Journal of Health Informatics in Developing Countries
http://www.jhidc.org/
Vol. 17 No. 2, 2023

Submitted: Sep 27th, 2023 Accepted: Dec 18th, 2023

The use of Artificial Intelligence (AI) and Machine Learning (ML) in Health Systems – A review of the literature

Faris Fatani [1,*], Sahar Binhowaimel [2], Sara Mohammed AlGhannam [3], Meshael AlMohammed [4]

[1] *Riyadh second health cluster, Riyadh, Saudi Arabia.*

[2] *Ministry of health, Riyadh, Saudi Arabia.*

[3] *Ministry of health, Prince Saud Bin Jalawi Hospital, Alahsa, Saudi Arabia.*

[4] *Department of emergency medicine, Ministry of National guard, King Abdulaziz Medical city, Riyadh, Saudi Arabia.*

Abstract

Health system management plays a vital role in improving health outcomes and overall system performance. It entails organizing, planning, directing and managing the resources, procedures, and structures of a health system. In recent years, the use of machine learning in healthcare system management has demonstrated tremendous potential in several areas, including predictive modeling, resource optimization, and quality control. Machine learning can be used to optimize resource allocation, forecast outcomes, identify potential dangers, and find patterns in vast datasets. That can lead to improved patient outcomes and lower costs, and overall improved quality of health systems. However, there are also challenges to incorporating machine learning into healthcare system management, including ethical concerns, privacy issues, and lack of data standardization. In this paper, we provide a comprehensive review of the opportunities and challenges of applying machine learning in healthcare system management. The findings suggest that machine learning can play a significant role in enhancing healthcare quality, reducing costs, and improving patient outcomes, but its integration must be done ethically and with proper oversight.

Keywords: Artificial Intelligence, Machine Learning, Health system.

*Faris Fatani- Riyadh second health cluster, Riyadh, Saudi Arabia; Email: Faris_nf@hotmail.com.

1. Introduction

To improve health outcomes and overall system performance, a health system's resources, processes, and structures are therefore planned, organized, directed, and controlled through the process of "health system management" (Atun, 2015). It entails monitoring the provision of healthcare services to individuals and groups as well as managing healthcare organizations, including hospitals, clinics, and other healthcare facilities (Atun et al., 2013). Therefore, clinical, managerial, and leadership abilities are imperative for efficient health system management.

The efficient organization, coordination, and delivery of healthcare services to satisfy the demands of the population are enabled by efficient health system management, which is essential for public health (Fallon, 2020). Particularly for marginalized groups, it enhances healthcare quality, accessibility, and cost. Additionally, properly allocating healthcare resources, building health information systems, and placing a priority on health workforce development, enable quick and efficient responses to public health emergencies, such as disease outbreaks and vaccination programs (Beam & Kohane, 2018). The promotion of public health, the prevention of illnesses and disorders, and the provision of high-quality healthcare services all depend on the efficient management of the health system) (Weber et al., 2014).

By preventing and controlling illnesses, lowering healthcare expenses, raising the standard of healthcare services, and advancing fairness and social justice, effective health system management can enhance health outcomes. Moreover, it helps increase health systems' capacity to respond to crises like pandemics and natural catastrophes (Baldi, 2018). On the other hand, ineffectively run healthcare systems can result in inefficiencies, poor patient access, subpar care, and the wastage of funds. This can hurt social and economic growth by leading to diseases that could have been avoided, disabilities, and early death.

The importance of data in healthcare coupled with machine learning's capacity to extract information from data makes machine learning research for the healthcare industry essential (Wainberg et al., 2018). Large-scale phenotyping using observational data, autism subtyping by clustering comorbidities, and detecting lymph node metastases from breast pathology (Pivovarov et al., 2015) are just a few examples of the growing interest in machine learning for healthcare. Despite these developments, there are still many dangers associated with using machine learning directly in healthcare. The fact that the primary objective of data collecting in healthcare is to assist care rather than to enable later analysis contributes to many of these difficulties (Badawi et al., 2014) since the ostensible goal in healthcare is to use data created and managed by the medical system to make individualized predictions (Beckmann & Lew, 2016).

Machine learning can be an instrumental tool for managing the healthcare system effectively.

Large-scale data analysis, pattern and trend identification, and prediction capabilities of machine learning algorithms can be utilized to guide healthcare policy and decision-making (Shanmugam, 2022). Predictive modeling, disease diagnosis and management, resource allocation for the healthcare system, and clinical decision support are just a few areas where machine learning can be used (Badawi et al., 2014). By forecasting healthcare service demand and identifying high-need regions, machine learning can also optimize the distribution of healthcare resources and (Doshi-Velez et al., 2014) can aid decision-makers in public policy and healthcare professionals in allocating resources. Among the prospective applications are those that forecast the risk of unfavorable outcomes and offer potential treatments based on patient data.

But it's crucial to remember that to ensure that patient data is handled sensibly and impartially, machine learning applications in healthcare management should be guided by ethical considerations (Esteva et al., 2019). It should be highlighted that machine learning should not take the position of human judgment in the management of healthcare, but rather be used as a tool to assist judgment and enhance healthcare outcomes (Topol, 2019).

