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How can AI-powered tools like Ubenwa improve neonatal care by enabling early detection of life-threatening conditions such as birth asphyxia?

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List of Acronyms

Acronym	**Full Term**
AI	Artificial Intelligence
APGAR	Appearance, Pulse, Grimace, Activity, Respiration
AUC	Area Under the Curve
BERT	Bidirectional Encoder Representations from Transformers
BI	Business Intelligence
CDC	Centers for Disease Control and Prevention
CDSS	Clinical Decision Support System
CNN	Convolutional Neural Network
CT	Computed Tomography
DDDM	Data-Driven Decision Making
DESA	Data Extraction and Semantic Analysis
DL	Deep Learning
ECG	Electrocardiogram
EHR	Electronic Health Record
EMR	Electronic Medical Record
ESA	Embedding-based Semantic Analysis
GDPR	General Data Protection Regulation
GPT	Generative Pre-trained Transformer
HIPAA	Health Insurance Portability and Accountability Act
ID	Identifier
IRB	Institutional Review Board
IT	Information Technology
LLM	Large Language Model
LSTM	Long Short-Term Memory
MFCC	Mel Frequency Cepstral Coefficients
ML	Machine Learning
MRI	Magnetic Resonance Imaging

MUHC	McGill University Health Centre
NER	Named Entity Recognition
NLP	Natural Language Processing
OCR	Optical Character Recognition
RADS	Radiology Reporting and Data System
RL	Reinforcement Learning
ROC	Receiver Operating Characteristic
RPA	Robotic Process Automation
SCP	Supervised Contrastive Pre-training
SF	Supervised Fine-tuning
SVM	Support Vector Machine
UAR	Unweighted Average Recall
UMR	University Medical Research
UN	United Nations
UPTH	University of Port Harcourt Teaching Hospital
US	Ultrasound
XAI	Explainable Artificial Intelligence

Greetings

First of all, I would like to express my deep gratitude to my dissertation supervisor, Professor Lorenza Morandini, for her guidance, patience, constant availability, and invaluable advice that guided my thinking throughout this research. Her guidance and unwavering support were invaluable and greatly contributed to the completion of this project. I also thank Professor Paolo Spagnoletti, my thesis co-supervisor, for his support and guidance. I also thank all the professors in the Master's in Data Science and Management at Libera Università Internazionale degli Studi Sociali "Guido Carli." Their outstanding teaching, passion for their specific fields, unwavering commitment, as well as the knowledge and inspiration they have shared, have greatly enriched my student life throughout these studies.

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Introduction

Technological advances and increased demand for effective patient-centered care are revolutionizing the health sector. Hospitals face increasing pressure to maximize resource management, streamline operations and improve patient outcomes, with further pressure from rising costs, an aging population, and increased demand for customized services. The UN Department for Economic and Social Affairs (DESA) projects the global population aged 60 years and older will increase by 72% in the next 25 years, from 1.22 billion in 2025, to 2.11 billion in 2050 (UN DESA, 2025), which equates to significantly more demand for healthcare resources. This trend indicates an urgent need to develop new models to limit healthcare costs, without affecting patient care. The Centers for Disease Control and Prevention (CDC) reported that chronic diseases account for approximately 75% of total healthcare spending in the United States (Prabhod, 2024)[1]. Traditional hospital management systems are important, but they have significantly more difficulty adjusting to growing demand created by disparate data collections, wasteful processes, and inefficient, less predictive systems. This situation has created an interest in exploring alternatives, and AI has emerged as a significantly transformative development. Traditional hospital management systems have difficulty managing resources efficiently, streamlining their operations for efficiency, and offering patients personalized care. This validates inefficient organisation, increased cost and the risk of diminishing patient outcomes. The limitations of managing this amount of data, real time patient level metrics and maintaining bespoke personalization have become unmistakable, creating a need for alternatives [2](Dangi, Sharma, & Vageriya, 2024). The aim of this research is significant in that it will seek to understand how AI can contribute to addressing these issues with data driven insights, automated management tasks and customized care.

The typical aim of this thesis is to critically evaluate the possible options to use AI to refine hospital management with respect to patient care, effectiveness, efficiency and ethical considerations;

[1] Prabhod, K. J. (2024). The role of artificial intelligence in reducing healthcare costs and improving operational efficiency. *Quarterly Journal of Emerging Technologies and Innovations*.

[2] Dangi, R. R., Sharma, A., & Vageriya, V. (2024). Transforming Healthcare in Low-Resource Settings With Artificial Intelligence: Recent Developments and Outcomes. *Public Health Nursing*, *0*, 1–14. https://doi.org/10.1111/phn.13500

whilst producing a framework for the transparent and appropriate use of AI in health. The typical aim leads into discrete objectives, which are:

-Review the effectiveness of AI developments in hospital management systems: determine what parts of AI and processes have already been integrated through administrative processes, clinical uses and patient engagement and the relative advantages and disadvantages of these automated processes;

-Compare the pathways of AI driven processes and traditional pathways: assess the cost, impacts and accuracy of AI based processes in terms of a hospital environment and their relationship to patient care, compared to accepted methods of care, and comparative patient outcomes;

-Research the practical challenges of implementation of AI: Research the logistics around the adoption of AI in a hospital environment, including barriers to meaning changing, the trustworthiness of data, and the competency or capacity to recruit professionals with sufficient knowledge to implement AI, and provide recommendations to mitigate these challenges;

-Design a framework to assess the implementation of AI in the hospital environment: provide actionable advice for the ethical, efficient, and timely deployment into hospital management contexts and in patient care services that consider ethical dilemmas, safeguards for data, and equitable location of such improved services;

This thesis will argue that as much as artificial intelligence is an opportunity to improve administration of hospitals and care for patients, any beneficial and ethical employment, depends on thorough comparative analysis with existing processes, careful scrutiny around the implementation of opportunities and limitations, and a plan of attack for respond to ethical dilemmas, safeguarding data, and equitable location of improved services. The thesis will consider core areas of hospital management: administrative processes, clinical work flows, data driven judgements about the management of services, and how patients might engage in that work. The above will include a comparison of both AI applications and traditional enablers.

Literature Review

Academic literature on artificial intelligence (AI) identifies that AI technology has the potential to disrupt a wide variety of fields in healthcare. Predictive analytics via AI algorithms have the opportunity to track historical patient information and look for patterns, as well as predict clinical outcomes; allowing the health care provider to take action before an intervention within a system resulted in hospitalization and possible significant cost (Prabhod, 2024). For example, regression models and decision trees are machine learning methods that can predict patient measures based on derived and considered background demographic variables.

Dangi, Sharma, and Vageriya (2024) demonstrate the opportunity with AI enabled Robotic Process Automation (RPA) application. In their work, RPA could automate some or all of the billing, coding, and claims disciplines; thus resulting in administrative efficiencies. RPA can result in operational efficiencies and staff time efficiencies while reducing unnecessary errors of a manual process. AI enabled frameworks for improvements to workflows represent a significant opportunity for administrative efficiencies, while also supporting engagement outcomes that improve patient engagement and satisfaction. The evolution of machine learning algorithms develops and updates using the complexity of data for interpreting clinical information with the goal of improving clinical decision-making efficiencies. The evolution of natural language processing (NLP) provides a mechanism for provider and patient engagement by offering chat bots and more recently virtual assistants. As articulated by Dangi, Sharma, and Vageriya (2024), these changes enable engagement of care with patients through a personal touch, while providing continuous monitoring of health events. The authors underscored, in addition to these ethical considerations, data privacy, algorithm bias and accountability as important issues that must be addressed for the safe adoption of AI. Additionally, data quality, data availability, and interoperability remain significant barriers for meaningful AI implementation in hospitals and health systems.

Charles C. Onu, Jonathan Lebensold, William L. Hamilton, and Doina Precup (2020) describe the high level of infant morbidity and mortality worldwide, despite medical advances, with an estimated six million + deaths each year. The authors focus their efforts on predicting pathologies caused to newborns through the analysis of cries. Such methods could eventually lead to cheap and readily available diagnostic methods, however, advancing it is hindered by the lack of annotated clinical data concerning infant's cries. They explore using a neural transfer learning approach to build robust and accurate models that can identify infants with perinatally asphyxiated history. The authors hypothesize that the representations learned from adult speech will improve the model's performance when applied to infant cries. The experiments implemented show that the models based on representations transfer are more robust with several types and levels of noise and signal loss in the time and frequency domains compared to standard machine learning methods. Specifically, the authors compare three source tasks for pre-training neural networks (Speaker ID, Gender Classification, and Word Recognition) and find that the model pre-trained on the Word Recognition task achieves the best performance for detecting perinatal asphyxia, achieving unweighted average recall (UMR) of 86.5%. Additionally, all of the neural models tested are more robust to noise than the traditional SVM model, underscoring the benefit of transfer learning for this type of medical task in situations where data is sparse.

