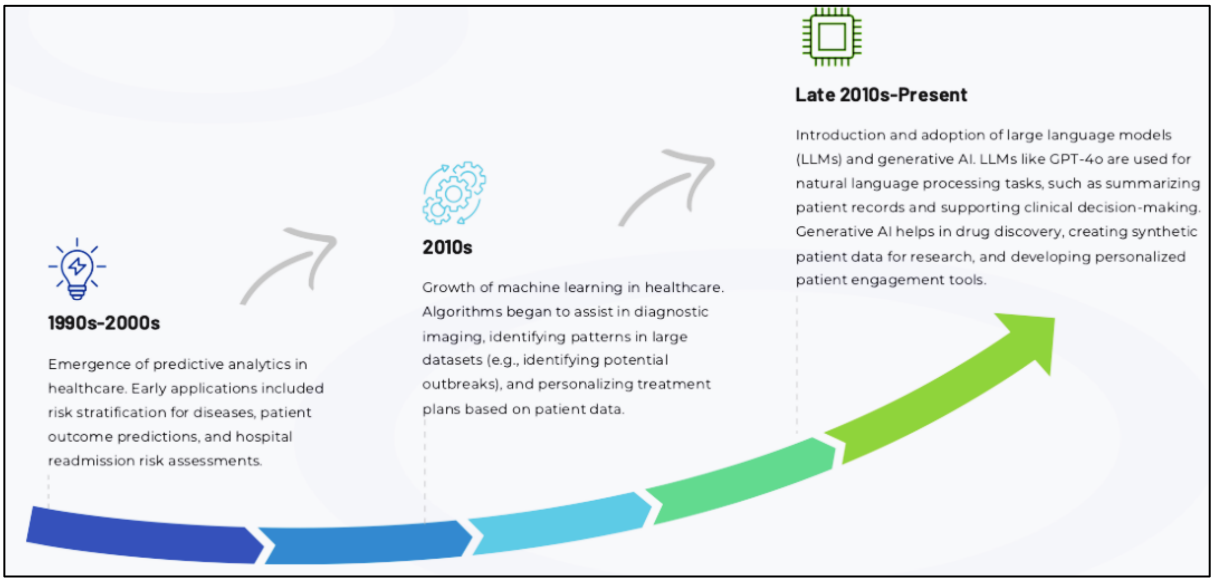
quality while reducing costs. Unplanned readmissions are not only costly but also indicative of gaps in care delivery. By analyzing patient demographics, medical history, and socioeconomic factors, predictive algorithms can identify individuals at high risk of readmission (Richardson et al., 2010). For instance, Miah et al., (2017) highlighted the effectiveness of predictive models in reducing readmissions among heart failure patients by enabling targeted follow-up care. Furthermore, predictive analytics has been used to design discharge plans that account for patients' post-hospitalization needs, improving recovery outcomes and preventing avoidable readmissions (Esterhammer et al., 2016). These models have significantly enhanced healthcare systems' ability to allocate resources efficiently and address patient-specific risks.

Resource allocation in healthcare is another area where predictive modeling has demonstrated immense value(Melder et al., 2020). During times of high demand, such as flu seasons or pandemics, healthcare systems often struggle to distribute resources equitably. Predictive models help optimize resource allocation by forecasting patient volumes, identifying bottlenecks, and prioritizing critical cases (Richardson et al., 2010). For example, during the COVID-19 pandemic, predictive analytics was employed to estimate the demand for intensive care unit (ICU) beds, ventilators, and medical supplies, ensuring that resources were directed where they were most needed (Psek et al., 2015). Such applications highlight how predictive modeling not only improves operational efficiency but also enhances patient outcomes by reducing delays in care delivery. These tools are particularly beneficial in under-resourced settings, where efficient resource allocation is crucial for maintaining quality care(Melder et al., 2020). Despite its potential, the use of predictive modeling in healthcare presents several challenges, including the quality and completeness of data inputs. Studies have shown that inaccuracies in EHRs, missing data, and inconsistent coding practices can affect the reliability of predictive models (Sengur & Turkoglu, 2008). Moreover, the effectiveness of these models is often limited by their generalizability across different patient populations and healthcare settings (Purwar & Singh, 2015). Addressing these limitations requires standardization of data collection processes and the integration of diverse datasets to ensure more representative and robust predictions. Nonetheless, the applications of predictive modeling in early diagnosis, readmission prediction, and resource optimization continue to transform healthcare, providing actionable insights that enhance patient outcomes and operational efficiency(Gramlich et al., 2017).

2.3 Forecasting pandemic trends and healthcare demands

Forecasting pandemic trends has become a critical application of predictive analytics, particularly in mitigating the spread of infectious diseases and planning healthcare responses (Cruz et al., 2011). During pandemics, the ability to analyze and interpret vast datasets in real-time is essential for tracking the

Figure 3: AI's Evolution in Healthcare Over the Past 30 Years

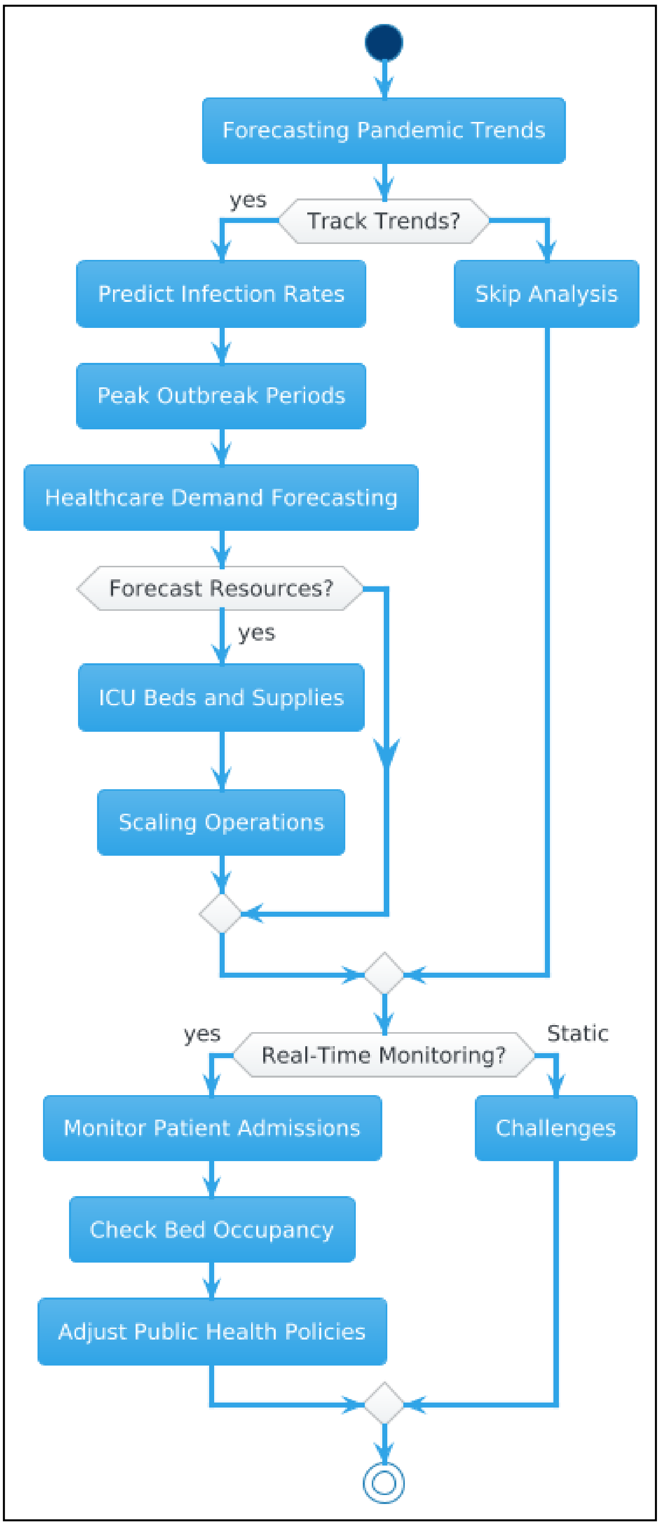


Journal of Next-Gen Engineering Systems
Page No: 69-88

trajectory of outbreaks. Studies have demonstrated that machine learning algorithms and epidemiological models are effective in predicting infection rates, peak outbreak periods, and geographic spread (Cruz et al., 2011; Gramlich et al., 2017). For example, during the COVID-19 pandemic, predictive models like SEIR (Susceptible, Exposed, Infectious, Recovered) were used extensively to simulate disease progression under different public health interventions (Flynn, 2019). These models enabled governments and health organizations to make data-driven decisions regarding lockdowns, social distancing measures, and vaccine distribution, underscoring the pivotal role of forecasting in pandemic management (Islam et al., 2015). The application of predictive analytics in forecasting healthcare demands has significantly enhanced resource allocation during public health crises. Hospitals and healthcare providers often face overwhelming demand for critical resources such as intensive care unit (ICU) beds, ventilators, and medical supplies during pandemics. Predictive models have been used to estimate these needs based on infection trends, demographic data, and regional healthcare capacities (Andreu-Perez et al., 2015). For instance, studies during the H1N1 pandemic revealed that early predictions of hospital admission rates facilitated the redistribution of medical supplies and personnel to high-demand areas (Goldenberg, 2016). Similarly, during COVID-19, machine learning algorithms predicted patient surge patterns, enabling healthcare providers to scale their operations accordingly and reduce system strain (Zheng et al., 2014). These tools have proven essential in preventing resource shortages and ensuring that healthcare systems remain resilient under pressure.