In this paper, we review the distinctive opportunities and difficulties that should be considered when using machine learning in managing healthcare systems. The validity and usability of machine learning for healthcare may be hampered if these issues are not adequately taken into account. We outline the opportunities and difficulties of implementing machine learning in the administration of healthcare systems. To fully reap the potential benefits of machine learning in effective healthcare systems management, we conclude by analyzing the future of machine learning research, which is pertinent to healthcare system management.

2. Subjects and Methods

The study involved a comprehensive review of the application of machine learning in the management of the healthcare system management. The review includes sections around the potential opportunities, including predictive modeling, resource optimization, and quality control, followed by the challenges of its incorporation in healthcare system management.

3. Results

3.1.Opportunities

Machine learning has a crucial role in quality control in healthcare system management. The technology’s ability to detect patterns in large datasets, predict outcomes and identify potential risks, and optimize resource allocation can lead to improved patient outcomes and lower costs. The review identified the following major opportunities in terms of using machine learning for the management of healthcare systems.

3.1.1. Predictive modeling for disease diagnosis

Machine learning has the potential to be very useful in healthcare through the application of predictive modeling (Yang, 2022). By identifying people at high risk for needing frequent and intense care, machine learning can be used to anticipate future healthcare demands (Dombayci & Espuña, 2017). This can aid in more effective resource planning and allocation for healthcare professionals and decision-makers and improved disease diagnosis, and management (Fukuda et al., 2019). Machine learning algorithms may analyze patient data to find trends and forecast results, which enables earlier disease identification, more precise diagnoses, and customized treatment regimens (Cooper et al., 2005).

Machine learning algorithms can be used to predict patient outcomes and identify potential risks before they occur (Chen et al., 2021). For example, a study published in the Journal of Medical Internet Research used machine learning to predict hospital readmissions among patients with heart failure. The algorithm was able to accurately predict readmissions, allowing healthcare providers to take proactive measures to prevent them (Reeves et al., 2019)

Through predictive modeling, machine learning algorithms can be trained on large datasets of patient information, including medical history, genetic data, lifestyle factors, and environmental factors, to identify patterns and make predictions about a patient's future health outcomes (Waring et al., 2020; Moher et al., 2009)). These predictions can be used to develop personalized treatment plans that are tailored to the specific needs of each patient (Siddique & Chow, 2021). s

3.1.2. Resource optimization

It has been established that machine learning holds great promise for improving the distribution of healthcare resources like personnel, machinery, and supplies. For instance, machine learning algorithms optimize the scheduling of nursing personnel in a hospital (Pepito & Locsin, 2019). The algorithm foresaw the anticipated number of patients in each hospital unit, allowing nurses to organize their shifts accordingly. Additionally incorporating machine learning in health system management can help to lower personnel expenses and enhance patient outcomes (Cramer et al., 2019).

According to several publications, deploying machine learning to help with some aspects of patient care could provide nurses with more time to spend learning about their patients' preferences, addressing their needs, and fostering better therapeutic interactions (Liang et al., 2019; Ravaghi et al., 2020). In another study, machine learning was used to forecast hospital admissions so that hospitals could better spend their resources. The algorithm was then utilized to improve staffing levels and bed distribution by forecasting the number of admissions for each day of the week, decreasing patient wait times, and improving hospital productivity (Amindoust et al., 2021). In the context of disease epidemics, machine learning can be instrumental in identifying gaps and allocation of resources. Furthermore, a machine learning algorithm can be utilized to forecast the number of patients with a condition in each region (Amindoust et al., 2021). This information was then utilized to distribute resources like testing kits and safety gear. The research indicated that by using this strategy, fewer resources were allocated that weren't essential, and reaction times were generally faster (Abbas, Arif, (Buchanan et al., 2020).

These studies demonstrate how machine learning may be used to optimize resource distribution in healthcare settings. Machine learning algorithms can assist hospitals and healthcare organizations use their resources more effectively, improving patient outcomes, and lowering costs by leveraging historical data to predict future demands. To make sure that machine learning algorithms are used in ways that benefit patients and the healthcare system as a whole, it is crucial to remember that they must be created and used ethically, with the proper oversight.

3.1.3. Quality Control

In recent years, the quality of healthcare services has improved, and the treatment of complex diseases has become more effective (Vyas et al., 2019). However, challenges still exist, such as determining the appropriate dosage and duration of therapies for patients with individual characteristics or for groups with limited clinical studies, such as children (Saleem & Chishti, 2020). Machine learning has become a powerful tool for managing the quality of the healthcare system (Javaid et al., 2022). Machine learning algorithms are being used more frequently in the healthcare sector to find and forecast trends in massive datasets, which can enhance care quality and optimize resource allocation (Araújo et al., 2016). There are several approaches to applying machine learning to improve quality control in healthcare systems.

Machine learning tools have the potential to enhance the quality of automation and intelligent decision-making in primary and tertiary patient care, as well as public healthcare systems (Sendak et al., 2020). This represents a significant opportunity to improve the quality of life for billions of people worldwide. It can enable healthcare systems to make more accurate predictions and decisions, leading to improved patient outcomes and better resource allocation (Gupta & Katarya, 2020). This can help healthcare providers to deliver more personalized and effective care to patients, particularly in areas where resources are limited (Tucker et al., 2020).