Forouzanfar and Varnosfaderani (2024)[3] provided an overview of AI implementation in the healthcare context, referring to its ability to tackle, health care expenses increasing, barriers to care access, and increasing demand for personalized care. The authors big picture framing is centered on potential AI solutions with respect to how algorithms support clinical decision making, whereby huge clinical decisions are required to scrutinize a ton of information to provide patterns and relationships a person would not experience with a manual examination of data. In particular, they mentioned AI applications in:

Clinical Decision Making: AI algorithms are being developed to support clinical management and disease diagnosis by providing insights into patient data for more accurate diagnosis and data management. The authors reference the example of oncology, where algorithms sift through genetics and radiographic results, which provide the capability for recognizing cancer earlier, and cardiology, where algorithm models provided insights for heart attacks and strokes via ECG rhythm models.

[3] Forouzanfar, M., & Varnosfaderani, S. M. (2024). The Role of AI in Hospitals and Clinics: Transforming Healthcare in the 21st Century. *Bioengineering*, *11*(4), 337. https://doi.org/10.3390/bioengineering11040337

Hospital Operations and Management: AI supports the decision-making process which enhance a hospitals operational side providing efficiencies in the areas of administrative tasks, logistics, and scheduling decisions.

Medical Imaging and Diagnostics: AI provides quality control recommendations for radiology and pathology by improving diagnostics speed and accuracy of imaging.

Patient Care and Monitoring: AI supports patients to provide remote monitoring options, telemedicine software, and virtual care options; all influencing the patient-physician relationship over time.

The authors also outline ethical considerations in the health sector related to the use of AI, such as data privacy, bias, and security, which is critical in any ethical application of AI. They also call for an interdisciplinary discussion among researchers, clinicians, and technologist to be able to informatively foster the complexities of AI implementation and to develop AI options based on ethical principles, equity and patient first principles.

Definition of key terms:

- **Artificial Intelligence (AI):**

Artificial Intelligence is a process that is based on the use of Machine Learning, Deep Learning, Natural Language Processing, and many other technologies to create artificial intelligence models that can perform high-level calculations and solve complex tasks. Artificial Intelligence is disrupting healthcare organizations through the use of cognitive technology to process an abundance of medical records and conduct sophisticated diagnosis[4].

[4] Edureka. (n.d.). *Artificial intelligence in healthcare*. Retrieved February 23, 2025, from https://www.edureka.co/blog/artificial-intelligence-in-healthcare/

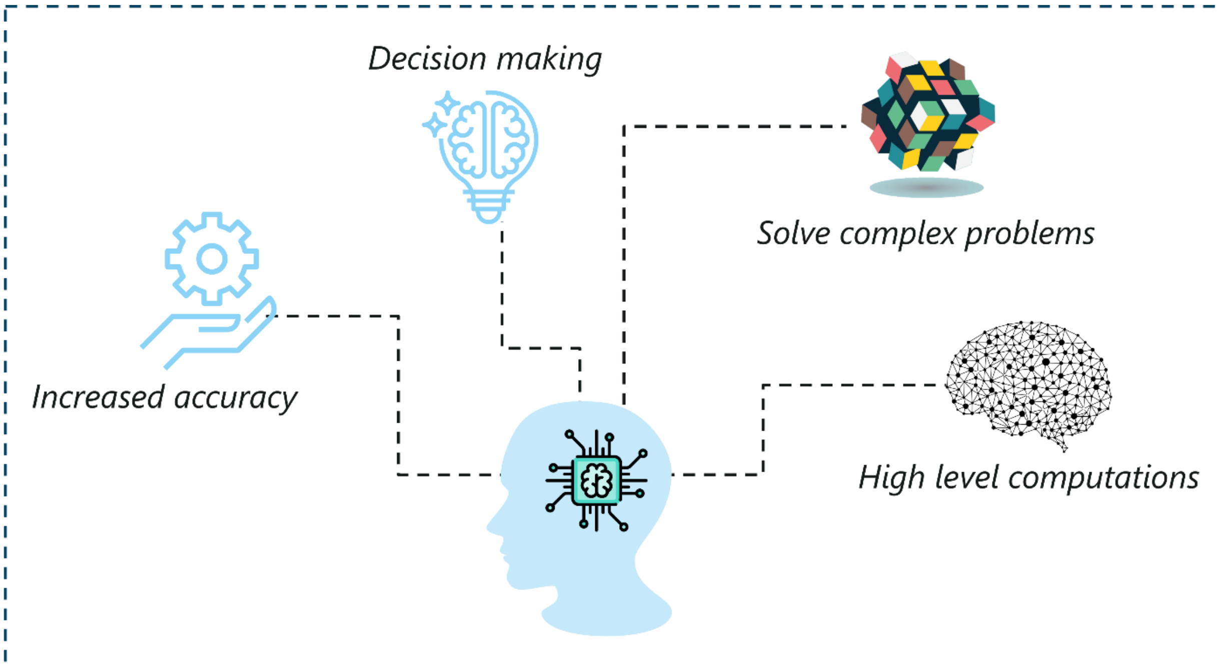

Figure 1. Artificial Intelligence In Healthcare – Edureka

- **Traditional Practices**

Traditional hospital administration and healthcare practices refer to the known, established practices and systems that were traditionally used in the management of hospital operations or the provision of patient care and clinical decision support. These practices will most likely depend on human judgment, hand-medicated processes and may or may not include non-artificial intelligence technologies.

- **Machine Learning (ML)**

Machine Learning (ML) is a subset of artificial intelligence to enable computer systems to learn and make decisions based on data without human involvement. ML is a vital aspect of predictive analytics as by analyzing the patient data ML is able to forecast the outcome, ambulation, and assist in clinical decision-making, through this there is an early detection, individualized treatment, and accurate resource management resulting in enhanced patient care (Dangi, Sharma, & Vageriya, 2024, pp. 3).

- **Deep Learning (DL)**

Deep Learning (DL) is a subset of machine learning (ML) which relies on neural networks with multiple layers to process information and learn from large amounts of electronic data. It allows for self-sufficient patterns learning systems and provides a way for systems to give meaning to the data in an intelligent fashion. DL is especially important in health care because it works with complex medical data such as images, genomes, and also electronic health records. DL programs can identify unique shapes and patterns which are almost too complicated for standard processes or humans to recognize (Sarker, 2021; Li & al., 2023).

- **Clinical Operations**

Clinical Operations is a compilation of several processes, activities, and systems that are associated with providing care to patients in medical facilities or organizations (i.e. clinics, hospitals, etc.). The operations comprise tasks such as diagnosis, treatment planning, patient tracking, and any other clinical operational tasks for the role of the clinical practitioner to adhere to good effective and accurate care. Clinical operations depend on clinical practitioners professionalism, standardized protocols, and systematic care of patients in typical practice.

- **Natural Language Processing (NLP)**

Natural Language Processing is a branch of Artificial Intelligence focused on the interaction of humans and computers through natural language. NLP is comprised of understanding, interpreting, and generating human language. NLP exploits a wide range of approaches to abate text, sentiment, speech, and translation machine processes[5].

- **Computer vision**

Computer vision allows machines to see visible information and act accordingly. Computer Vision is rooted in visual information, which links the gap between virtual space and the physical worlds.

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[5] Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., Aldairem, A., Alrashed, M., Bin Saleh, K., Badreldin, H. A., Al Yami, M. S., Al Harbi, S., & Albekairy, A. M. (2023). Revolutionizing healthcare: The role of artificial intelligence in clinical practice. *BMC Medical Education, 23*(689). https://doi.org/10.1186/s12909-023-04698-z
Olaoye, G., Joseph, S. B., & Kayode, S. (2023). *The symbiotic relationship: Exploring the intersection of artificial intelligence and human intelligence*. Retrieved February 27, 2025, from https://www.researchgate.net/publication/376310105_The_Symbiotic_Relationship_Exploring_the_Intersection_of_Artificial_Intelligence_and_Human_Intelligence

The Applications of computer vision is used in facial recognition, object recognition, driver-less cars, and medical image analysis.

- **Data-Driven Decision-Making (DDDM)**

Data-driven decision-making (DDDM) is the framework describing a systematic way of data usage when making decision-based operational and strategy decisions. A process is to collect and analyze, and interpret data from as many sources making health practitioners make decisions that are empirical and fact-based.

- **Patient Engagement**

Patient engagement refers to actively engaging in healthcare experiences. The action is a two-way communication between healthcare providers and patients with the shared intentions to better quality care, enhance patient satisfaction, and ultimately better clinical outcomes. The key to patient engagement is enabling people to become active participants in decisions about their healthcare through educational actions, communication, and access.