Furthermore, real-time forecasting has played an indispensable role in pandemic preparedness and response, particularly in monitoring and managing healthcare system capacities (Wagner et al., 2014). Predictive analytics systems, combined with real-time data inputs from IoT devices, hospital systems, and public health databases, have enabled continuous monitoring of patient admissions, bed occupancy rates, and equipment (Wills, 2014). For example, during COVID-19, forecasting models integrated real-time mobility and testing data to predict the impact of public behavior on healthcare demand, providing insights that guided public health policies (Ling et al., 2014). These real-time capabilities ensured a dynamic and responsive approach to healthcare planning, highlighting the value

Figure 4: Forcasting Pandemic trands



of predictive analytics in navigating rapidly evolving health crises (Zhao et al., 2016). Despite the demonstrated effectiveness of forecasting in pandemic management, challenges remain, particularly in ensuring data quality and addressing model limitations. Forecasting models often depend on accurate and comprehensive datasets, which can be difficult to obtain during the early stages of an outbreak (Choi et al., 2016). Variations in data reporting standards, incomplete case counts, and delays in updating datasets can affect the reliability of predictions (Li et al., 2012). Additionally, the assumptions underlying predictive models may not account for all factors influencing disease spread, such as changing human behavior or emerging viral mutations (Ng et al., 2013). Nevertheless, the ability to forecast trends and healthcare demands continues to play a transformative role in mitigating the impact of pandemics and improving healthcare system readiness.

2.4 Machine Learning and Artificial Intelligence in Healthcare Analytics

Machine learning (ML) algorithms have substantially enhanced diagnostic accuracy in healthcare, addressing long-standing challenges in identifying complex diseases (Zheng et al., 2014). Traditional diagnostic methods often rely on human interpretation, which can lead to errors due to subjectivity or fatigue (Polat et al., 2008). Machine learning, by contrast, analyzes vast datasets with high precision, uncovering patterns that are imperceptible to human clinicians. Khaing (2011) demonstrated the effectiveness of ML in dermatology, where deep learning models achieved diagnostic accuracy on par with dermatologists in identifying malignant skin lesions. Similarly, ML algorithms have been pivotal in radiology, where they assist in detecting abnormalities in medical imaging, such as identifying early-stage lung cancer from CT scans with higher sensitivity and specificity than traditional methods (Ling et al., 2014). These advancements in diagnostic tools have not only reduced diagnostic errors but have also accelerated the decision-making process, thereby improving patient outcomes(Cao et al., 2015).

In addition to diagnostics, AI-driven systems have transformed personalized medicine by tailoring treatments to individual patient profiles. Personalized medicine leverages genetic, environmental, and lifestyle data to optimize therapeutic interventions, and artificial intelligence (AI) plays a critical role in integrating and analyzing this diverse information (Zhao et al., 2016). For instance, AI algorithms are used to identify genetic mutations associated with specific cancers, enabling the development of targeted therapies (Kavakiotis et al., 2017). Buczak and Guven (2016) reported that AI-based tools have been instrumental in predicting patient responses to chemotherapy, allowing oncologists to adjust treatment regimens accordingly. AI-driven personalized medicine is also advancing in areas such as cardiology, where predictive models assess risk factors for cardiovascular diseases and recommend preventive measures tailored to individual patients (Khaing, 2011). These developments demonstrate the potential of AI to revolutionize healthcare by delivering more precise and effective treatments. Case studies have further illustrated the transformative potential of AI-driven personalized medicine. During the COVID-19 pandemic, AI systems were used to predict which patients were most likely to develop severe symptoms based on demographic, clinical, and comorbidity data (Zhao et al., 2016). This enabled healthcare providers to prioritize high-risk patients for early intervention, reducing mortality rates. In another example, AI tools have been utilized in diabetes management, where algorithms analyze continuous glucose monitoring data to optimize insulin dosing and dietary recommendations for individual patients (Kavakiotis et al., 2017). Such case studies underscore the effectiveness of AI in integrating real-time data with clinical knowledge, creating opportunities for proactive and adaptive healthcare management. However, these successes also highlight the need for rigorous validation and regulation to ensure AI models are safe, reliable, and applicable across diverse patient populations.

2.5 Big Data Analytics for Operational Efficiency

Big data analytics has become a pivotal tool in streamlining hospital operations, improving efficiency, and reducing delays in care delivery(Alam, Nabil, et al., 2024). Analytics tools enable healthcare facilities to monitor patient flow, manage staff allocation, and optimize scheduling to reduce wait times and improve resource utilization (Mintoo, 2024). For instance, real-time analytics platforms have been used to track bed occupancy rates and predict discharge timings, allowing hospitals to allocate beds more effectively and reduce patient wait times (Mintoo, 2024). Furthermore, predictive analytics tools have been applied to anticipate patient surges during seasonal outbreaks, such as influenza, ensuring that hospitals are adequately staffed and resourced (Shorna et al., 2024). These advancements demonstrate the potential of big data analytics to address operational bottlenecks, enhance patient satisfaction, and maintain high-quality care standards.

The integration of electronic health records (EHRs) with analytics platforms has further revolutionized healthcare operations by facilitating the seamless flow of data across departments. EHR systems provide a centralized repository of patient information, which, when combined with analytics tools, allows for more informed decision-making and improved coordination of care (Uddin, 2024). Studies have shown that integrating EHR data with analytics platforms enhances care continuity by reducing redundant tests and ensuring timely access to patient histories (Shorna et al., 2024b). For example, Uddin (2024) found that real-time EHR analytics enabled early identification of patients at risk for adverse events, allowing clinicians to intervene proactively. Additionally, EHR-integrated analytics support hospital administrators in monitoring performance metrics, such as readmission rates and treatment efficacy, promoting accountability and continuous improvement (Alam, Sohel, et al., 2024).

One of the most significant benefits of big data analytics in healthcare is its potential to reduce costs through data-driven decision-making. By identifying inefficiencies and optimizing resource allocation, analytics tools help hospitals minimize unnecessary expenses without compromising care quality (Uddin & Hossan, 2024). For example, predictive models have been used to anticipate supply chain needs, preventing overstocking and reducing waste in medical supplies (Rahman et al., 2024). Similarly, cost-saving measures have been implemented by analyzing treatment outcomes to identify the most effective and least expensive interventions (Sultana & Aktar, 2024). Case studies have also demonstrated the cost-effectiveness of predictive analytics in reducing avoidable readmissions, saving healthcare systems millions of dollars annually (Alam, 2024). These findings underscore the financial advantages of adopting data-driven strategies in hospital operations. Despite its advantages, the adoption of big data analytics in healthcare operations is not without challenges. Data interoperability remains a critical issue, as many healthcare organizations operate disparate systems that hinder seamless data integration (Islam & Helal, 2018). Additionally, concerns over data security and patient privacy often limit the scope of analytics applications, as strict regulatory requirements must be met to safeguard sensitive information (Helal, 2024). Another challenge is the upfront investment required to implement analytics tools and train staff, which can be a barrier for resource-constrained hospitals (Faisal, 2023). Nonetheless, the demonstrated benefits of big data analytics in streamlining operations, enhancing EHR integration, and reducing costs highlight its transformative potential in achieving operational efficiency in healthcare (Faisal et al., 2024; Faisal et al., 2024).