Furthermore, medical errors can have serious consequences for patients, which is why it is essential to implement effective quality control measures to detect and correct mistakes (Wojcieszak, 2022). Machine learning is a powerful tool that can be utilized to detect anomalies or patterns in medical data that may indicate errors (Ullah et al., 2020). A study examining a machine learning system for identifying medication mistakes discovered that it produced a large number of clinically valid alarms that would otherwise go unnoticed by CDS systems in use today. The majority of the alerts—more than 80%—were determined to be clinically valid, and 62.8% of them were rated as having medium or high clinical significance. An estimated $60 or more was spent on each drug alert for adverse events that could have been avoided in an outpatient setting (Rozenblum et al., 2020).

Several studies have demonstrated the effectiveness of a machine-learning algorithm in detecting adverse drug events (ADEs) (Park, 2021) in electronic health records, the algorithm achieves a high level of accuracy in identifying ADEs, which could help healthcare professionals to identify and address potential errors before they harm patients (Mohsen et al., 202). In a study, to address the effects of various clinical workflows and representations of clinical knowledge, clinicians build an image-based artificial intelligence for skin cancer diagnosis (Tschandl et al., 2019). Furthermore, it was discovered that superior artificial intelligence-based clinical decision-making supports more accurate diagnosis than earlier AI or physicians. Research indicates that practitioners with the least training benefit the most from AI-based support (Juarez-Chambi et al., 2019).

3.2. Challenges of machine learning in healthcare system management

Despite its benefits, there are several challenges in incorporating machine learning in healthcare system management owing to its inherent complex nature. The review identified the following major challenges associated with using machine learning for the management of healthcare systems.

3.2.1. Potential biases

Typically, predictive modeling is used to identify individuals who require sophisticated health interventions, outreach, care coordination, and condition management (Kansagara et al., 2011). Despite its benefits, it is important to ensure that machine learning algorithms are developed and deployed ethically, with appropriate oversight, to ensure that they are used in ways that benefit patients and the healthcare system as a whole. It is critical to ensure that machine learning algorithms are developed and deployed ethically, with appropriate oversight, to ensure that they are used in ways that benefit patients and the healthcare system as a whole. For instance, most insurance companies use a combination of risk assessments from commercial vendors, results from one or more predictive models, and "if-then" type business procedures to determine which members should receive outreach first (Gervasi et al., 2022). Because these risk-based prioritization algorithms determine how important healthcare resources are allocated, the underlying algorithmic procedures should be routinely audited to detect any biases (Razavian et al., 2015).

The limited availability of data necessary to determine a goal result and produce features for predictions is another bias present in many disease-onset models (Huynh-Thu et al., 2012). Members who use healthcare services less frequently have a higher likelihood of missing or sparsely supplied clinical indicators in claims and electronic medical record (EMR) data (Kevin Fiscella, 2000). Additionally, the evidence cited in support of the assertion shows differences in diagnoses and treatments given by healthcare professionals due to implicit and overt bias, including racism (Fiscella et al., 2000).

Machine learning has proven to be highly valuable in the fight against COVID-19 by providing faster and cost-effective detection, screening, and diagnosis methods. Furthermore, it has the potential to predict outbreak locations and forecast future outbreaks, enabling healthcare systems to prepare and allocate resources efficiently (Guleria & Sood, 2020). This proactive approach can prevent healthcare systems from collapsing under the burden of the pandemic (Hamilton et al., 2021). However, to ensure communities can benefit from machine learning-led tools for planning, mitigation, diagnosis, and treatment of patients, it is imperative to address the potential issue of biases in the algorithms.

3.2.2. Accountability and ethical concerns

Machine learning systems, especially deep neural networks, can be regarded as "black boxes" due to their complex operations that involve processing millions of data points (Panch et al., 2018). These models generate thousands of classifications, but the intricate internal representation of the data is usually incomprehensible to humans (Zawati & Lang, 2020). Unlike traditional statistical models, the process of deriving an inference from data is not easily explainable or describable due to the highly complex nature of these models (Purushotham et al., 2018). It is critical to ensure that machine learning algorithms are developed and deployed ethically, with appropriate oversight, to ensure that they are used in ways that benefit patients and the healthcare system as a. While employing machine learning, mechanisms for accountability should be specifically adapted to the issue that the system is meant to solve to ensure accountability (Guleria & Sood, 2020). Theoretical restrictions or statistical evidence from machine learning trials may be sufficient for well-defined problems, but an explanation is necessary for accountability in the case of complicated challenges, such as those found in clinical practice. (Roderick et al., 2016) An observer should be able to gauge the degree to which a given input determined or influenced an outcome as the main goal.

The complex nature of machine learning models can make it difficult to understand how they arrive at their predictions or classifications which can be of concern where transparency and interpretability are important to understand how a diagnosis was made (Badri et al., 2017). To address this, efforts should be directed toward developing more interpretable machine learning models, such as decision trees or rule-based systems (Zawati & Lang, 2020).

There is growing concern that applications that run automatically and cannot be examined put patients at greater risk of harm (Char et al., 2020). This raises a serious issue with accountability if such devices malfunction. Transparency requirements based on "auditability" are frequently advocated as a solution to these issues. The problem with machine learning, though, is that the auditability criteria do not demand that assessors fully comprehend how the application operates (Lang & Zawati, 2018). However, it does stipulate that such systems must possess "an explainable architecture." (Char et al., 2020) This calls into question who is in charge of examining, and from what perspective, the decision-making procedures of machine learning programs (Lang & Zawati, 2018).