I. Background: Hospital governance and AI

1.The present challenges of hospital governance

In this time, hospital governance requires more than patient care coordination and logistical planning of resources. Hospital leaders are caught up in a complicated system of performance expectations, financial limitations, technology transitions, and patient requirements, all working to navigate operational changes. Healthcare systems are attempting to address combined mounting pressures of patient demands for health services due to the aging population and an increased prevalence of chronic conditions, while feeling compelled to change their operations to achieve timely, equitable, and quality care [6](Bhagat & Kanyal, 2024). These challenges are even more pronounced in some countries in sub-Saharan Africa. There is firstly an infrastructure deficit, secondly a deficit of a well-trained workforce and skilled managers, and finally, a deficit of

[6] Bhagat, S. V., & Kanyal, D. (2024). Navigating the future: The transformative impact of artificial intelligence on hospital management – A comprehensive review. *Cureus, 16*(2), e54518. https://doi.org/10.7759/cureus.54518

available easy to use, integrated digital solutions can inhibit hospital functioning. As Dangi et al. (2024) emphasize, if hospital-related processes (e.g., patient triage upon admission) are not effectively managed, they become a potent bottleneck when in places where there are still few front line health workers given that successful anticipation of patient flows, or the ability to make timely decisions becomes the key determinate of whether the desired objectives are achieved in regard to performance objects.

2. Artificial Intelligence as a Change Catalyst in Healthcare

Artificial intelligence (AI) has quickly emerged as a valuable change catalyst in the innovation ecosystem related to change in the healthcare system. AI facilitates timely, data enabled and predictive capacities for hospitals based on digital things such as machine learning, real-time data analysis, and decision support systems. AI will soon be part of hospitals in providing resources to identify and monitor admissions and patterns, risk stratify patients, and develop adaptable models for resourcing within hospitals (Nieuwhof, 2023). These AI tools are augmenting health professionals, not replacing them, and aimed at achieving improved decision-making and operational efficiency. According to [7]Kaushik et al. (2020), even cheap smart devices are effective. Smart devices that use AI are already being used, particularly in resource limited contexts, since these devices are powerful enough to either denote disease or allow remote monitoring of a patient with limited equipment. Edge AI may now be further away from an hospital setting and fits into health, care or institutional behaviours that are remote and decentralized.

3. Artificial Intelligence for optimizing hospital workflows

Artificial intelligence is also essential for enhancing patient flow and maximizing resource allocation in hospitals. Leading hospitals such as Johns Hopkins Hospital have implemented central command centers that use AI to facilitate coordinating activities related to bed assignment, surgical scheduling, and emergency triaging with workers. According to Bhagat and Kanyal (2024), the introduction of enhanced shared information, faster processing of requests, and decision-making dashboards utilizing real-time information for improved and more responsible

[7] Kaushik, A., & al. (2020). *Electrochemical SARS-CoV-2 Sensing at Point-of-Care and Artificial Intelligence for Intelligent COVID-19 Management*. *Sensors and Actuators B: Chemical*, 329, 129019.

patient flow created shorter patient wait times and enhanced patient experience with patient-centered process standards.

On other ends of the impact spectrum, the Ubenwa application in Nigeria is a high-level example of how AI can augment resource drive decentralized care delivery. Ubenwa uses AI (to listen to and analyses the cry of a newborn) to determine if there are any indicators of birth asphyxia for the newborn from the use of a mobile phone or device. [8] Onu, C. C., Lebensold, J., Hamilton, W. L., & Precup, D. (2020) described the use of Ubenwa in remote and rural communities and health workers using Ubenwa are able to make clinical decisions and judgments without specialist equipment or laboratory-based testing decisions regarding valid and reasonable clinical decisions. While both populations are drastically different in access to resources or technology, there is a collective aim of decision to improve hospital systems to be more accessible, more efficient, and more patient-centered.

In both examples, they illustrate some of the possibilities of ways that AI can extend the management of hospitals, but they do not ignore the challenges and limitations. First, the usefulness of AI in its application to medical technology depends on the data input used for training. In various regions in sub-Saharan Africa, there is not much or any medical data, poorly configured datasets, or policies/practices support inconsistent recording or documented uses of medical data and AI algorithms become unreliable. [9]Nieuwhof (2023) has stated that the most sophisticated algorithm would become biased or non-useful based on bad data; and secondly, knowledge of the acceptance of AI will be variable at best from health care workers. In instances where health care workers perceive AI as invasive or abstract when pushed by policy makers that work in symbols of technology, they will resist AI rather than support AI. Dangi et al. (2024) work suggests that training, transparency of implementation, and working directly with health care professionals in respect to co- developing content with them, will help be the moving factor towards acceptance, and thereby long-term use and trust of health care workers. Thirdly, if a successful implementation of AI is to be enjoyed, there has to be an understanding needs but also of cultural contexts. If AI is meant to be used in a highly developed health care system; often times

[8] Onu, C. C., Lebensold, J., Hamilton, W. L., & Precup, D. (2020). *Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia*. Mila – Québec AI Institute. https://arxiv.org/abs/1906.10199
[9] Nieuwhof, M. P. (2023). *Optimizing AI Implementation in Healthcare: Identifying Effective Management Practices*. Master's Thesis, University of Twente.

the context for use would be deemed not applicable in a more constrained setting, unless there the technology was meant to be flexible to local needs of community. This is illustrated by the use of Ubenwa, as it demonstrated a contextualized, frugal innovation, that had genuine international research impact in medical education, even in the absence of advanced infrastructure to support it. For this realization, there is no doubt that artificial intelligence cannot be hailed as a silver bullet for all hospital systems, it must additionally be seen as a compliment, an adjunct, an extent of support for decision -making, and operational efficiency, and, fair access to care only if done properly and ethically.

II. Applications of AI in Hospital Management

1.The Types of Artificial Intelligence in Healthcare

Machine Learning

Machine Learning (ML) represents a range of algorithms that essentially teach a machine to learn from its prior historical data, with the ability to learn from the data in order to enhance its own performance as it sees fit and without being explicitly programmed to the solution. In general, clinical practice using ML entails developing predictive models that help to characterize patient risk profiles, develop personalized treatments, or automate healthcare workflows. For example, Forouzanfar, M., & Varnosfaderani, S. M. (2024) used ensemble learning models including Random Forest, XGBoost, and AdaBoost on clinical data including biomarkers, demographics, and medical history resulting in an overall prediction accuracy for heart disease of 98.5%, which is substantially higher than traditional diagnostic scores. ML is also often combined with Clinical Decision Support Systems (CDSS) that produce recommendations for physicians using electronic health records (EHRs) and guideline based logic to enable more efficent and evidence based care decisions.

Deep Learning

Deep Learning (DL) is an area of machine learning which has rapidly accelerated advances to healthcare fields. As pointed out by [10]Rong et al. (2020), deep learning is well identified as neural networks which contain many layers called deeper networks that allow for more complex learning processes and a better emulation of human thinking. With the introduction of powerful computing, primarily utilizing graphical processing unit architectures (GPUs), neural networks have advanced us into deeper and better frameworks to which feature extraction and classification are performed as one architecture. It is evident that more functions can be integrated into the neural networks, e.g. incorporating feature extraction and classification in one deep network architecture, hence the name 'deep learning (Rong et al., 2020, p. 292). DL makes it possible for models to learn from the raw data representations from the start to end, and can in essence perform image, speech, or disease prediction and often outperform traditional machine learning for accuracy.

In addition, Maleki Varnosfaderani and Forouzanfar (2024) highlight how DL is intriguing in being able to process a large volume of unstructured data, and heterogeneous data. DL can extract and process from a large volume of unstructured data, including medical images, electronic health records and sensor data to further capacity from wearable devices that will not be achievable using the traditional methods. Their review indicates that DL has revolutionized the fields of medical imaging, pathology, and genomics taking on automation of feature extraction and recognize patterns as well with one hundred years of speed and scale. They also provide examples of advanced clinical decision support systems, predictive analytics and personalized medicine now using DL models. While DL has healthcare applications, they speak of effective implementation relying on having large sufficiently annotated datasets, and addressing data quality and model interpretability (Maleki Varnosfaderani & Forouzanfar, 2024).

In summary, we see both Rong et al. (2020) and Maleki Varnosfaderani & Forouzanfar (2024) note that deep learning is becoming a formidable technology for use in healthcare, enabling automated analysis and clinical decision making from increasingly complex biomedical data. DL comprises several features of learning from raw data, and the evolution of new data-native computational

[10] Rong, G., Mendez, A., Bou Assi, E., Zhao, B., & Sawan, M. (2020). Artificial Intelligence in Healthcare: Review and Prediction Case Studies. *Engineering, 6*(3), 291–301. https://doi.org/10.1016/j.eng.2019.08.015

hardware has made DL, a premier innovative modality for diagnostics, patient monitoring, and biomedical research.