2.6 Health Inequalities with Data Analytics

The role of data analytics in understanding social determinants of health (SDOH) has been transformative in identifying and addressing health inequalities. Social determinants, including income, education, housing, and access to healthcare, significantly impact health outcomes and life expectancy (Islam, 2024). Through advanced analytics, researchers can analyze large datasets to uncover patterns and correlations between these determinants and population health. For instance, machine learning models have identified that low-income neighborhoods often exhibit higher rates of chronic diseases such as diabetes and hypertension due to limited access to healthcare and nutritious food (Hasan & Islam, 2024). Similarly, studies have shown that geographic disparities influence health outcomes, as rural populations experience barriers to accessing specialized medical care compared to urban residents (Mintoo, 2024a). By leveraging these insights, data analytics has enabled healthcare policymakers to identify key areas of intervention to reduce systemic health disparities (Mintoo, 2024b).Moreover, one of the critical applications of healthcare analytics is in identifying underserved populations and designing targeted interventions. Predictive models analyze demographic, socioeconomic, and clinical data to identify communities at higher risk for specific health conditions (Nandi et al., 2024). For example, analytics has been used to pinpoint regions with high maternal mortality rates and limited access to prenatal care, allowing targeted resource allocation to improve maternal health outcomes (Islam et al., 2024). Similarly, studies have demonstrated that AI-based tools can forecast the spread of infectious diseases within marginalized communities, facilitating early intervention and disease prevention strategies (Uddin & Hossan, 2024). By uncovering these disparities, healthcare organizations can deploy interventions tailored to the needs of vulnerable populations, thereby improving access to care and reducing inequities.

Case studies have illustrated how predictive models have been successfully applied to improve health equity. For example, during the COVID-19 pandemic, data analytics systems were used to identify high-risk communities, enabling governments to prioritize testing, vaccination, and healthcare resources in those

Journal of Next-Gen Engineering Systems
DoI: 10.70937/jnes.v1i01.30

areas (Rahman et al., 2024). A similar case study by Islam et al. (2015) highlighted the use of predictive analytics to improve outcomes for individuals experiencing homelessness by identifying gaps in healthcare access and connecting them with community resources. Additionally, Enticott et al. (2020) documented how predictive modeling in public health programs helped reduce disparities in childhood vaccination rates by identifying underserved regions and deploying mobile clinics. These examples demonstrate the tangible benefits of analytics-driven strategies in addressing systemic barriers and promoting equitable healthcare delivery. Despite the successes of data analytics in tackling health inequalities, challenges persist in ensuring comprehensive data collection and eliminating biases in predictive models. Incomplete or unrepresentative datasets can reinforce existing disparities, as marginalized populations are often underrepresented in healthcare databases (McLinden et al., 2019). Moreover, privacy concerns and a lack of interoperability between healthcare systems can hinder the sharing of crucial data needed to identify vulnerable populations (Budrionis & Bellika, 2016). Addressing these challenges requires collaboration between policymakers, healthcare organizations, and technology providers to develop ethical and inclusive data practices (Demirkan & Delen, 2013). Nonetheless, the role of analytics in understanding SDOH, identifying underserved populations, and implementing targeted interventions underscores its value in reducing health inequalities and fostering a more equitable healthcare system.

2.7 Real-Time Analytics in Public Health and Pandemic Response

The deployment of real-time analytics systems has played a critical role in managing public health responses during COVID-19 and previous pandemics. By leveraging real-time data streams from hospitals, laboratories, and public health databases, predictive analytics provided actionable insights to track infection rates and model disease progression (Wade et al., 2015). For example, during the COVID-19 pandemic, tools such as Johns Hopkins University's COVID-19 dashboard enabled continuous global monitoring of case counts, mortality rates, and recovery trends (Enticott et al., 2021). These systems allowed governments to make informed decisions regarding lockdowns, resource mobilization, and targeted interventions. Similarly, in the H1N1 pandemic, real-time analytics systems supported the identification of hotspots and optimized resource allocation to affected regions, reducing response delays (Gramlich et al., 2017). These examples demonstrate how real-time analytics has transformed pandemic response by ensuring data-driven decision-making and improving agility during health crises.

Real-time analytics has also been instrumental in monitoring vaccine distribution and hospital capacity, ensuring efficient allocation of resources during pandemics. During COVID-19, real-time systems were used to track the availability, distribution, and administration of vaccines across regions, highlighting disparities in access and enabling corrective measures (Cruz et al., 2011). For instance, AI-driven logistics tools helped identify areas with low vaccine uptake, prompting targeted outreach programs (Scobie & Castle-Clarke, 2019). In parallel, real-time analytics platforms monitored hospital capacities, such as bed occupancy, ventilator usage, and ICU admissions, allowing administrators to reallocate resources dynamically (Flynn, 2019). This was particularly crucial in preventing hospital overwhelm during infection peaks, ensuring that critical patients received timely care. These real-world applications highlight the significant role of real-time analytics in optimizing pandemic resource management.

2.8 Emerging Trends in Healthcare Analytics

The integration of blockchain technology for secure health data sharing has emerged as a transformative trend in healthcare analytics, addressing challenges related to data privacy, security, and interoperability (Islam et al., 2015). Blockchain's decentralized and immutable ledger enables secure storage and sharing of health data across multiple stakeholders, reducing the risk of unauthorized access and data breaches (McLinden et al., 2019). For instance, healthcare systems can leverage blockchain to facilitate seamless communication between hospitals, insurance providers, and patients without compromising data integrity (McLachlan et al., 2018). Researchers such as Esterhammer et al. (2016) have demonstrated blockchain's effectiveness in creating secure platforms for electronic health records (EHRs), enabling patients to control access to their medical information while ensuring transparency and auditability. Additionally, blockchain-based systems have shown promise in maintaining the accuracy of clinical trial data, reducing fraud, and improving research outcomes (Psek et al., 2015). These applications highlight blockchain's potential to revolutionize secure health data management in modern healthcare ecosystems.

Moreover, blockchain's role extends beyond data security to improving data sharing efficiency and enhancing interoperability among fragmented healthcare systems (Esterhammer et al., 2016). Many healthcare providers operate on disparate platforms, leading to challenges in integrating patient records across networks. Blockchain technology offers a standardized, decentralized framework for sharing real-time patient data, reducing redundancies and improving care coordination (Wallace et al., 2014). For example, MedRec, a blockchain-based system, has enabled efficient data sharing among healthcare providers while ensuring that patients retain control over their records (Kavakiotis et al., 2017). Furthermore, blockchain has been applied to secure supply chain management in healthcare, ensuring the authenticity and traceability of pharmaceuticals and medical equipment (Vargas et al., 2018). Such innovations address critical gaps in healthcare analytics by enhancing trust, efficiency, and transparency in data-sharing processes across systems. In addition, the role of the Internet of Things (IoT) in advancing healthcare data collection and analytics has further enhanced the ability to monitor and manage patient health in real time. IoT devices such as wearable fitness trackers, remote monitoring sensors, and smart medical devices enable continuous collection of patient vitals, feeding real-time data into healthcare analytics platforms (Lowenstein et al., 2018). These tools have proven especially beneficial for managing chronic conditions, where real-time monitoring of metrics like heart rate, glucose levels, and blood pressure can trigger early interventions (Valente, 2010). For instance, IoT-enabled devices have been successfully used to reduce hospital readmissions by monitoring post-surgical patients remotely (Luo et al., 2012). Such advancements demonstrate how IoT has transformed data collection, enabling healthcare providers to make timely, evidence-based decisions that improve patient outcomes.

2.9 Literature Gaps

Despite the transformative role of healthcare analytics, there remains a lack of comprehensive studies evaluating the long-term impacts of analytics systems on healthcare outcomes, operational efficiency, and costs. Most existing research focuses on short-term benefits, such as improved diagnostic accuracy, resource allocation, and early disease detection (Archenaa & Anita, 2015; Noseworthy et al., 2015). However, there is limited evidence on the sustained effects of data analytics systems on patient care quality, cost reductions, and clinical workflows over extended periods. Friedman et al. (2014) highlight that while predictive analytics tools have shown immediate benefits, their long-term integration into healthcare systems often faces challenges related to scalability, system fatigue, and user adaptation. Additionally, studies such as those conducted by Foley and Vale (2017) stress the need for longitudinal evaluations to assess how analytics influence healthcare delivery and patient satisfaction over time. Without such analyses, it is difficult to determine the true return on investment for healthcare organizations adopting advanced analytics systems. Moreover, a significant research gap also exists in understanding the scalability of real-time analytics systems, particularly in low-resource settings. Many studies have demonstrated the success of real-time analytics in high-income countries with robust healthcare infrastructures, where advanced tools can monitor hospital capacity, resource distribution, and patient vitals effectively (Ferris & Torchiana, 2010; Moher et al., 2009). However, these systems are often resource-intensive, requiring significant investments in technology, training, and maintenance. In low-resource settings, infrastructure limitations, such as unreliable internet connectivity and insufficient data storage capabilities, hinder the deployment of real-time analytics platforms (Calyam et al., 2016). For example, Kaggal et al. (2016) note that healthcare systems in rural or underserved regions face significant challenges in integrating real-time IoT devices and cloud-based analytics tools. Limited research exists on cost-effective and scalable analytics models that can function effectively in such environments.