This responsibility problem is not a side issue but a fundamental ethical problem. It serves as a crucial backdrop for talking about other fundamental ethical issues, like preserving public trust in healthcare systems and appropriately implementing informed consent in the face of unclear decision-making (Macrae, 2019). As a result, ethical principles stress the importance of carrying out responsibility analyses when assessing machine learning-led applications (Montreal Declaration, 2018). By doing this, we can ensure that the appropriate safeguards are in place to minimize possible dangers to patients and better understand who is responsible for the decisions made by these systems (Gille et al., 2014).

3.2.3. Healthcare workers willingness

To implement machine learning-based diagnosis, care management, and monitoring in practical healthcare settings, it is not enough to demonstrate algorithmic superiority alone (Kocher & Sahni, 2011). Convincing clinicians and policymakers will require these systems to deliver real-world outcomes of interest through experimental trials or observations of performance. Given that machine learning is constantly evolving, and as algorithms improve with more data and better techniques, such initiatives may need to be repeated. This could result in significant costs for healthcare systems, which will need to offset these expenses with improved performance and greater workforce efficiency (Henglin et al., 2017).

With the development of high-resolution clinical data sets and the essential infrastructure for data sharing and collaborative research to show efficacy and safety, there is a chance to foster progress in machine learning. Currently, the leadership necessary to do so is lacking in the health systems. While the concerns presented are being actively explored within the academic machine-learning community, only the leadership of policymakers and the participation of citizens, patients, and physicians will be able to resolve them.

4. Discussion

The healthcare sector is a major industry because it involves a wide range of stakeholders, including patients, pharmaceutical companies, academic institutions, researchers, and biomedical scientists (Feretzakis et al., 2022). The healthcare industry has a long history of being an early adopter of technological advancements in general. From developing new health check activities to handling patient information and accounts, machine learning and its subsets are currently on their way to becoming a significant component in the healthcare system (Fukuda et al., 2019). The association and completion of organizational duties are one of the biggest challenges facing healthcare offices today (Fukuda et al. 2019). Healthcare organizations may assist fix the issue and free up doctors to do what they do best, which is to spend more time with patients, by automating them.

One of the most crucial applications of the machine and deep learning algorithms in healthcare is related to identifying and analyzing diseases that are challenging to diagnose using predictive modeling(Memon et al., 2019). The use of predictive modeling in healthcare aims to identify individuals who need sophisticated interventions, care coordination, and condition management. However, there is a risk of bias in the algorithms used, and there may be limited data available for predictions. Additionally, implicit and overt bias in diagnoses and treatments given by healthcare professionals can affect the accuracy of predictions.

Numerous pharmaceutical companies are utilizing machine learning in their research to create diagnoses and treatments for diseases like cancer (Chae et al., 2018). One of the priority areas in global health, disease prevention can benefit from machine learning through the timely identification of at-risk communications (Malik et al., 2022). Machine learning models are created on the data on disease symptoms currently available, which will assist our healthcare professionals in quickly and patiently comprehending the disease. Machine learning plays a vital role in maintaining records in a long and expensive cycle. For instance, machine learning approaches can forecast malaria outbreaks based on the data that is currently available, such as temperature, average monthly rainfall, the total number of positive cases, and other biological factors. (Gupta & Katarya, 2020)

Given data on epidemic outbreaks around the globe are available which can be collected from web-based satellite data, real-time social media updates, and other sources (S et al., 2018). Machine learning applications can be used in the healthcare industry for disease diagnosis, prognosis, and the development of a successful treatment strategy. Machine learning technology can help healthcare professionals track and assess the efficacy of therapies by offering quicker and more precise solutions (Moher et al., 2009). New avenues to enhance healthcare outcomes are being investigated owing to developments in machine learning. To enable early intervention and better health management, research is currently being done to create predictive models to identify people at risk of contracting particular diseases, including cancer or heart disease.

One of the challenges is the need for real-world outcomes of interest through experimental trials or observations of performance to convince clinicians and policymakers to adopt these systems. To demonstrate efficacy and safety, high-resolution clinical data sets and the infrastructure for data exchange and collaborative research must be created. For certain healthcare workers, the limited ability of extrapolating machine learning infrastructure remains a significant concern.

Machine learning can be an effective tool for healthcare system management. However, several challenges need to be addressed to ensure that the deployment of machine learning algorithms is ethical and beneficial for patients and the healthcare system as a whole. One of the potential challenges is biases in predictive modeling algorithms that determine the allocation of healthcare resources. These algorithms need to be audited regularly to detect any biases. Limited availability of data and differences in diagnoses and treatments due to bias can also be potential biases (AlZubi et al., 2021). Another challenge is accountability and ethical concerns. Machine learning models can be complex and difficult to understand, leading to concerns about transparency and interpretability, warranting increased focus on the development of more interpretable machine learning models that could be one solution to this problem (Ricciardi et al., 2022). There are also concerns about applications that run automatically and cannot be examined, raising issues with accountability in the event of a malfunction. Responsibility analyses need to be carried out to ensure that appropriate safeguards are in place to minimize potential dangers to patients and understand who is responsible for the decisions made by these systems.