Natural language processing

[11]Natural Language Processing (NLP) tools and algorithms can extract clinically significant data buried in the massive amount of human-produced textual data that exists in medical records and articles. NLP is utilized for two main functions in the healthcare arena: first is speech recognition which eliminates the work and time associated with clinicians entering (recording) EHR notes, and lastly unstructured data processing, which can offer ease of later interpretation of the information, e.g., by tagging or classifying, and/or extracting multi-level underlying themes and synthesizing the information derived.

NLP relies on five basic techniques:

- Optical Character Recognition (OCR) used to digitize clinical notes, medical records, patient intake forms, etc. that have been handwritten or scanned.
- Named entity recognition (NER) designates named entities into categories e.g., medication, dosage, disease.
- Sentiment analysis identifies text sentiment, whether the sentiment is negative, positive or neutral.
- Text classification: Provides tag associations to different words, phrases, based on predetermined categories.
- Topic modeling: groups documents together by the same word or phrase they all belong to.

[11] Velichko, Y. (2021, December 2). *Types and applications of AI in healthcare*. Postindustria. Retrieved May 7, 2025, from https://postindustria.com/types-and-applications-of-ai-in-healthcare/

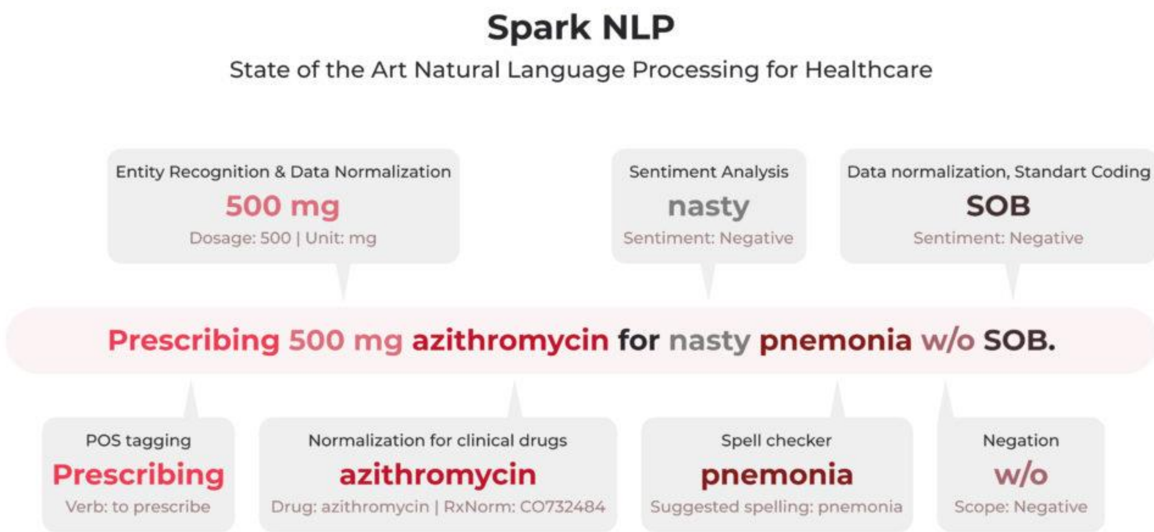

Figure 2. *Example of Spark NLP applications in healthcare (from Velichko, 2021)*

Source: *https://postindustria.com/types-and-applications-of-ai-in-healthcare/*

Natural language processing (NLP) algorithms first extract data from electronic health record (EHR) or medical document. It methodologically processes the data using the multiple techniques (i.e., OCR, NER, and topic modeling), and classifies patients or data into groups and subgroups based on all the data obtained from analysis.

Computer vision

Computer vision is a subsection of Artificial Intelligence, and is actively changing healthcare by giving machine systems the ability to understand visual information like medical images and videos. The most disruptive area is in medical imaging and diagnosis. Computer vision is replacing visual inspections that are labor intensive with a deep learning model or computational algorithms that identify anomalies in computed tomography (CT), magnetic resonance imaging (MRI), and x-ray images. Computer vision has already surpassed these traditional methods of disease identification in earlier and often more accurate patterns such as early cancer detection and segmentation, the diagnosis of diabetic retinopathy and other retinal diseases. In non-medical imaging areas, computer vision and associated concepts have improved point of care systems by enabling patient tracking in hospitals with fall detection, fall detections to monitor mobility, or as part of pain or delirium assessments to increase patient safety while also decreasing clinical workflow and workload demands [12](Lumenalta, 2025). Computer vision has enabled higher standards of surgical guidance with on-demand models and instrument tracking for improved accuracy and patient outcomes. Finally, computer vision can support remote patient monitoring and telehealth by enabling a more standardized and consistent patient assessment than might be done in a face-to-face clinical environment [13](Velichko, 2021). While these advances are underway, there remain general healthcare concerns about the quality of the data, patient privacy, model interpretability, or integration risk with existing healthcare systems. Ethical considerations also need to include patient consent and algorithmic intolerance as these technologies advance responsibly (Lumenalta, 2025). Computer vision is progressing at a rapid pace and continues to enhance healthcare focusing on care delivery, operational effectiveness, and patient outcomes (Lumenalta, 2025; Velichko, 2021).

Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a vital part of artificial intelligence applications in today's healthcare environment, and particularly in the processing and analysis of complex medical imaging. CNNs are a form of deep neural networks that automatically extract hierarchical features from imaging data, removing the human (manual) model and information (features) extraction which are subject to human biases, and also improve efficiency and accuracy. CNNs consist of multiple layers, in addition to many deeper layers of convolutional, pooling, activation, and fully connected layers, that permit the extraction of features with differing levels of abstraction that are utilized in classification, segmentation, and detection tasks in practice. CNNs are being adopted at a growing pace in contemporary medicine across all domains. CNNs have demonstrated outstanding performance in disease detection and classification involving cancers, diabetic retinopathy and other ocular disorders, and lung disorders such as tuberculosis and pneumonia. For instance, CNN-based systems have been successfully utilized in skin disease diagnosis, detection of tuberculosis in sputum smear images, and lung CT image segmentation, generally

[12] Lumenalta. (2025, January 20). 15 computer vision applications in healthcare. Retrieved May 8, 2025, from https://lumenalta.com/insights/15-computer-vision-applications-in-healthcare
[13] Velichko, Y. (2021, December 2). Types and applications of AI in healthcare. Postindustria. Retrieved May 8, 2025, from https://postindustria.com/types-and-applications-of-ai-in-healthcare/

with greater accuracy and efficiency as compared to earlier diagnostic methods [14](Liu, Dai, & Zhou, 2023, pp. 120–124). The benefit of CNNs in health care is the ability to compress and reduce imaging, improving operational functioning and robustness to variances in image quality (e.g. with regards to brightness and orientation). There are still many challenges to the application of CNNs, predominantly around clinical practice, dealing with annotated and non-annotated datasets, including volume, concerns about privacy and data protection, and for the deep learning paradigm, issues regarding interpretability, which must be addressed for the safe and effective application of CNNs within clinical practices. CNNs are a disruptive technology in health care that can make significant gains in accuracy and workflow effectiveness. It can be expected that as CNNs evolve and are increasingly integrated into health systems, along with advances in computing infrastructure and data governance, the impact of CNNs on patient care will grow (Liu et al., 2023).

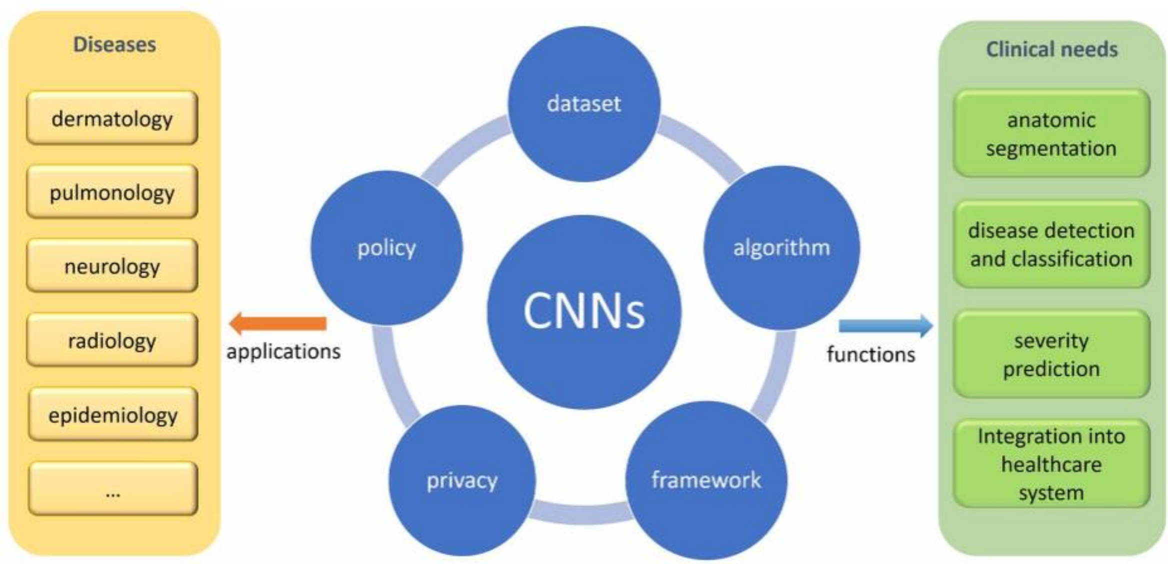

Figure 3. Application fields and functions of CNNs in healthcare (adapted from Liu, Dai, & Zhou, 2023, p. 122)