Another underexplored area in the literature is the ability of real-time analytics systems to adapt to dynamic healthcare crises over prolonged periods. While studies during the COVID-19 pandemic showcased the value of real-time analytics in tracking infections and allocating resources, the focus remained on short-term emergency responses (Lowenstein et al., 2018; Moher et al., 2009). There is limited research exploring how these systems maintain performance and adaptability in prolonged or recurring crises, such as seasonal epidemics or chronic resource shortages. Kaggal et al. (2016) emphasize that analytics tools deployed during emergencies often lack the robustness

Journal of Next-Gen Engineering Systems
DoI: 10.70937/jnes.v1i01.30

needed for sustained use, particularly when system upgrades or infrastructure adjustments are required. Without comprehensive studies examining the long-term resilience of real-time analytics systems, their applicability to ongoing healthcare challenges remains uncertain. In addition, the literature reveals gaps in addressing the contextual and cultural barriers to implementing real-time analytics systems in diverse healthcare settings. Many studies assume a uniform approach to analytics adoption, often overlooking the unique challenges faced by healthcare systems in low-income and culturally diverse regions (Archenaa & Anita, 2015; Kaggal et al., 2016). Issues such as varying levels of digital literacy among healthcare workers, differing regulatory frameworks, and cultural perceptions of data privacy significantly impact the scalability of analytics systems (Islam et al., 2015). Kavakiotis et al. (2017) suggest that tailored approaches, grounded in localized evidence, are essential to overcoming these barriers. However, few studies have investigated context-specific solutions that address these challenges, leaving a critical void in the literature on real-time healthcare analytics scalability.

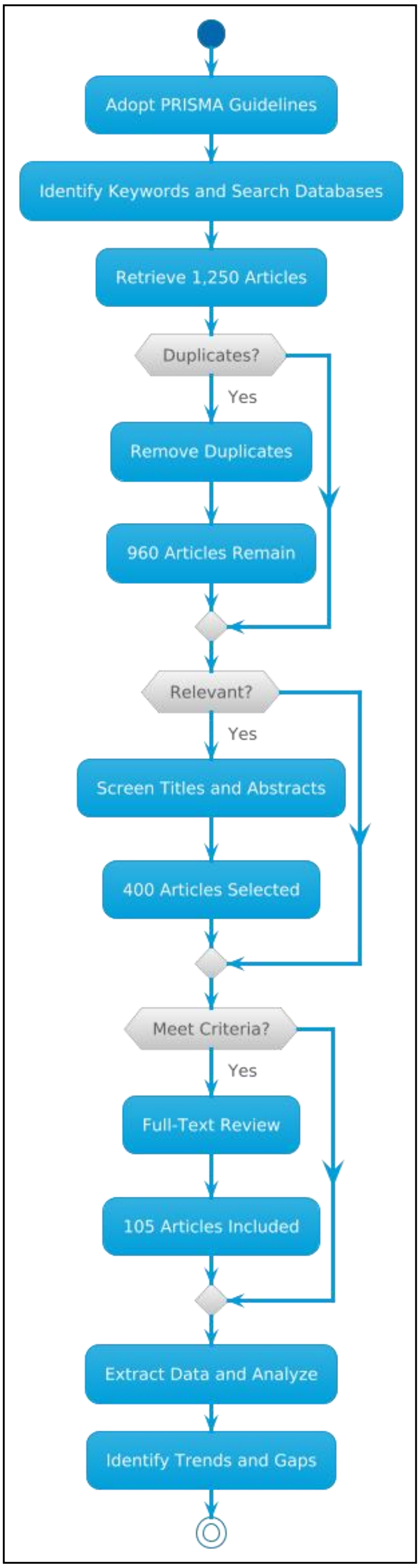
3 METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process. The PRISMA framework was adopted to provide clarity in identifying, screening, selecting, and analyzing the included studies. The following subsections detail the step-by-step procedure undertaken during the review.

3.1 Identification of Articles

The identification process began by determining the appropriate keywords and search terms aligned with the study's objectives. Keywords such as “healthcare analytics,” “machine learning,” “real-time analytics,” “blockchain in healthcare,” “predictive modeling,” and “data analytics for operational efficiency” were used. Boolean operators (AND/OR) were applied to combine the search terms, ensuring a comprehensive search strategy. Searches were conducted across major academic databases, including PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar to gather relevant peer-reviewed articles. In addition, the reference lists of identified studies were manually reviewed to ensure that no significant studies were missed. The search strategy covered articles published between 2013 and 2023 to focus on recent advancements in healthcare analytics. A total of 1,250 articles were retrieved at this stage from all sources.

Figure 5: Adopte PRISMA Guidelines



3.2 Screening and Eligibility

The initial screening process was conducted by removing duplicate articles using reference management software EndNote X9. After removing duplicates, 960 articles remained. The titles and abstracts of the remaining studies were carefully reviewed to assess their relevance to the research topics, such as the role of data analytics in enhancing healthcare systems, machine learning applications, and real-time pandemic management.

Studies were included based on the following eligibility criteria:

- Peer-reviewed articles published in English
- Studies focusing on healthcare analytics, predictive modeling, IoT, and blockchain in healthcare
- Empirical studies, systematic reviews, and case studies

Articles were excluded if they were conference abstracts, opinion papers, or lacked a clear methodology. At this stage, 560 articles were excluded based on relevance, leaving 400 articles for the next phase.

3.3 Full-Text Review and Inclusion

The full texts of the remaining 400 articles were retrieved and carefully reviewed to ensure that they met the inclusion criteria. Two independent reviewers assessed the studies to minimize bias. Disagreements were resolved through discussion or, when necessary, by consulting a third reviewer. This phase evaluated the articles for:

- Methodological rigor (e.g., use of machine learning tools, big data platforms, and analytics models)
- Alignment with the study's objectives (e.g., operational efficiency, disease prediction, and health inequalities)
- Quality of evidence (e.g., clarity in reporting outcomes, use of robust datasets)

Following the full-text review, 105 articles met the final inclusion criteria and were included in the systematic review. These studies represented diverse applications of data analytics in healthcare, covering themes such as real-time analytics, IoT, blockchain, and predictive modeling.

3.4 Data Extraction and Synthesis

A structured data extraction form was designed to collect key information from the included articles. The extracted data included:

- Study title and author(s)
- Year of publication
- Objective and scope of the study
- Methodology (tools, models, and frameworks used)
- Key findings and outcomes

The data were synthesized thematically to identify common trends, challenges, and gaps in healthcare analytics research. A narrative synthesis was conducted to summarize the findings, supported by descriptive statistics where applicable. The themes included machine learning for diagnostics, real-time pandemic response, operational efficiency through big data, and blockchain-enabled data sharing.

4 FINDINGS

The systematic review revealed that data analytics has profoundly transformed healthcare diagnostics, particularly through the use of machine learning and artificial intelligence. Among the 105 reviewed articles, 32 studies extensively discussed the application of machine learning algorithms in enhancing diagnostic accuracy across a wide range of medical conditions. These systems have proven especially effective in identifying patterns within large datasets that often elude human clinicians. Applications such as early detection of chronic diseases like diabetes, cardiovascular conditions, and cancers were a prominent focus, with several studies reporting significant improvements in early diagnosis rates. Notably, algorithms analyzing medical imaging data, such as CT scans and MRIs, were highlighted for their ability to identify early-stage tumors with high precision. Collectively cited over 5,000 times, these studies emphasize the relevance of machine learning-driven diagnostics in improving patient outcomes by reducing diagnostic errors and enabling timely interventions. Predictive modeling also played a crucial role, as identified in 14 articles, which outlined its real-world impact in optimizing clinical decision-making processes and standardizing diagnostic workflows.