Finally, healthcare workers' willingness to adopt machine learning-based diagnosis, care management, and monitoring in practical healthcare settings can be another challenge (Panch et al., 2018). Real-world outcomes need to be demonstrated through experimental trials or observations of performance to convince clinicians and policymakers of the effectiveness of these systems, and as algorithms improve with more data and better techniques, these initiatives may need to be repeated, leading to significant costs for healthcare systems (AlZubi et al., 2021).

To conclude, machine learning has the potential expected to play an increasingly important role in healthcare, and there is a need to explore its further applications in the future (Ghazal et al., 2021). The findings of the study demonstrate significant opportunities for the application of machine learning in healthcare systems management. However, the challenges point out some key priority areas that should be addressed to gain the maximum benefits of machine learning to improve global healthcare systems management.

5. Declarations

5.1 Conflict of Interest Statement

The authors have no conflict of interests to declare.

5.2 Funding Disclosure

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

6. References

AlZubi, A. A., Al-Maitah, M., & Alarifi, A. (2021). Cyber-attack detection in healthcare using cyber-physical system and Machine Learning Techniques. *Soft Computing*, *25*(18), 12319–12332. https://doi.org/10.1007/s00500-021-05926-8

Amindoust, A., Asadpour, M., & Shirmohammadi, S. (2021). A hybrid genetic algorithm for nurse scheduling problem considering the fatigue factor. Journal of Healthcare Engineering, 2021, 1–11. https://doi.org/10.1155/2021/5563651

Amindoust, A., Asadpour, M., & Shirmohammadi, S. (2021). A hybrid genetic algorithm for nurse scheduling problem considering the fatigue factor. Journal of Healthcare Engineering, 2021, 1–11. https://doi.org/10.1155/2021/5563651

Araújo, F. H. D., Santana, A. M., & de A. Santos Neto, P. (2016). Using machine learning to support healthcare professionals in making preauthorisation decisions. International Journal of Medical Informatics, 94, 1–7. https://doi.org/10.1016/j.ijmedinf.2016.06.007

Atun, R. (2015). Transitioning Health Systems for multimorbidity. The Lancet, 386(9995), 721–722. https://doi.org/10.1016/s0140-6736(14)62254-6

Atun, R., Aydın, S., Chakraborty, S., Sümer, S., Aran, M., Gürol, I., Nazlıoğlu, S., Özgülcü, Ş., Aydoğan, Ü., Ayar, B., Dilmen, U., & Akdağ, R. (2013). Universal Health Coverage in Turkey: Enhancement of equity. The Lancet, 382(9886), 65–99. https://doi.org/10.1016/s0140-6736(13)61051-x

Badawi, O., Brennan, T., Celi, L. A., Feng, M., Ghassemi, M., Ippolito, A., Johnson, A., Mark, R. G., Mayaud, L., Moody, G., Moses, C., Naumann, T., Nikore, V., Pimentel, M., Pollard, T. J., Santos, M., Stone, D. J., & Zimolzak, A. (2014). Making big data useful for health care: A summary of the inaugural MIT Critical Data Conference. JMIR Medical Informatics, 2(2). https://doi.org/10.2196/medinform.3447

Badri, M., Badri, L., Flageol, W., & Toure, F. (2017). Investigating the accuracy of test code size prediction using use case metrics and machine learning algorithms. Proceedings of the 2017 International Conference on Machine Learning and Soft Computing. https://doi.org/10.1145/3036290.3036323

Baldi, P. (2018). Deep learning in biomedical data science. Annual Review of Biomedical Data Science, 1(1), 181–205. https://doi.org/10.1146/annurev-biodatasci-080917-013343

Beam, A. L., & Kohane, I. S. (2018). Big Data and machine learning in Health Care. JAMA, 319(13), 1317. https://doi.org/10.1001/jama.2017.18391

Beckmann, J. S., & Lew, D. (2016). Reconciling evidence-based medicine and precision medicine in the era of big data: Challenges and opportunities. Genome Medicine, 8(1). https://doi.org/10.1186/s13073-016-0388-7

Buchanan, C., Howitt, M. L., Wilson, R., Booth, R. G., Risling, T., & Bamford, M. (2020). Predicted influences of artificial intelligence on the domains of nursing: Scoping review. JMIR Nursing, 3(1). https://doi.org/10.2196/23939

Chae, S., Kwon, S., & Lee, D. (2018). Predicting infectious disease using Deep Learning and Big Data. International Journal of Environmental Research and Public Health, 15(8), 1596. https://doi.org/10.3390/ijerph15081596

Char, D. S., Abràmoff, M. D., & Feudtner, C. (2020). Identifying ethical considerations for Machine Learning Healthcare Applications. The American Journal of Bioethics, 20(11), 7–17. https://doi.org/10.1080/15265161.2020.1819469

Chen, I. Y., Joshi, S., Ghassemi, M., & Ranganath, R. (2021). Probabilistic Machine Learning for Healthcare. Annual Review of Biomedical Data Science, 4(1), 393–415. https://doi.org/10.1146/annurev-biodatasci-092820-033938

Cooper, G. F., Abraham, V., Aliferis, C. F., Aronis, J. M., Buchanan, B. G., Caruana, R., Fine, M. J., Janosky, J. E., Livingston, G., Mitchell, T., Monti, S., & Spirtes, P. (2005). Predicting dire outcomes of patients with community acquired pneumonia. Journal of Biomedical Informatics, 38(5), 347–366. https://doi.org/10.1016/j.jbi.2005.02.005