[14] Liu, H., Dai, L., & Zhou, M. (2023). Recent applications of convolutional neural networks in medical data analysis. In A. Hassan, V. K. Prasad, P. Bhattacharya, P. Dutta, & R. Damaševičiu (Eds.), *Federated Learning and AI for Healthcare 5.0* (Chapter 7). IGI Global. https://pureportal.coventry.ac.uk/files/82342117/Liu2023AAM.pdf

2.Administrative Efficiency

One of the prime applications of artificial intelligence (AI) in the hospital sector is on the administrative side. AI is automating ordinary administrative responsibilities, whether it's scheduling appointments, organizing electronic medical records (EMR), administering billing, or monitoring patient admissions, offering a significant amount of time back to healthcare professionals. According to Bhagat and Kanyal (2024), AI is decreasing wait times, eliminating administrative redundancy and improving patient care utilizing predictive algorithms and accessing information from the hospital's information system. AI is also making it easier for hospital administration to manage patient flows and appointments, with the ability to predict peak demand periods [15](Maleki Varnosfaderani & Forouzanfar, 2024). Billing processes with AI are able to electronically create claims and, therefore, cut and identify errors or discrepancies while providing reductions in any financial losses due to delays in reimbursements. Predictive systems, including epidemiological datasets, and historical data sets, are capable of predicting needs regardless of bed count (equipment, allocations of staff); and, therefore, optimizing reserves in a hospital healthcare department (Maleki Varnosfaderani & Forouzanfar, 2024).

Once natural language processing (NLP) is developed and integrated into the healthcare organizations such as hospitals, it will have the capability of ontology as it extracts key information from unstructured documents (clinical notes) that may be coupled with the recording, data coding, analytics, and distribution of patient data (Shiwlani et al., 2024).

3. Clinical Operations

AI integration into clinical activities as potential to fundamentally increase the diagnostic, predictive, and personalized potential of care. Deep learning models for analysis of medical images using algorithms (e.g. CNN - convolutional neural networks) are frequently being used to assist in medical diagnoses and are increasingly more accurate than the radiologist's interpretation; with notable examples including breast cancer or neurological deficit (Maleki Varnosfaderani & Forouzanfar, 2024). Bhagat & Kanyal (2024) state that AI tools are increasingly being utilized to prioritize medical cases based upon perceived urgency, permitting suitable time management and

[15] Forouzanfar, M., & Varnosfaderani, S. M. (2024). The role of AI in hospitals and clinics: Transforming healthcare in the 21st century. *Bioengineering, 11*(4), 337. https://doi.org/10.3390/bioengineering11040337

triage. In addition, AI models can also recommend patient specific treatments using clinical, genetic and behavioral information. Shiwlani et al. (2024) suggest that AI has the potential for more effective preventive health care, in that analyzing information from multiple sources may help identify patients at greater risk. For instance, LSTM networks (long short-term memory) could monitor physiological signals continuously for signs of clinical deterioration. In pharmaceuticals research, AlphaFold, generative adversarial networks (GANs), etc., are at hand to inform various phases of drug discovery by simulating a molecule's tendencies. In addition, intelligent systems to support surgical settings will capably provide a high fidelity of surgical actions by managing adverse post-operative events (Shiwlani et al., 2024).

4. Patient Engagement

AI is also shifting the patient-hospital relationship by improving personalization of services. Technologies such as medical chatbots and virtual assistants usually based on models like GPT or BERT, support patients by answering questions for patients, leading patients through the care process, and/or reminding patients about medications and appointments (Maleki Varnosfaderani & Forouzanfar, 2024). Dangi et al. (2024) note the importance AI represents through telemedicine and remote monitoring, where connected devices remain engaged to collect real-time data (heart rate, temperature, sleep), subsequently analyzed in predictive models to detect early signs of complications. As Shiwlani et al. (2024) indicate, this model is an act of preventative healthcare, providing an ongoing connection between the hospital and the patient, while the patient remains at home, which avoids unnecessary admissions. In a smart-healthcare model, AI employs data from multiple data sources, electronic medical records (EMRs), wearable devices, and patient-reported outcomes, to derive an evolving, holistic perspective of the patient's health status. This personalization is increasing perceived quality of care, improving patient trust, and fostering greater participatory and preventative medicine approaches.

While potential applications of artificial intelligence within hospital-based contexts appear impressive regarding advancements in performance, quality of care, and patient experience, this remains an uphill battle. First, the ultimate effective use of technologies, depends on the quality of the data available, the breadth of application, and the transferability of that data. Algorithms developed from a limited data source, can produce biased data, that offer unreasonable suggestions for subsequent clinical decision-making processes. Second, with the increasing automation of clinical or administrative tasks, there remains the concern for the de-skilling of health care professionals. Artificial intelligence can promote perfection and precision, but will not replicate clinical intuition, decision making, or clinician-patient relationships. Further to this, that technology can be incorporated into hospitals where there are already macro and micro-staffing and funding issues, the organization must now commit and develop change management strategies. Dangi et al. (2024) clearly indicates that user acceptance will also be a prerequisite of any successful digital transformation. Last, the ethical ambiguities regarding transparency of algorithms and responsibility for decisions made by AI and availability of patient data privacy, have not even been sufficiently addressed, and signal the need for strong, flexible governance frameworks which will address the ethical boundaries of implementing AI in health care environments. In summary, AI should be considered as indirectly beneficial, and a complementary technology to the existing internal support systems and processes, and, organizations should employ gradual, purposeful, and responsible implementation of AI, as they work with the global complexity of hospital management systems.

III. Optimizing Care Through AI

Artificial intelligence (AI) is becoming known as a paradigm-changer within healthcare, changing how both health practitioners and administrators analyze data, manage patients, and provide care. The infusion of AI into the healthcare sector promotes highly accurate, efficient, and patient-centered care. This section examines three main areas in which AI is enhancing care: data driven decision making, personalized treatment plans, and improvement in patient outcomes.

1. Data-Driven Decision Making

The avalanche of data available to the healthcare sector is expanding exponentially, capturing everything from electronic health records (EHRs), to imaging, and sensor data presents both a challenge and opportunity for the field of medicine.

AI, through the use of machine learning (ML) and deep learning (DL) models, gives healthcare professionals a computational power and analytical sophistication to extract useful information and insights from very large and complex data sets (Rong et al., 2020, p. 291). AI systems can reveal hidden or unexplored patterns, predict patterns based on the data, and make clinical and administrative evidence-based recommendations.

Predictive analytics is one of the best-known applications for AI. Using historical and real time data, AI can forecast patients' desired needs, hospital admissions, and risk for complications or readmissions (Rong et al., 2020, p. 293). For example, AI can help predict compressions during hours of packed emergency departments, select optimal staffing and resources during a surge in emergency department visits, and assist administrators develop a system to manage supplies and inventory, which reduces waste, and ensures necessary supplies are utilized when patient care delivery is needed. As per Maleki Varnosfaderani and Forouzanfar (2024), data-driven methods are a necessary tool for managing a hospital; especially in settings where resources are scarce.

2. Principles of Personalized Treatment Algorithms

AI's ability to integrate and analyze data from various patient types is likely changing the way we introduced personalized treatment algorithms. Previous protocols were based on producing a protocol using existing knowledge; however, systems based on AI can marry an individual patient's characteristics including genetic information, medical history, and lifestyle to develop treatment plans (Rong et al., 2020, p. 291-292). The use of deep learning models exemplifies AI's potential, as it can utilize data from both clinically reviewed images and genomic data to suggest probable outcomes allowing the clinician to select the best therapy best suited for the specific patient while minimizing risks to the patient.

Meanwhile, reinforcement learning (RL) and adaptive ability allow patient progression and patient feedback to intervene treatment choices so that there is continuous improvement in care (Maleki Varnosfaderani & Forouzanfar, 2024). Clinical decision support systems using AI that adapt treatment would now include individualized medication, dosage changes, and behavior based interventions that rely on information from the monitored patient.

3. Enhancement of Patient Outcomes

AI-assisted interventions will be a tool for the purpose of improving patient outcomes; increasing diagnostic accuracy, reducing medical errors, and providing timely interventions are all direct efforts for improvement that AI can effect. AI-assisted diagnostics, which include deep learning models applied to medical imaging, have demonstrated human-level accuracy or better across many disease domains including cancer, cardiovascular, and neurological disease (Rong et al., 2020, p. 292). AI Diagnostic tools aid clinicians in improving diagnostic accuracy and appropriateness, which are the keys to timely diagnosis and intervention that could improve prognosis.