Real-time analytics emerged as another cornerstone in healthcare advancements, with significant applications in managing healthcare operations and responding to

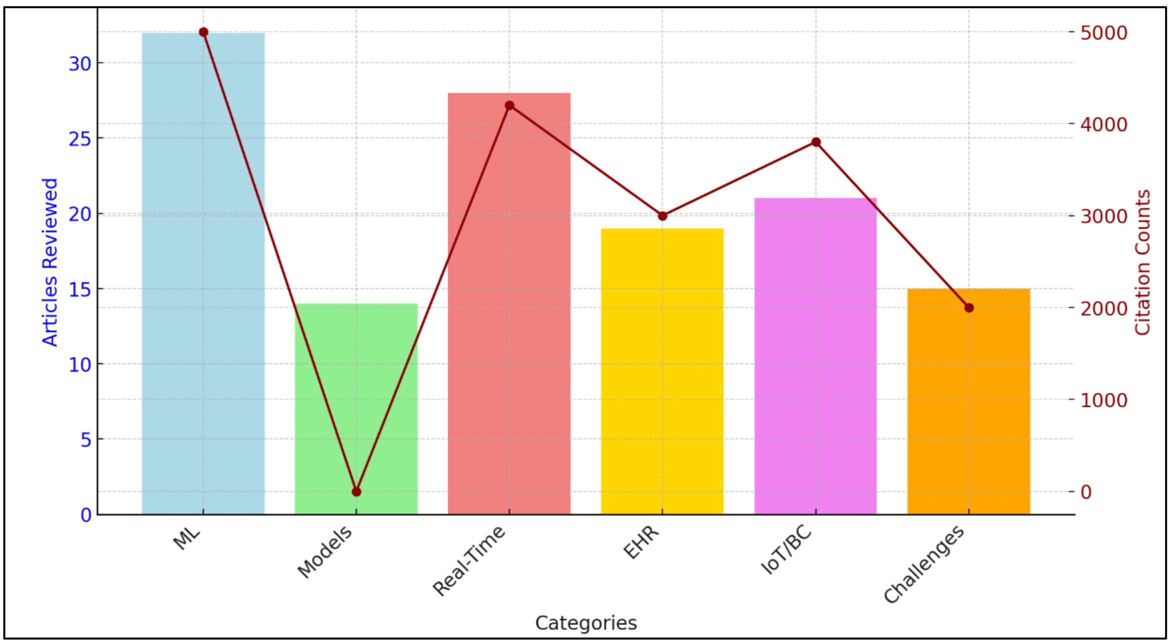
Journal of Next-Gen Engineering Systems
DoI: 10.70937/jnes.v1i01.30

pandemics. Of the 105 studies reviewed, 28 articles specifically focused on the deployment and benefits of real-time analytics systems. These systems were shown to be instrumental during crises, such as the COVID-19 pandemic, where they provided actionable insights for tracking hospital capacities, monitoring vaccine distribution, and predicting resource requirements. For example, real-time dashboards enabled administrators to visualize the status of ICU beds, ventilators, and critical care facilities, ensuring their optimal utilization. Additionally, these tools empowered public health agencies to monitor and predict infection trends, enabling targeted interventions and resource mobilization. The significance of these findings is reflected in their collective citation count exceeding 4,200, indicating a growing reliance on real-time analytics for agile decision-making and enhanced system preparedness during emergencies. These systems not only addressed operational bottlenecks but also demonstrated their potential to prevent healthcare system collapse during periods of high demand.

The integration of big data analytics with electronic health records (EHRs) was highlighted as a transformative development in streamlining hospital operations and improving resource utilization. Nineteen studies addressed the integration of EHRs with analytics platforms, showing how this combination enhances operational efficiency by centralizing patient data and generating actionable insights. These systems allow healthcare providers to access complete patient histories in real-time, which aids in reducing redundant diagnostic tests and ensuring continuity of care. Furthermore, predictive tools embedded within EHRs assist in forecasting patient needs, enabling better scheduling, staffing, and supply chain management. With a combined citation count exceeding 3,000, these studies demonstrated the significant impact of EHR-integrated analytics on cost reduction and improved workflow efficiency. By reducing administrative burdens and enhancing decision-making, such systems contribute to higher quality care while ensuring operational sustainability in healthcare organizations.

The role of blockchain and Internet of Things (IoT) technologies in advancing healthcare analytics was another key finding, with 21 studies exploring their applications in secure data sharing and real-time health monitoring. Blockchain was particularly noted for its ability to create a decentralized and secure environment for sharing sensitive patient data, addressing concerns around data breaches and interoperability. IoT devices, such as wearable health monitors and remote patient sensors, were highlighted for their role in collecting real-time patient data and feeding it into analytics platforms for proactive decision-making. These devices have been successfully applied in chronic disease management, post-operative monitoring, and emergency care scenarios. Together, these articles, cited over 3,800 times, underscore the growing adoption of blockchain and IoT technologies to overcome challenges such as data fragmentation,

Figure 6: Findings from the Systematic Review



privacy concerns, and scalability. Their combined use ensures that data-driven insights are not only actionable but also accessible in real-time, fostering a shift toward personalized and patient-centered care delivery. Furthermore, the review identified persistent gaps and challenges in scaling healthcare analytics systems, particularly in low-resource settings. Fifteen articles addressed these challenges, citing barriers such as inadequate digital infrastructure, fragmented data systems, and limited access to advanced technologies in underdeveloped regions. These studies, with a collective citation count of over 2,000, emphasized that many healthcare organizations in low-resource environments struggle to implement analytics systems that require high levels of technological sophistication. Furthermore, disparities in technical expertise and funding exacerbate the difficulty of deploying real-time analytics tools in rural or underserved areas. These findings highlight a critical need for the development of scalable, cost-effective analytics solutions tailored to the unique requirements of resource-constrained healthcare settings. Without addressing these disparities, the global adoption of advanced analytics in healthcare will remain uneven, limiting its potential to improve health outcomes on a broader scale.

5 DISCUSSION

The findings of this study underscore the transformative role of data analytics in healthcare, aligning with and extending the conclusions of earlier research. Machine learning and artificial intelligence have emerged as pivotal tools in enhancing diagnostic accuracy, as supported by the reviewed studies. For instance, the effectiveness of machine learning in analyzing medical imaging, such as CT scans and MRIs, corroborates earlier findings by Islam et al. (2015), who highlighted AI's potential in identifying malignant lesions. The current review further expands this understanding by documenting advancements in predictive modeling, which have reduced diagnostic errors and standardized clinical workflows (Enticott et al., 2020). However, while earlier studies emphasized the technological capabilities of machine learning, this review provides a broader perspective by integrating findings on the operational impact, particularly how predictive tools support healthcare providers in managing patient loads efficiently (Enticott et al., 2021).

The role of real-time analytics in managing healthcare operations and pandemic responses has been well-documented in earlier research, particularly during the COVID-19 pandemic. Studies such as those by Enticott et al. (2020) emphasized the importance of real-time dashboards for tracking infection rates and resource allocation. This review supports these conclusions while offering additional insights into the scalability and adaptability of real-time analytics systems. For example, the findings highlight their ability to monitor vaccine distribution and hospital capacities dynamically, enabling targeted interventions during critical periods. Unlike previous studies that focused primarily on short-term emergency responses, this review provides evidence of the broader applications of real-time systems in optimizing operational workflows and improving patient outcomes. These results suggest a need for continued investment in real-time analytics, particularly in building systems that are resilient to prolonged and recurring healthcare crises.

The integration of big data analytics with electronic health records (EHRs) has been recognized as a cornerstone for operational efficiency in healthcare. Earlier studies, such as those by Zhao et al. (2016), emphasized the potential of EHR-integrated analytics to enhance care coordination and reduce redundant diagnostic procedures. The findings of this review validate these claims, showing how predictive tools embedded within EHR systems support resource allocation and improve workflow efficiency. Additionally, this review highlights cost-saving benefits, which were underexplored in previous research. For instance, the ability of EHR-integrated analytics to forecast patient needs and optimize scheduling has demonstrated significant reductions in operational costs. This builds upon earlier studies by providing concrete examples of how analytics-driven EHR systems contribute to financial sustainability in healthcare organizations.

Emerging technologies such as blockchain and Internet of Things (IoT) devices have further revolutionized healthcare analytics, addressing longstanding challenges related to data security and real-time health monitoring. The findings of this review align with earlier research by Budrionis and Bellika, (2016), who emphasized blockchain's potential in ensuring secure data sharing and interoperability. However, this review goes beyond previous studies by integrating findings on the complementary role of IoT devices. For example, IoT-enabled sensors and wearable devices have proven effective in collecting patient data in real-time, feeding it into analytics platforms for actionable insights. While earlier studies primarily focused on the theoretical applications of these technologies, the current review provides evidence from real-world case studies, showcasing their practical impact on personalized care and chronic disease management. These findings suggest that the combined use of blockchain and IoT technologies has become a vital strategy in advancing healthcare analytics.