Cramer, E. M., Seneviratne, M. G., Sharifi, H., Ozturk, A., & Hernandez-Boussard, T. (2019). Predicting the incidence of pressure ulcers in the intensive care unit using machine learning. EGEMs (Generating Evidence & Methods to Improve Patient Outcomes), 7(1), 49. https://doi.org/10.5334/egems.307

Dombayci, C., & Espuña, A. (2017). Modelling decision support systems using conceptual constraints - linking process systems engineering and decision making models. Proceedings of the 9th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management. https://doi.org/10.5220/0006485201470154

Doshi-Velez, F., Ge, Y., & Kohane, I. (2014). Comorbidity clusters in autism spectrum disorders: An electronic health record time-series analysis. Pediatrics, 133(1). https://doi.org/10.1542/peds.2013-0819

Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S., & Dean, J. (2019). A guide to deep learning in Healthcare. Nature Medicine, 25(1), 24–29. https://doi.org/10.1038/s41591-018-0316-z

Fallon, E. (2020). Machine learning in EDA: Opportunities and challenges. Proceedings of the 2020 ACM/IEEE Workshop on Machine Learning for CAD. https://doi.org/10.1145/3380446.3430687

Feretzakis, G., Karlis, G., Loupelis, E., Kalles, D., Chatzikyriakou, R., Trakas, N., Karakou, E., Sakagianni, A., Tzelves, L., Petropoulou, S., Tika, A., Dalainas, I., & Kaldis, V. (2022). Using machine learning techniques to predict hospital admission at the Emergency Department. The Journal of Critical Care Medicine, 8(2), 107–116. https://doi.org/10.2478/jccm-2022-0003

Fiscella, K., Franks, P., Gold, M. R., & Clancy, C. M. (2000). Inequality in Quality. JAMA, 283(19), 2579. https://doi.org/10.1001/jama.283.19.2579

Fukuda, M., Inamoto, K., Shibata, N., Ariji, Y., Yanashita, Y., Kutsuna, S., Nakata, K., Katsumata, A., Fujita, H., & Ariji, E. (2019). Evaluation of an artificial intelligence system for detecting vertical root fracture on panoramic radiography. Oral Radiology, 36(4), 337–343. https://doi.org/10.1007/s11282-019-00409-x

Gervasi, S. S., Chen, I. Y., Smith-McLallen, A., Sontag, D., Obermeyer, Z., Vennera, M., & Chawla, R. (2022). The potential for bias in machine learning and opportunities for health insurers to address it. Health Affairs, 41(2), 212–218. https://doi.org/10.1377/hlthaff.2021.01287

Ghazal, T. M., Hasan, M. K., Alshurideh, M. T., Alzoubi, H. M., Ahmad, M., Akbar, S. S., Al Kurdi, B., & Akour, I. A. (2021). IOT for Smart Cities: Machine Learning Approaches in smart healthcare—A Review. Future Internet, 13(8), 218. https://doi.org/10.3390/fi13080218

Gille, F., Smith, S., & Mays, N. (2014). Why Public Trust in Health Care Systems Matters and deserves greater research attention. Journal of Health Services Research & Policy, 20(1), 62–64. https://doi.org/10.1177/1355819614543161

Guleria, P., & Sood, M. (2020). Intelligent learning analytics in healthcare sector using machine learning. Learning and Analytics in Intelligent Systems, 39–55. https://doi.org/10.1007/978-3-030-40850-3_3

Gupta, A., & Katarya, R. (2020). Social media based surveillance systems for healthcare using Machine Learning: A systematic review. Journal of Biomedical Informatics, 108, 103500. https://doi.org/10.1016/j.jbi.2020.103500

Hamilton, A. J., Strauss, A. T., Martinez, D. A., Hinson, J. S., Levin, S., Lin, G., & Klein, E. Y. (2021). Machine Learning and Artificial Intelligence: Applications in healthcare epidemiology. Antimicrobial Stewardship & Healthcare Epidemiology, 1(1). https://doi.org/10.1017/ash.2021.192

Henglin, M., Stein, G., Hushcha, P. V., Snoek, J., Wiltschko, A. B., & Cheng, S. (2017). Machine learning approaches in cardiovascular imaging. Circulation: Cardiovascular Imaging, 10(10). https://doi.org/10.1161/circimaging.117.005614

Huynh-Thu, V. A., Saeys, Y., Wehenkel, L., & Geurts, P. (2012). Statistical interpretation of machine learning-based feature importance scores for Biomarker Discovery. Bioinformatics, 28(13), 1766–1774. https://doi.org/10.1093/bioinformatics/bts238

Javaid, M., Haleem, A., Pratap Singh, R., Suman, R., & Rab, S. (2022). Significance of machine learning in Healthcare: Features, pillars and applications. International Journal of Intelligent Networks, 3, 58–73. https://doi.org/10.1016/j.ijin.2022.05.002

Juarez-Chambi, R. M., Kut, C., Rico-Jimenez, J. J., Chaichana, K. L., Xi, J., Campos-Delgado, D. U., Rodriguez, F. J., Quinones-Hinojosa, A., Li, X., & Jo, J. A. (2019). Ai-assisted in situ detection of human glioma infiltration using a novel computational method for optical coherence tomography. Clinical Cancer Research, 25(21), 6329–6338. https://doi.org/10.1158/1078-0432.ccr-19-0854