AI assists in enhancing patient safety by interfacing with real-time clinical decision support to provide alerts to potential drug interactions, informing teams of early signs of deterioration in patients' health. Maleki Varnosfaderani & Forouzanfar (2024) report treatment paths that utilize AI have reduced mortality rates, hospital re-admissions, and improved patient satisfaction. Predictive models that help identify high-risk patients for sepsis, or postoperative complications, can lead to earlier intervention which improves survival and recovery rates.

IV. Applications of AI Compared to Traditional Methods

Healthcare systems have traditionally been the foundation of healthcare. These systems often rely on hierarchies, face-to-face consultations, paper-based medical records, and the clinical reasoning of providers for diagnosis, treatment, and coordination [16](FasterCapital, 2024). While traditional systems yield towering gains for public health, there are significant disadvantages that limit their usefulness health systems today that enable patients to access the data, information, and point of care treatment needed in such an environment of data overload and quick change. Traditional systems often rally around hospitals or clinics where care is delivered from person to person face-to-face. Fragmented medical records under one facility (especially when in various departments) and slow interprofessional communication and data transfer create time lags for patients (FasterCapital, 2024; Rong et al., 2020). Decision-making still comes primarily from experience, and although experience could be supported with analytic tools, and real-time monitoring devices, it is often still based on clinicians' opinions or unadapted to completely different patient contexts and scenarios. Inefficiencies and delays created by manual processes might be one of the biggest disadvantages traditional systems, such as administrative management and approval processes that delay patient waiting times or delays in getting a diagnosis or treatment. Access to care can still also have geographic, economic or social factors, particularly in rural or under-served

[16] FasterCapital. (2024). Traditional Healthcare Delivery Systems: Challenges and Opportunities. https://fastercapital.com/topics/traditional-healthcare-delivery-systems.html/1

communities. On top of that, limited integration of EHRs will create continued gaps in patient history and provider reporting, moving more toward the posture of risk than accuracy. In the end, limitations in available human and material resources, as well as a tendency to react, rather than act, for the best applicable healthcare leads to limited quality of care and adverse effects on patient outcomes.

Recognizing these issues, artificial intelligence (AI)-based solutions provide new ways to address them. AI allows integration and analysis of large s heterogeneous data sets, automates repetitive clinical and administrative tasks, and has predictive analytical capabilities to infer patient needs (Rong et al., 2020; Maleki Varnosfaderani & Forouzanfar, 2024). In one example, the application can be used to optimize how staff schedule appointments, automate radiological interpretation of medical images, and monitor patients remotely; thereby providing care more quickly, making the diagnostic process more accurate, and increasing access to care. AI-based systems provide greater efficiency of opportunity by removing delays related to administrative procedures also data analysis, allowing healthcare providers more time and opportunities to focus on clinical care. They improve access to care using telemedicine and automated online triage tools to support patients in remote and isolated settings. The shared data in interoperable electronic records and information transmitted quickly, allows practitioners to see the entire patient in the moment when they need clinical care, allowing better decision-making. Furthermore, AI mitigates problems when populations transition from a very reactive, as well as a completely admiring mentality, to a less reactive and medically proactive approach, with early identification of patients at risk and opportunities for prevention. Finally, AI lends itself to optimized management of institutional resources, given the responsive adjustment of clinical staff, equipment, and patient flows.

Many studies are now demonstrating that AI models can outperform existing approaches on important clinical tasks. A recent study by [17]Cao, Z., Deng, Z., Yang, Z., Ma, J., & Ma, L. (2025) focused on breast cancer screening via mammography, demonstrated that supervised contrastive pre-training (SCP+SF) models performed better than traditional methods. The dual-view SCP+SF model achieved an AUC of 0.9046, with a specificity of 98.41% at fixed sensitivity of 20%, while

[17] Cao, Z., Deng, Z., Yang, Z., Ma, J., & Ma, L. (2025). Supervised contrastive pre-training models for mammography screening. *Journal of Big Data, 12*(24). https://doi.org/10.1186/s40537-025-01075-z

having no errors made on high-risk patients (BI-RADS 4 to 6). When detecting biopsy confirmed malignancy, the model achieved an AUC of 0.9270 with 100% specificity, outperforming other top models including Shen and Yala's models. Moreover, these performance gains are not confined to any specific modality. For instance, Shang et al. (2024) showed an AI-based breast cancer screening tool produced 9.4% fewer false negatives than radiologist assessments. Likewise, Ubenwa's AI solution for detecting neonatal asphyxia through infant cries. As a CNN based solution, Ubenwa is a fast (< 60 seconds), non-invasive and affordable assessment and is ideal for low resource settings. Importantly, Ubenwa can be used for initial triage immediately after childbirth, while traditional Apgar scoring, requires expert clinical observation, and requires a complete hospital environment. By enabling immediate triage, Ubenwa reduces time to diagnosis, and increases the chance of timely intervention.

In this section, we analyzed what traditional systems and AI systems both leveraged for the various critical aspects of healthcare - like clinical decision making, care coordination, diagnostic accuracy, and access to services - in order to compare both paradigms. We think traditional systems are more of a starting point for modern medicine, while the traditional systems do offer a starting point, it's more clear that with the increasing complexity and increasing expectations of healthcare delivery, we will be unable to achieve improved operational effectiveness, diagnostic effectiveness, or improvements to quality in care, with these systems. AI technologies offer a viable option for addressing these limitations.

In summary, while traditional systems have been critical to developing modern medicine, these systems' inadequacies have never been as apparent in the same way, given our previous reliance on these models, current demands, and the ever-increasing complexity of clinical decision-making. AI technology, which allows healthcare systems to operate differently, represents a potential way to avoid these issues, with the evidence of diagnostic accuracy, efficiency of operations, and overall quality of care (Rong et al., 2020; Maleki Varnosfaderani & Forouzanfar, 2024). Nevertheless, owed to our reliance on traditional systems and preparedness skills and behaviours, moving into AI technologies is still going to take considerable amounts of change management, investment in digital infrastructure, and training of these AI-based systems intended to allow people to train constantly, while also moving to the next step of technologies together. Additionally, many ethical questions concerning where the data resides, as well as models and algorithms used, also need to be examined very closely in order to avoid systems that promote oppression, discrimination, and non-fair medical practices powered by AI solutions. A hybrid approach, which utilizes traditional clinical judgement alongside AI's administrative functions, may be the most realistic view of an intelligent, equitable, and human-centered, future healthcare system.

To support the comparative analysis, the following table summarizes the performance indicators from academic studies that quantify the differences between traditional methods and AI-based systems for the characteristics of digestibility, operational efficiency, cost-effectiveness, and responsiveness. The Ubenwa study is also cited as an example of an AI system applied to neonatal care.

Comparison of AI-Based vs. Traditional Methods in Clinical Practice

Metric	Traditional Methods	AI-Based Systems	Source
Diagnostic Accuracy (AUC)	0.8452 – 0.8946	Up to 0.9270 (SCP+SF)	Cao, Z., Deng, Z., Yang, Z., Ma, J., & Ma, L. (2025)
Breast Cancer Specificity	87–95%	98.41% (anomalous) / 100% (malignant)	Cao, Z., Deng, Z., Yang, Z., Ma, J., & Ma, L. (2025)
Neonatal Asphyxia Detection Time	2–3 min (Apgar, manual)	< 60 seconds, automated	Onu, C. C., Lebensold, J., Hamilton, W. L., & Precup, D. (2020).
MRI No-Show Rate	19.3%	Reduced to 15.9% with AI scheduling	Maleki Varnosfaderani & Forouzanfar, 2024
Oncology Operational Costs	No automation	15–40% reduction via AI planning	
Lung Nodule Early Detection	Up to 46 days delay	Detected in 8 days with AI	Dangi & al., 2024
Pneumonia Specificity (X-Ray)	73%	Sensitivity: 96%, Specificity: 64%	Alowais & al., 2023

Note: AUC is an abbreviation for Area Under the Curve, a measure used to evaluate the predictive performance of classification models, typically portrayed as Area Under the Receiver Operating Characteristics Curve (AUC-ROC). An AUC closer to 1 indicates better model performance; an AUC of 0.5 indicates no better performance than random guessing.

These numbers clearly demonstrate the function and clinical advantages to using AI technologies in health care environments. Although traditional systems play an essential role, AI-based approaches have some opportunity to provide more functionality, reduce inequities in care, and respond more quickly to patient needs.