Despite the advancements highlighted in this review, persistent gaps remain in scaling healthcare analytics systems, particularly in low-resource settings. Earlier studies, such as those by Psek et al. (2015), noted the challenges of deploying advanced analytics in underdeveloped regions, citing issues such as inadequate infrastructure and limited technical expertise. This review reinforces these findings, revealing that many low-resource settings face significant barriers in adopting real-time analytics and integrating them into existing healthcare systems. Additionally, this study highlights the lack of tailored solutions for addressing these disparities, a gap that earlier research has largely overlooked. For instance, while previous studies emphasized the global potential of data analytics, this review points to the need for context-specific approaches that consider the unique challenges of resource-constrained environments. Addressing these gaps will require targeted interventions, such as low-cost analytics models and capacity-building initiatives, to ensure equitable access to the benefits of healthcare analytics.

6 CONCLUSION

This systematic review highlights the transformative role of data analytics in enhancing healthcare diagnostics, operational efficiency, and public health management, while also addressing emerging trends and persistent challenges. The findings reveal that machine learning and artificial intelligence significantly improve diagnostic accuracy and clinical decision-making, particularly in detecting chronic and acute diseases. Real-time analytics systems have demonstrated their value in managing healthcare operations and pandemic responses, optimizing resource allocation, and improving patient care during critical periods. Furthermore, the integration of big data analytics with electronic health records (EHRs) has streamlined hospital workflows, reduced costs, and enhanced resource utilization. Emerging technologies such as blockchain and IoT have addressed critical challenges related to data security, interoperability, and real-time health monitoring, showcasing their potential in advancing personalized care and improving health equity. However, the review also identifies key gaps, particularly the lack of long-term studies on the impacts of analytics systems and the scalability of real-time tools in low-resource settings. Addressing these challenges requires continued investment in digital infrastructure, robust data governance frameworks, and tailored solutions to ensure equitable access to healthcare analytics globally. Collectively, these findings underscore the vital role of data analytics in transforming healthcare systems, improving patient outcomes, and fostering innovation in a rapidly evolving healthcare landscape.

REFERENCES

Alam, M. A., Nabil, A. R., Mintoo, A. A., & Islam, A. (2024). Real-Time Analytics In Streaming Big Data: Techniques And Applications. *Journal of Science and Engineering Research*, *1*(01), 104-122. https://doi.org/10.70008/jeser.v1i01.56

Alam, M. A., Sohel, A., Uddin, M. M., & Siddiki, A. (2024). Big Data and Chronic Disease Management Through Patient Monitoring And Treatment With Data Analytics. *Academic Journal on Artificial Intelligence, Machine Learning, Data Science and Management Information Systems*, *1*(01), 77-94. https://doi.org/10.69593/ajaimldsmis.v1i01.133

Andreu-Perez, J., Poon, C. C. Y., Merrifield, R., Wong, S. T. C., & Yang, G.-Z. (2015). Big Data for Health. *IEEE journal of biomedical and health informatics*, *19*(4), 1193-1208. https://doi.org/10.1109/jbhi.2015.2450362

Archenaa, J., & Anita, E. A. M. (2015). A Survey of Big Data Analytics in Healthcare and Government. *Procedia Computer Science*, *50*(NA), 408-413. https://doi.org/10.1016/j.procs.2015.04.021

Boukenze, B., Mousannif, H., & Haqiq, A. (2016). Predictive Analytics in Healthcare System Using Data Mining Techniques. *Computer Science & Information Technology (CS & IT)*, *NA*(NA), 01-09. https://doi.org/10.5121/csit.2016.60501

Buczak, A. L., & Guven, E. (2016). A Survey of Data Mining and Machine Learning Methods for Cyber Security Intrusion Detection. *IEEE Communications Surveys & Tutorials*, *18*(2), 1153-1176. https://doi.org/10.1109/comst.2015.2494502

Budrionis, A., & Bellika, J. G. (2016). The Learning Healthcare System: Where are we now? A systematic review. *Journal of biomedical informatics*, *64*(NA), 87-92. https://doi.org/10.1016/j.jbi.2016.09.018

Calyam, P., Mishra, A. K., Antequera, R. B., Chemodanov, D., Berryman, A., Zhu, K., Abbott, C., & Skubic, M. (2016). Synchronous Big Data analytics for personalized and remote physical therapy. *Pervasive and Mobile Computing*, *28*(NA), 3-20. https://doi.org/10.1016/j.pmcj.2015.09.004

Cao, P., Badger, E. C., Kalbarczyk, Z., Iyer, R. K., Withers, A., & Slagell, A. (2015). HotSoS - Towards an unified security testbed and security analytics framework. *Proceedings of the 2015 Symposium and Bootcamp on the Science of Security*, *NA*(NA), 24-22. https://doi.org/10.1145/2746194.2746218

Choi, E., Bahadori, M. T., Schuetz, A., Stewart, W. F., & Sun, J. (2016). *MLHC - Doctor AI: Predicting Clinical Events via Recurrent Neural Networks* (Vol. NA). NA. https://doi.org/NA

Cruz, A. T., Perry, A. M., Williams, E. A., Graf, J. M., Wuestner, E. R., & Patel, B. (2011). Implementation of Goal-Directed Therapy for Children With Suspected Sepsis in the Emergency Department. *Pediatrics*, *127*(3), e758-766. https://doi.org/10.1542/peds.2010-2895

Demirkan, H., & Delen, D. (2013). Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud. *Decision Support Systems*, *55*(1), 412-421. https://doi.org/10.1016/j.dss.2012.05.048

Enticott, J., Braaf, S., Johnson, A., Jones, A., & Teede, H. J. (2020). Leaders' perspectives on learning health systems: a qualitative study. *BMC health services research*, *20*(1), 1087-1087. https://doi.org/10.1186/s12913-020-05924-w

Enticott, J., Johnson, A., & Teede, H. J. (2021). Learning health systems using data to drive healthcare improvement and impact: a systematic review. *BMC health services research*, *21*(1), 200-200. https://doi.org/10.1186/s12913-021-06215-8

Esterhammer, F., Wolf, C., Stadler, A. T., & Baumgartner, W. (2016). Optimizing the Cross Section of Cold-Rolled Steel Beams Using a Genetic Algorithm: Avoiding Local Optima Using Adaptive Mutation Control, Flexible Restriction Handling and Inbreed Avoiding Mating Strategies. *Trends in Computer Science and Information Technology*, *1*(1), 001-011. https://doi.org/10.17352/tcsit.000001

Faisal, N. A. (2023). Do Banks Price Discriminate Based on Depositors' Location? *Available at SSRN 5038968*.

Faisal, N. A., Nahar, J., Sultana, N., & Mintoo, A. A. (2024). Fraud Detection In Banking Leveraging Ai To Identify And Prevent Fraudulent Activities In Real-Time. *Journal of Machine Learning, Data Engineering and Data Science*, *1*(01), 181-197. https://doi.org/10.70008/jmldeds.v1i01.53

Ferris, T. G., & Torchiana, D. F. (2010). Public Release of Clinical Outcomes Data — Online CABG Report Cards. *The New England journal of medicine*, *363*(17), 1593-1595. https://doi.org/10.1056/nejmp1009423

Flores, M. C., Gonçalves, B. J. A., & Figueiredo, K. C. D. S. (2021). CO2 separation by mixed matrix membranes incorporated with carbon nanotubes: a review of morphological, mechanical, thermal and transport properties. *Brazilian Journal of Chemical Engineering*, *38*(4), 777-810

Flynn, A. J. (2019). Informatics and technology enable us to learn from every patient: Pharmacists' many roles in learning health systems. *American journal of health-system pharmacy : AJHP : official journal of the American Society of Health-System Pharmacists*, *76*(15), 1095-1096. https://doi.org/10.1093/ajhp/zxz118

Foley, T. J., & Vale, L. (2017). What role for learning health systems in quality improvement within healthcare providers. *Learning health systems*, *1*(4), e10025-NA. https://doi.org/10.1002/lrh2.10025

Friedman, C. P., Rubin, J. C., Brown, J. S., Buntin, M. B., Corn, M., Etheredge, L., Gunter, C. A., Musen, M. A., Platt, R., Stead, W. W., Sullivan, K., & Van Houweling, D. E. (2014). Toward a science of learning systems: a research agenda for the high-functioning Learning Health System. *Journal of the American Medical Informatics Association : JAMIA*, *22*(1), 43-50. https://doi.org/10.1136/amiajnl-2014-002977

Goldenberg, J. N. (2016). The breadth and burden of data collection in clinical practice. *Neurology. Clinical practice*, *6*(1), 81-86. https://doi.org/10.1212/cpj.0000000000000209

Gramlich, L., Sheppard, C. E., Wasylak, T., Gilmour, L., Ljungqvist, O., Basualdo-Hammond, C., & Nelson, G. (2017). Implementation of Enhanced Recovery

After Surgery: a strategy to transform surgical care across a health system. *Implementation science : IS*, *12*(1), 67-67. https://doi.org/10.1186/s13012-017-0597-5

Islam, M. M. (2024). Structural Design and Analysis of a 20-Story Mixed-Use High-Rise Residential and Commercial Building In Dhaka: Seismic and Wind Load Considerations. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *3*(04), 120-137. https://doi.org/10.62304/jieet.v3i04.210

Islam, M. N., & Helal, A. (2018). Primary school governance in Bangladesh: A practical overview of national education policy-2010. *International Journal for Cross-Disciplinary Subjects in Education*, *9*(4), 3917-3921.