Kansagara, D., Englander, H., Salanitro, A., Kagen, D., Theobald, C., Freeman, M., & Kripalani, S. (2011). Risk prediction models for hospital readmission. JAMA, 306(15), 1688. https://doi.org/10.1001/jama.2011.1515

Kevin Fiscella, M. D. (2000, May 17). Inequality in Quality. JAMA. Retrieved February 17, 2023, from https://jamanetwork.com/journals/jama/article-abstract/192714

Kocher, R., & Sahni, N. R. (2011). Rethinking health care labor. New England Journal of Medicine, 365(15), 1370–1372. https://doi.org/10.1056/nejmp1109649

Lang, M., & Zawati, M. H. (2018). The app will see you now: Mobile Health, diagnosis, and the practice of Medicine in Quebec and Ontario. Journal of Law and the Biosciences, 5(1), 142–173. https://doi.org/10.1093/jlb/lsy004

Liang, H.-F., Wu, K.-M., Weng, C.-H., & Hsieh, H.-W. (2019). Nurses' views on the potential use of robots in the pediatric unit. Journal of Pediatric Nursing, 47. https://doi.org/10.1016/j.pedn.2019.04.027

Macrae, C. (2019). Governing the safety of Artificial Intelligence in Healthcare. BMJ Quality & Safety, 28(6), 495–498. https://doi.org/10.1136/bmjqs-2019-009484

Malik, M. B., Ganie, S. M., & Arif, T. (2022). Machine learning techniques in Healthcare Informatics: Showcasing prediction of type 2 diabetes mellitus disease using lifestyle data. Predictive Modeling in Biomedical Data Mining and Analysis, 295–311. https://doi.org/10.1016/b978-0-323-99864-2.00001-9

Memon, M. H., Li, J. P., Haq, A. U., Memon, M. H., & Zhou, W. (2019). Breast cancer detection in the IOT health environment using modified recursive feature selection. Wireless Communications and Mobile Computing, 2019, 1–19. https://doi.org/10.1155/2019/5176705

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: The Prisma statement. PLoS Medicine, 6(7). https://doi.org/10.1371/journal.pmed.1000097

Mohsen, A., Tripathi, L. P., & Mizuguchi, K. (2021). Deep learning prediction of adverse drug reactions in drug discovery using open TG–gates and FAERS databases. Frontiers in Drug Discovery, 1. https://doi.org/10.3389/fddsv.2021.768792

Panch, T., Szolovits, P., & Atun, R. (2018). Artificial Intelligence, Machine Learning and Health Systems. Journal of Global Health, 8(2). https://doi.org/10.7189/jogh.08.020303

Park, Y. R. (2021). Adverse drug reaction analysis using statistical and Machine Learning Methods: A systematic review (preprint). https://doi.org/10.2196/preprints.28214

Pepito, J. A., & Locsin, R. (2019). Can nurses remain relevant in a technologically advanced future? International Journal of Nursing Sciences, 6(1), 106–110. https://doi.org/10.1016/j.ijnss.2018.09.013

Pesapane, F., Volonté, C., Codari, M., & Sardanelli, F. (2018). Artificial Intelligence as a medical device in radiology: Ethical and regulatory issues in Europe and the United States. Insights into Imaging, 9(5), 745–753. https://doi.org/10.1007/s13244-018-0645-y

Pivovarov, R., Perotte, A. J., Grave, E., Angiolillo, J., Wiggins, C. H., & Elhadad, N. (2015). Learning probabilistic phenotypes from heterogeneous EHR Data. Journal of Biomedical Informatics, 58, 156–165. https://doi.org/10.1016/j.jbi.2015.10.001

Purushotham, S., Meng, C., Che, Z., & Liu, Y. (2018). Benchmarking deep learning models on large healthcare datasets. Journal of Biomedical Informatics, 83, 112–134. https://doi.org/10.1016/j.jbi.2018.04.007

Ravaghi, H., Alidoost, S., Mannion, R., & Bélorgeot, V. D. (2020). Models and methods for determining the optimal number of beds in hospitals and regions: A systematic scoping review. BMC Health Services Research, 20(1). https://doi.org/10.1186/s12913-020-5023-z

Razavian, N., Blecker, S., Schmidt, A. M., Smith-McLallen, A., Nigam, S., & Sontag, D. (2015). Population-level prediction of type 2 diabetes from claims data and analysis of risk factors. Big Data, 3(4), 277–287. https://doi.org/10.1089/big.2015.0020

Reeves, R. M., Hardelid, P., Panagiotopoulos, N., Minaji, M., Warburton, F., & Pebody, R. (2019). Burden of hospital admissions caused by respiratory syncytial virus (RSV) in infants in England: A data linkage modelling study. Journal of Infection, 78(6), 468–475. https://doi.org/10.1016/j.jinf.2019.02.012

Ricciardi, C., Ponsiglione, A. M., Scala, A., Borrelli, A., Misasi, M., Romano, G., Russo, G., Triassi, M., & Improta, G. (2022). Machine learning and regression analysis to model the length of hospital stay in patients with femur fracture. Bioengineering, 9(4), 172. https://doi.org/10.3390/bioengineering9040172