V. Challenges, Limitations, and Ethical Considerations

While AI offers a significant opportunity for changing hospital administration, it also has a complicated set of challenges and constraints. Hospitals, if they are going to use AI for its benefits to patient care and operations, need to overcome technical issues, address human and organizational resistance, understand the limitations of AI algorithms, respond to complex ethical issues, and identify suitable practices for responsible integration. This section will consider each of these factors in turn. This will be accomplished drawing on the information we received from current literature and the questions posed for this research.

1. Technical and Infrastructural Challenges

The implementation of AI in hospital contexts requires a sound technology infrastructure and quality data neither of which are strengths for many healthcare organizations. One of the primary challenges is the absence of suitable infrastructures to support sophisticated AI systems, particularly in resource-poor contexts. For example, hospitals in poorer contexts, are frequently lacking even basic IT infrastructure, reliable internet, or computational capacity making the deployment of AI challenging. There are many limitations, particularly in some sub-Saharan Africa hospitals, which experience a infrastructure deficit and lack of integrated digital systems, thereby limiting hospitals' ability to operate efficiently. Even in the best hospitals, the integration of AI into legacy hospital information systems presents a considerable challenge; existing Electronic Health Record (EHR) systems and hospital databases do not interface well with new AI tools making AI integration problematic (Velichko, 2021). Velichko (2021) has pointed out that the issue of interoperability between AI and hospital IT systems remains a significant technical barrier, whereby disparate data ecosystems challenge effective AI implementation, since data that could be needed may not be available. Closely related is the issue of data quality and availability. AI algorithms depend on ordered data that is predominantly both large, diverse, and representative. In practice, hospital data are typically siloed, incomplete, or poorly ordered restricting both the scope and validity of available data that can be used to train AI (Dangi et al., 2024). Dangi, Sharma, and Vageriya (2024) describe data availability and interoperability as substantial challenges for successful AI deployment in hospitals, and lament that a key problem in hospitals is siloed databases and a lack of standards regarding data quality, which restrict AI systems' access to developed knowledge. Often, historical health records contain errors or omissions, or different departments might record data in systems with incompatible formats, compromising the impact AI could have. In some contexts, there are simply poor amounts of digital data; Maleki Varnosfaderani and Forouzanfar (2024), discussed how data-driven practices are critical for a hospital to be better managed, but that under-resourced contexts often do not have enough patient data, yielding unreliable outputs of the algorithms. As a result, this poor or shallow data quality or access can lead to various unpredictable biases and performances of AI models, as algorithms trained on data that are incomplete and/or limited can have biased outputs. Indeed, access to the amount of health data needed for AI is often hindered by fragmentation of the data in systems incompatible with each other. [18]Chustecki (2024) described how relevant data are often in many different places, and hospitals may be averse to sharing access to other institutions, thus limiting the continuance of having data on which to build on the AI training. Hence, the fragmentation of data supports the need for much better data integration as a part of data infrastructure development.

A further barrier from an infrastructure point of view is the need for the computing power. Training and deploying AI (deep learning models especially) requires considerable computing power, which necessitates better hardware (GPUs, and servers) and software optimizations. Hospitals much invest into this type of technology, but then have to sustain the technology as well which can lead to greater expenses than predicted. As Rong et al. (2020), stated, since the inception of AI, the rate of development has been rapid as there have been improvements in computational power (hardware), and algorithms. However, not every healthcare organization has adopted those

[18] Chustecki, M. (2024). Benefits and Risks of AI in Health Care: Narrative Review. Interactive Journal of Medical Research, 13(1), e53616. DOI: 10.2196/53616

advanced resources (Rong et al., 2020). That disparity is leading to a situation where only well-resourced hospitals can take advantage of AI, and risk widening health inequalities.

A final somewhat nebulous technical challenge is access to expertise and assistance. AI systems are not plug and play solutions; require continuous, ongoing maintenance, updates and monitoring and tuning, by technically skilled people (data scientists, other IT trained people). Hospitals, especially smaller ones, do not have their own technical skills, they depend on external vendors and/or consultants. Even if the AI pilot project was successful at the outset, the AI solution will not remain in a state of sustainability without long-term support. In essence, addressing these technical and infrastructural challenges whether it requires upgrades of hardware and software or quality of data or how interoperability works must happen before AI implementations can even happen and be sustainable. There is potential for technology to fail; however, the technology cannot be any more effective than what is possible from a human perspective, which is why the human and organization side is equally as important.

2. Human and Organizational Resistance

The integration of AI into the management of a hospital will incent substantial individual and organizational resistance, born of multiple psychological, cultural, and structural issues. The healthcare professionals and administrative key staff are at the forefront of the change. Their acceptance or rejection of AI in their workplace may very well make or break the adequacy of any adoption. A major issue is resisting change, and fear. Many clinicians and hospital employees may be skeptical or fearful of AI systems worrying AI will steal their jobs, or, take away their power as professionals. These fears can be justified, as for instance a hospital might start using a software program to automate a key order entry with administrative tasks performed by clerical staff. This train of thought could be tugging on those clerical staff jobs as well. Furthermore, some doctors may distrust AI diagnostic or decision support tools, uncertain an algorithm can truly capture what takes place during clinical care. If AI is thought to be intrusive or abstract, those interventions could even be born of more emergency conditions than supportive ones. In those cases, healthcare workers may actively engage in resistance to using AI, rather than supporting it. Examples of resistance to acting based on AI support could be low adoption rates of new systems, refusing to considering AI recommendations, or even becoming political blockers to AI projects in their organization. There are certainly reported misconceptions that AI, at least fully, will take over worker jobs in the healthcare ecosystem were noted to contribute toward increasing skepticism and backlash among staff to these proposals (Chustecki, 2024). However, experts suggest the advent of AI will not typically mean job loss (i.e., obsolescence), but instead, job reengineering AI will likely redefine jobs, rather than eliminate them. Addressing this skepticism requires competence in communicating and educating staff on the abilities and limitations of AI. Staff can be reassured when they can understand that AI is a tool to augment, rather than a competitor. Chustecki (2024) suggests that a commitment to trust, involves building understanding with transparent and open dialogue and education, so that healthcare workers see the tool (AI) as a means to help them do their job (rather than posing a threat to their professional identity).

Another human-factor challenge is lacking AI literacy and training. Introducing an AI tool without training, may expose staff to many aspects they don't understand, thus creating overwhelm or a sense of incompetence, which create resentment or mistaken use. Dangi et al. (2024) suggest that education, transparency and training around implementing the new AI tool will be very important to users' acceptance of AI in healthcare contexts. It has been established that when hospital workers were educated about what the AI tool was, what it wasn't, how it worked, and how it could assist them (rather than replace) their work, they were more perceivably likely to trust and adopt the AI tool. On the contrary, if medical staff were not educated about the new AI tool, they believed the tool was a black box, it was making arbitrary decisions, and therefore were reluctant to trust and use it. Clearly, change management is essential; hospitals need to manage the change by involving staff early in the process, providing education, and making clear that AI is a tool to help professionals do their work it is not meant to replace them. Dangi et al. (2024) mention that user acceptance is a necessary condition for effective implementation of any digital transformation. As a result, the technical aspects of the innovation should be reinforced by activities that promote acceptance for healthcare practitioners. Chustecki (2024) also reminds us that training clinicians to use AI is not a simple or quick endeavor, taking time and effort. If time is not dedicated to proper training, staff might have trouble integrating AI into their regular workflow, resulting in resistance to the AI or the use of it as it was not intended to be used. This again demonstrates the important need for training programs and responsible, gradual implementation to allow staff not only develop confidence in using AI systems but to become competent with the technology.

Organizational culture and leadership also impact how AI, or technology is viewed or embraced. In some hospital settings, there is a deeply engrained belief or culture of working at a slow and steady pace, and hierarchy, and a preference to use traditional practice. It may be just as difficult to persuade management level and department leaders of the value in using AI in clinical practice as it is to persuade front-line workers. Initiatives that are not endorsed and championed by senior leaders with a clear implementation strategy for AI might ultimately fail. On the other hand, hospitals have examples of collaborating with AI successfully where leadership supported leaders collaborating with managers to provide an environment for leaders to take risks and learn from losses (Bhagat & Kanyal, 2024). For example, Johns Hopkins Hospital launched a centralized AI-based command centre as a part of an AI-based request to improve operations. Leadership supported the development, and there were notable improvements in operations – for example, decreasing wait times and improved inter-departmental exchange of information (Bhagat & Kanyal, 2024). In these examples, there appears to be support from the organization that helped mitigate resistance, and the rationale for organizational change with AI implementation appeared to yield positive results.