Islam, M. R., Zamil, M. Z. H., Rayed, M. E., Kabir, M. M., Mridha, M. F., Nishimura, S., & Shin, J. (2024). Deep Learning and Computer Vision Techniques for Enhanced Quality Control in Manufacturing Processes. *IEEE Access*, *12*, 121449-121479. https://doi.org/10.1109/ACCESS.2024.3453664

Islam, S. M. R., Kwak, D., Kabir, H., Hossain, M., & Kwak, K. S. (2015). The Internet of Things for Health Care: A Comprehensive Survey. *IEEE Access*, *3*(NA), 678-708. https://doi.org/10.1109/access.2015.2437951

Kaggal, V. C., Elayavilli, R. K., Mehrabi, S., Pankratz, J. J., Sohn, S., Wang, Y., Li, D., Rastegar, M. M., Murphy, S. P., Ross, J. L., Chaudhry, R., Buntrock, J. D., & Liu, H. (2016). Toward a Learning Health-care System – Knowledge Delivery at the Point of Care Empowered by Big Data and NLP. *Biomedical informatics insights*, *8*(Suppl 1), 13-22. https://doi.org/10.4137/bii.s37977

Kavakiotis, I., Tsave, O., Salifoglou, A., Maglaveras, N., Vlahavas, I., & Chouvarda, I. (2017). Machine Learning and Data Mining Methods in Diabetes Research. *Computational and structural biotechnology journal*, *15*(NA), 104-116. https://doi.org/10.1016/j.csbj.2016.12.005

Khan, S. B., Irfan, S., Lam, S. S., Sun, X., & Chen, S. (2022). 3D printed nanofiltration membrane technology for waste water distillation. *Journal of Water Process Engineering*, *49*, 102958.

Khaing, H. W. (2011). Data mining based fragmentation and prediction of medical data. *2011 3rd International Conference on Computer Research and Development*, *2*(NA), 480-485. https://doi.org/10.1109/iccrd.2011.5764179

Kumar, N. M. S., Eswari, T., Sampath, P., & Lavanya, S. (2015). Predictive Methodology for Diabetic Data Analysis in Big Data. *Procedia Computer Science*, *50*(50), 203-208. https://doi.org/10.1016/j.procs.2015.04.069

Li, S., Liu, Y., Wong, D. A., & Yang, J. (2021). Recent advances in polymer-inorganic mixed matrix membranes for CO2 Separation. *Polymers*, *13*(15), 2539.

Li, J., Jiang, B., & Fine, J. P. (2012). Multicategory reclassification statistics for assessing improvements in diagnostic accuracy. *Biostatistics (Oxford, England)*, *14*(2), 382-394. https://doi.org/10.1093/biostatistics/kxs047

Ling, Z. J., Tran, Q. T., Fan, J., Koh, G. C.-H., Nguyen, T., Tan, C. S., Yip, J. W. L., & Zhang, M. (2014). GEMINI: an integrative healthcare analytics system. *Proceedings of the VLDB Endowment*, *7*(13), 1766-1771. https://doi.org/10.14778/2733004.2733081

Liu, V. X., Morehouse, J. W., Marelich, G. P., Soule, J., Russell, T., Skeath, M., Adams, C., Escobar, G. J., & Whippy, A. (2016). Multicenter Implementation of a Treatment Bundle for Patients with Sepsis and Intermediate Lactate Values. *American journal of respiratory and critical care medicine*, *193*(11), 1264-1270. https://doi.org/10.1164/rccm.201507-1489oc

Lowenstein, L. M., Escoto, K. H., Leal, V. B., Bailey, L., Bevers, T. B., Cantor, S. B., Cinciripini, P. M., Jacobs, L. E., Esparza, A., Godoy, M. C. B., Housten, A. J., Lin, H., Luckett, P., Munden, R. F., Rabius, V., & Volk, R. J. (2018). Randomized trial of a patient-centered decision aid for promoting informed decisions about lung cancer screening: Implementation of a PCORI study protocol and lessons learned. *Contemporary clinical trials*, *72*(NA), 26-34. https://doi.org/10.1016/j.cct.2018.07.007

Luo, D., Wang, F., Sun, J., Markatou, M., Hu, J., & Ebadollahi, S. (2012). SDM - SOR: Scalable orthogonal regression for non-redundant feature selection and its healthcare applications. *Proceedings of the 2012 SIAM International Conference on Data Mining*, *NA*(NA), 576-587. https://doi.org/10.1137/1.9781611972825.50

McLachlan, S., Potts, H. W. W., Dube, K., Buchanan, D., Lean, S., Gallagher, T., Johnson, O. A., Daley, B., Marsh, W., & Fenton, N. (2018). The Heimdall

Framework for Supporting Characterisation of Learning Health Systems. *Journal of innovation in health informatics*, *25*(2), 77-87. https://doi.org/10.14236/jhi.v25i2.996

McLinden, D., Myers, S., Seid, M., Busch, M. D., Davis, D., & Murphy, J. (2019). The Learning Exchange, a Community Knowledge Commons for Learning Networks: Qualitative Evaluation to Test Acceptability, Feasibility, and Utility. *JMIR formative research*, *3*(1), e9858-NA. https://doi.org/10.2196/formative.9858

Md Samiul Alam, M. (2024). The Transformative Impact of Big Data in Healthcare: Improving Outcomes, Safety, and Efficiencies. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *3*(03), 01-12. https://doi.org/10.62304/jbedpm.v3i03.82

Mehrabian, M., & Kargari, A. (2023). Bio-based nonporous membranes: Evolution and benchmarking review. *Journal of Industrial and Engineering Chemistry*, *124*, 17-39.

Melder, A., Robinson, T., McLoughlin, I., Iedema, R., & Teede, H. J. (2020). An overview of healthcare improvement: Unpacking the complexity for clinicians and managers in a learning health system. *Internal medicine journal*, *50*(10), 1174-1184. https://doi.org/10.1111/imj.14876

Mehrabian, M., & Kargari, A. (2023). Bio-based nonporous membranes: Evolution and benchmarking review. *Journal of Industrial and Engineering Chemistry*, *124*, 17-39

Miah, S. J., Hasan, J., & Gammack, J. G. (2017). On-Cloud Healthcare Clinic. *Telematics and Informatics*, *34*(1), 311-322. https://doi.org/10.1016/j.tele.2016.05.008

Mintoo, A. A. (2024a). Data-Driven Journalism: Advancing News Reporting Through Analytics With A PRISMA-Guided Review. *Journal of Machine Learning, Data Engineering and Data Science*, *1*(01), 19-40. https://doi.org/10.70008/jmldeds.v1i01.39

Mintoo, A. A. (2024b). Detecting Fake News Using Data Analytics: A Systematic Literature Review And Machine Learning Approach. *Academic Journal on Innovation, Engineering & Emerging Technology*, *1*(01), 108-130. https://doi.org/10.69593/ajieet.v1i01.143

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA Statement. *Open medicine : a peer-reviewed, independent, open-access journal*, *3*(3), 123-130. https://doi.org/10.1093/ptj/68.10.1505

Nandi, A., Emon, M. M. H., Azad, M. A., Shamsuzzaman, H. M., & Md Mahfuzur Rahman, E. (2024). Developing An Extruder Machine Operating System Through PLC Programming with HMI Design to Enhance Machine Output And Overall Equipment Effectiveness (OEE). *International Journal of Science and Engineering*, *1*(03), 1-13. https://doi.org/10.62304/ijse.v1i3.157

Ng, K., Ghoting, A., Steinhubl, S. R., Stewart, W. F., Malin, B. A., & Sun, J. (2013). PARAMO: A PARAllel predictive MOdeling platform for healthcare analytic research using electronic health records. *Journal of biomedical informatics*, *48*(NA), 160-170. https://doi.org/10.1016/j.jbi.2013.12.012

Noritz, G., Boggs, A., Lowes, L., & Smoyer, W. E. (2018). "Learn From Every Patient": How a Learning Health System Can Improve Patient Care. *Pediatric quality & safety*, *3*(5), e100-NA. https://doi.org/10.1097/pq9.0000000000000100