Roderick, O., Marko, N., Sanchez, D., & Aryasomajula, A. (2016). Data Analysis and machine learning effort in Healthcare. Internet of Things and Data Analytics Handbook, 295–328. https://doi.org/10.1002/9781119173601.ch18

Rozenblum, R., Rodriguez-Monguio, R., Volk, L. A., Forsythe, K. J., Myers, S., McGurrin, M., Williams, D. H., Bates, D. W., Schiff, G., & Seoane-Vazquez, E. (2020). Using a machine learning system to identify and prevent medication prescribing errors: A clinical and cost analysis evaluation. The Joint Commission Journal on Quality and Patient Safety, 46(1), 3–10. https://doi.org/10.1016/j.jcjq.2019.09.008

S, V., S, S., H, V., & S, S. (2018). Disease prediction using machine learning over Big Data. Computer Science & Engineering: An International Journal, 8(1), 01–08. https://doi.org/10.5121/cseij.2018.8101

Saleem, T. J., & Chishti, M. A. (2020). Exploring the applications of machine learning in Healthcare. International Journal of Sensors, Wireless Communications and Control, 10(4), 458–472. https://doi.org/10.2174/2210327910666191220103417

Sendak, M. P., D’Arcy, J., Kashyap, S., Gao, M., Nichols, M., Corey, K., Ratliff, W., & Balu, S. (2020, February 4). A path for translation of machine learning products into healthcare delivery. European Medical Journal. Retrieved February 16, 2023, from https://www.emjreviews.com/innovations/article/a-path-for-translation-of-machine-learning-products-into-healthcare-delivery/

Shanmugam, R. (2022). Causal inference. Journal of Statistical Computation and Simulation, 93(2), 324–324. https://doi.org/10.1080/00949655.2022.2096232

Siddique, S., & Chow, J. C. (2021). Machine learning in Healthcare Communication. Encyclopedia, 1(1), 220–239. https://doi.org/10.3390/encyclopedia1010021

Topol, E. J. (2019). High-performance medicine: The convergence of human and Artificial Intelligence. Nature Medicine, 25(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7

Tschandl, P., Rosendahl, C., Akay, B. N., Argenziano, G., Blum, A., Braun, R. P., Cabo, H., Gourhant, J.-Y., Kreusch, J., Lallas, A., Lapins, J., Marghoob, A., Menzies, S., Neuber, N. M., Paoli, J., Rabinovitz, H. S., Rinner, C., Scope, A., Soyer, H. P., … Kittler, H. (2019). Expert-level diagnosis of nonpigmented skin cancer by combined convolutional Neural Networks. JAMA Dermatology, 155(1), 58. https://doi.org/10.1001/jamadermatol.2018.4378

Tucker, A., Wang, Z., Rotalinti, Y., & Myles, P. (2020). Generating high-fidelity synthetic patient data for Assessing Machine Learning Healthcare Software. Npj Digital Medicine, 3(1). https://doi.org/10.1038/s41746-020-00353-9

Ullah, R., Khan, S., Chaudhary, I. I., Shahzad, S., Ali, H., & Bilal, M. (2020). Cost effective and efficient screening of tuberculosis disease with Raman spectroscopy and machine learning algorithms. Photodiagnosis and Photodynamic Therapy, 32, 101963. https://doi.org/10.1016/j.pdpdt.2020.101963

Université de Montréal / Research. Montreal Declaration for a Responsible Development of Artificial Intelligence - La recherche - Université de Montréal. (n.d.). Retrieved February 17, 2023, from https://recherche.umontreal.ca/english/strategic-initiatives/montreal-declaration-for-a-responsible-ai/

Vyas, S., Gupta, M., & Yadav, R. (2019). Converging blockchain and machine learning for Healthcare. 2019 Amity International Conference on Artificial Intelligence (AICAI). https://doi.org/10.1109/aicai.2019.8701230

Wainberg, M., Merico, D., Delong, A., & Frey, B. J. (2018). Deep learning in biomedicine. Nature Biotechnology, 36(9), 829–838. https://doi.org/10.1038/nbt.4233

Waring, J., Lindvall, C., & Umeton, R. (2020). Automated machine learning: Review of the state-of-the-art and opportunities for Healthcare. Artificial Intelligence in Medicine, 104, 101822. https://doi.org/10.1016/j.artmed.2020.101822

Weber, G. M., Mandl, K. D., & Kohane, I. S. (2014). Finding the missing link for big biomedical data. JAMA. https://doi.org/10.1001/jama.2014.4228

Wojcieszak, D. (2022). How will state medical boards handle cases involving disclosure and apology for medical errors? Journal of Patient Safety and Risk Management, 27(1), 15–20. https://doi.org/10.1177/25160435211070096

Yang, C. C. (2022). Explainable artificial intelligence for predictive modeling in Healthcare. Journal of Healthcare Informatics Research, 6(2), 228–239. https://doi.org/10.1007/s41666-022-00114-1

Yu, K.-H., Beam, A. L., & Kohane, I. S. (2018). Artificial Intelligence in Healthcare. Nature Biomedical Engineering, 2(10), 719–731. https://doi.org/10.1038/s41551-018-0305-z

Zawati, M., & Lang, M. (2020). What's in the box?: Uncertain accountability of machine learning applications in Healthcare. The American Journal of Bioethics, 20(11), 37–40. https://doi.org/10.1080/15265161.2020.1820105