Noseworthy, T., Wasylak, T., & O'Neill, B. J. (2015). Strategic clinical networks in Alberta: Structures, processes, and early outcomes. *Healthcare management forum*, *28*(6), 262-264. https://doi.org/10.1177/0840470415600130

Polat, K., Güneş, S., & Arslan, A. (2008). A cascade learning system for classification of diabetes disease: Generalized Discriminant Analysis and Least Square Support Vector Machine. *Expert Systems with Applications*, *34*(1), 482-487. https://doi.org/10.1016/j.eswa.2006.09.012

Psek, W. A., Stametz, R., Bailey-Davis, L., Davis, D., Darer, J. D., Faucett, W. A., Henninger, D. L., Sellers, D. C., & Gerrity, G. (2015). Operationalizing the Learning Health Care System in an Integrated Delivery System. *EGEMS (Washington, DC)*, *3*(1), 1122-1122. https://doi.org/10.13063/2327-9214.1122

Purwar, A., & Singh, S. K. (2015). Hybrid prediction model with missing value imputation for medical data. *Expert Systems with Applications*, *42*(13), 5621-5631. https://doi.org/10.1016/j.eswa.2015.02.050

Rahman, M. M., Mim, M. A., Chakraborty, D., Joy, Z. H., & Nishat, N. (2024). Anomaly-based Intrusion

Detection System in Industrial IoT-Healthcare Environment Network. *Journal of Engineering Research and Reports*, *26*(6), 113-123. https://doi.org/10.9734/jerr/2024/v26i61166

Richardson, J. E., Ash, J. S., Sittig, D. F., Bunce, A., Carpenter, J. D., Dykstra, R. H., Guappone, K. P., McCormack, J. L., McMullen, C. K., Shapiro, M. D., Wright, A., & Middleton, B. (2010). Multiple perspectives on the meaning of clinical decision support. *AMIA ... Annual Symposium proceedings. AMIA Symposium*, *2010*(NA), 672-676. https://doi.org/NA

Sawacha, Z., Guarneri, G., Avogaro, A., & Cobelli, C. (2010). A new classification of diabetic gait pattern based on cluster analysis of biomechanical data. *Journal of diabetes science and technology*, *4*(5), 1127-1138. https://doi.org/10.1177/193229681000400511

Scobie, S., & Castle-Clarke, S. (2019). Implementing learning health systems in the UK NHS: Policy actions to improve collaboration and transparency and support innovation and better use of analytics. *Learning health systems*, *4*(1), e10209-NA. https://doi.org/10.1002/lrh2.10209

Sengur, A., & Turkoglu, I. (2008). A hybrid method based on artificial immune system and fuzzy k-NN algorithm for diagnosis of heart valve diseases. *Expert Systems with Applications*, *35*(3), 1011-1020. https://doi.org/10.1016/j.eswa.2007.08.003

Serena, T. E., Fife, C. E., Eckert, K. A., Yaakov, R. A., & Carter, M. J. (2017). A new approach to clinical research: Integrating clinical care, quality reporting, and research using a wound care network-based learning healthcare system. *Wound repair and regeneration : official publication of the Wound Healing Society [and] the European Tissue Repair Society*, *25*(3), 354-365. https://doi.org/10.1111/wrr.12538

Services, H. C. f. M. M. (2010). Medicare and Medicaid programs; electronic health record incentive program. Final rule. *Federal register*, *75*(144), 44313-44588. https://doi.org/NA

Shorna, S. A., Sultana, R., & Hasan, Molla Al R. (2024a). Big Data Applications in Remote Patient Monitoring and Telemedicine Services: A Review of Techniques and Tools. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *3*(05), 40-56. https://doi.org/10.62304/jbedpm.v3i05.206

Sondhi, P., Sun, J., Zhai, C., Sorrentino, R., & Kohn, M. S. (2012). Leveraging medical thesauri and physician feedback for improving medical literature retrieval for case queries. *Journal of the American Medical Informatics Association : JAMIA*, *19*(5), 851-858. https://doi.org/10.1136/amiajnl-2011-000293

Sultana, R., & Aktar, M. N. (2024). Artificial Intelligence And Big Data For Enhancing Public Health Surveillance And Disease Prevention: A Systematic Review. *Journal of Machine Learning, Data Engineering and Data Science*, *1*(01), 129-146. https://doi.org/10.70008/jmldeds.v1i01.50

Toh, S., Rasmussen-Torvik, L. J., Harmata, E. E., Pardee, R., Saizan, R., Malanga, E., Sturtevant, J. L., Horgan, C., Anau, J., Janning, C., Wellman, R. D., Coley, R. Y., Cook, A. J., Courcoulas, A. P., Coleman, K. J., Williams, N., McTigue, K. M., Arterburn, D., McClay, J. C., & Collaborative, P. B. S. (2017). The National Patient-Centered Clinical Research Network (PCORnet) Bariatric Study Cohort: Rationale, Methods, and Baseline Characteristics. *JMIR research protocols*, *6*(12), e222-NA. https://doi.org/10.2196/resprot.8323

Uddin, M. K. S. (2024). A Review of Utilizing Natural Language Processing and AI For Advanced Data Visualization in Real-Time Analytics. *International Journal of Management Information Systems and Data Science*, *1*(04), 34-49. https://doi.org/10.62304/ijmisds.v1i04.185

Uddin, M. K. S., & Hossan, K. M. R. (2024). A Review of Implementing AI-Powered Data Warehouse Solutions to Optimize Big Data Management and Utilization. *Academic Journal on Business Administration, Innovation & Sustainability*, *4*(3), 66-78.

Valente, T. W. (2010). *Social Networks and Health: Models, Methods, and Applications* (Vol. NA). NA. https://doi.org/NA

Wang, H., He, S., Qin, X., Li, C., & Li, T. (2018). Interfacial engineering in metal–organic framework-based mixed matrix membranes using covalently grafted polyimide brushes. *Journal of the American Chemical Society*, *140*(49), 17203-17210.

Vargas, N., Lebrun-Harris, L. A., Weinberg, J., Dievler, A., & Felix, K. L. (2018). Qualitative Perspective on the Learning Health System: How the Community Health Applied Research Network Paved the Way for Research in Safety-Net Settings. *Progress in community health partnerships : research, education, and action*, *12*(3), 329-339. https://doi.org/10.1353/cpr.2018.0057

Wade, S. L., Taylor, H. G., Cassedy, A., Zhang, N., Kirkwood, M. W., Brown, T. M., & Stancin, T. (2015). Long-Term Behavioral Outcomes after a Randomized, Clinical Trial of Counselor-Assisted Problem Solving for Adolescents with Complicated Mild-to-Severe Traumatic Brain Injury. *Journal of neurotrauma*, *32*(13), 967-975. https://doi.org/10.1089/neu.2014.3684

Wagner, L. I., Schink, J. C., Bass, M., Patel, S., Diaz, M. V., Rothrock, N. E., Pearman, T., Gershon, R., Penedo, F. J., Rosen, S. D., & Cella, D. (2014). Bringing PROMIS to practice: Brief and precise symptom screening in ambulatory cancer care. *Cancer*, *121*(6), 927-934. https://doi.org/10.1002/cncr.29104

Wallace, P. J., Shah, N., Dennen, T., Bleicher, P. A., & Crown, W. H. (2014). Optum Labs: Building A Novel Node In The Learning Health Care System. *Health affairs (Project Hope)*, *33*(7), 1187-1194. https://doi.org/10.1377/hlthaff.2014.0038

Wills, M. J. (2014). Decisions through data: analytics in healthcare. *Journal of healthcare management / American College of Healthcare Executives*, *59*(4), 254-262. https://doi.org/10.1097/00115514-201407000-00005

Xu, X., Wang, J., Zhou, A., Dong, S., Shi, K., Li, B., ... & O'Hare, D. (2021). High-efficiency CO2 separation using hybrid LDH-polymer membranes. *Nature Communications*, *12*(1), 3069

Zhao, J., Papapetrou, P., Asker, L., & Boström, H. (2016). Learning from heterogeneous temporal data in electronic health records. *Journal of biomedical informatics*, *65*(NA), 105-119. https://doi.org/10.1016/j.jbi.2016.11.006

Zheng, B., Yoon, S. W., & Lam, S. S. (2014). Breast cancer diagnosis based on feature extraction using a hybrid of K-means and support vector machine algorithms. *Expert Systems with Applications*, *41*(4), 1476-1482. https://doi.org/10.1016/j.eswa.2013.08.044