Another dimension of human acceptance is professional ethical or liability concerns. Clinicians may be asking: If I follow and AI recommendation that leads to adverse outcomes, am I liable or is the technology liable? This uncertainty can drive clinicians to be more comfortable with practice as usual where they can clearly identify their own judgement as rationale for action. Clear descriptions of duty and the function of AI as an advisory tool (not a decision-maker) can be useful to these concerns and are further elaborated in the section on ethical considerations. To summarize, overcoming human- and organization-related resistance requires creating trust in AI systems, which can be achieved by co-designing AI systems with healthcare professionals, making clear how algorithms come to conclusions, providing extensive training, and ensuring that open communication about the intentions and limitations of AI occur. With these procedures, a medical staff member is more likely to perceive AI as a partner in care delivery not as a threat. Regardless, staff adoption of AI, there are still the natural limitations of AI algorithms itself to contend with, which is the next important aspect to consider.

3. Limitations of AI Algorithms

AI algorithms, no matter how advanced, have inherent limitations that diminish their potential for hospital management. For instance, algorithmic bias and generalizability is one major limitation. AI algorithms learn by analyzing historical data, and if that data is biased or does not represent data that is diverse enough, the algorithms may reinforce, or be even worse, amplify the bias. As an example, if a hospital's historical data has systematically fewer data entries for a certain subset of patients or conditions, an AI model will be less accurate in predicting outcomes for those cases - which is a fairness issue and an accuracy issue according to Dangi et al. (2024). Dangi et al. (2024) argues that algorithmic bias is a serious issue with AI and an AI can be unsafe or suggest inappropriate actions if it was trained on a narrow data set that is not representative of the diversity of actual patients. This is directly linked to data quality issues noted before as inadequate or biased data leads to biased predictions or predictions that have artifacts. Researchers have also warned that even the most sophisticated models will yield biased or unhelpful results based on inadequate datasets, stressing that AI will always depend on the data it learns from.

Another limitation is the lack of transparency and explainability of many AI algorithms, especially more complex machine learning models, such as deep neural networks. These models are black-box and typically don't provide an easily interpretable rationale for their predicted behaviors or operational decisions. In the hospital setting, this lack of transparency can be an issue. Doctors are understandably apprehensive to act on a recommendation (for example, a diagnosis or resource utilization) if they do not know why that recommendation was made by the AI. It should be added, as noted by Velichko (2021), that interpretability is still an issue; most healthcare AI systems will still struggle to give an explanation that makes sense to a human. Because of this model interpretability issue, clinicians cannot fully backstop the reasoning of the AI, which can undermine trust, and creates issues with potentially identifying faults or biases in the logic of the AI. Further, it has relevant legal considerations, because with regulations and ethical guidelines for AI in healthcare increasingly demanding explainability, and transparency a stronger issue overall.

AI algorithms also have limitations in that they are not able to contextualize what they know outside what they were trained for. AI algorithms are good at discovery and predicting patterns that are repeated within the window of data they have experienced, but face considerable challenges when faced with types of situations that the model has not seen (the so-called edge cases). An example may involve an AI system that performs nearly flawless in providing a prediction for patient admission in conventional circumstances (for example, a traditional flu season), but falters in an unprecedented time (such as a pandemic with a novel virus, or a mass casualty event), because the model has never seen those patterns before. Rong et al.(2020) discuss AI as being still very early in its development as an active field of inquiry, which means that many of the algorithms are not able to operate with the variations in complexity present in real clinical environments meaning that AI-based tools need considerable testing and sometimes retraining when deployed in new hospitals or patient populations an algorithm that worked perfectly in one hospital will not likely be transferable to another hospital with varying demographics and workflows. In addition, a great deal of AI's solutions in healthcare do not have sustained real world testing against whatever unique circumstances the AI was trained in. Chustecki (2024), for example, notes that a great deal of AI research is still at the preclinical or proof of concept level, with only a handful of prospective clinical trials that are being deployed to show that AI in practice is making a real impact . When there is a lack of real-world evidence about the safety or effectiveness of AI, then implementing those tools into practice becomes difficult, especially when hospitals are reluctant to trust new technologies with little to no direct evidence supporting their claims. As a result, there is frequently a necessity to generate actual clinical evidence and publish pilot studies before any tool has been deployed.

Additionally, AI lacks the elements of judgement, empathy, and common sense which are often fundamental in decision-making in the world of health care. An algorithm cannot truly appreciate a patient’s emotional needs; or the complexity that comes along with a clinical situation; or the ethical intricacies of care. It fundamentally lacks the imagination to think anything beyond what is outlined in the programmed objective function. As previously noted, AI cannot replicate the clinical intuition or the deeply interpersonal nature of the clinician-patient relationship. For example, a scheduling AI might find the most optimal way to coordinate operating rooms, while a human manager might know that finding a way to meet a particular surgeon’s schedule for personal reasons, matters for team dynamics which an algorithm will not know unless it is programmed to. This lack of understanding points to why AI should not operate in a fully autonomous mode as a decision-maker and should only serve in a support function in healthcare. There is additional risk involved in that over-dependence on automation; if health professionals are quick to defer to the outputs of the AI without analysing the outcomes, then the one time the algorithm makes a mistake, or provides a recommendation outside of its scope, and goes unchallenged could be harmful to patients. There is also the possible risk of de-skilling; clinicians who routinely use AI for their decisions and come to rely on the support, may de-skill their decision-making over time (as could be observed in other industries with significant automation).

Finally, many AI algorithms require ongoing data input and re-training to remain functional in their accuracy. Healthcare is a situationally dynamic environment; the populations of patients flux, medical practices evolve and new diseases emerge. An AI model becomes stale rapidly without continual data to keep it relevant, though re-training models are neither uncomplicated nor always affordable. The dynamic nature of AI complicates their performance limitations an algorithm is not a one and done install and forget tool, the algorithm must be fluid or it will inevitably underperform. Ultimately, the constraints associated with AI algorithms bias, explainability, context insensitivity, lack of potential to fully replace human judgement, and the requirement for maintenance represent a clear point for hospitals to be judicious use. Understanding these constraints enables hospitals to put realistic expectations on AI, while also marking out usage limits and boundaries to ensure safe practice in applying tools to healthcare. In fact, noting the limitations of AI is significant in the need for sound ethical guidelines, as many of the limitations (such as bias and non-transparency) have a direct pathway into ethical consideration.

4. Major Ethical Considerations

Bringing AI into the management of hospitals prompts serious ethical considerations that must be resolved to ensure patient trust and the integrity of medical ethics. One of the biggest ethical issues is that of patient data privacy and confidentiality. AI systems often run off of large amounts of patient data; that is, electronic health records, clinical notes, imaging data, etc. AI has the possibility of transforming healthcare by allowing faster analytics, but this consolidation of patient data raises the possibility of breaches of patient privacy of varying degrees. Hospitals also need to be able to keep sensitive personal health information safe and secure while meeting the ethical and legal obligations to ensure patient data is kept private and secure. Breaches, misuse, and lack of privacy precautions can all increase distrust in both the hospital and AI technology. It is important to remember data security is intertwined with data privacy; hospitals will always need to have strong cybersecurity policies in place to minimize hacking or breaches of AI systems and patient data as our hospitals become more digital. Forouzanfar and Varnosfaderani (2024) emphasize the importance of data privacy and security when implementing AI stating that patient data must be protected to ensure the responsible use of AI in healthcare. If patients are concerned that AI means they are exposing their previous medical records or that their medical records would be used for purposes beyond consent or intent, they may hold back on disclosing vital information in the event of an emergency, or lose trust in the healthcare system altogether. Likewise, [19]Abujaber and Nashwan (2024) state that AI's dependence on large amounts of patient data poses privacy and confidentiality challenges that require good data governance to ensure public trust. They also point out that if appropriate protections and transparency are not in place, AI could threaten patient privacy and gut the trust that is essential to patient-provider relationships.

A second important ethical issue is algorithmic bias and fairness, which is related to and can be viewed against the technical bias issue we discussed above, but put when from a moral perspective. If an AI scheduling system is providing systematically fewer resources to patients of a certain demographic, or an AI diagnostic tool is under-detecting disease in minority populations due to biased training data, this represents an ethical issue of inequitable care. It is a moral obligation that AI does not perpetuate health disparities. Dangi et al. (2024) warn algorithmic bias can escalate to unfair or unsafe outcomes, so removing bias is an ethical obligation when designing AI. Removing bias in AI design entails ensuring the training data is diverse and representative, and that AI tools, prior to their release, have been tested for bias. The justice principle in healthcare ethics the provision of care that is reasonably equitably provided requires that AI is designed and used in ways that collectively benefit the different patient groups it is being used for, and in an equitable way. Similarly, Abujaber and Nashwan (2024), argue that bias in AI algorithms is a significant ethical concern and warn that biased AI may pose the risk of perpetuating existing disparities in healthcare outcomes. Fairness and equity in these cases is critical since both are a responsibility of maintaining ethical standards and ensuring technology does not reinforce inequities found in society. More than fairness in designing algorithms, we also need consider equity in access to the benefits of AI . Not all hospitals or patient populations will have the same access to cutting-edge

[19] Abujaber, A. A., & Nashwan, A. J. (2024). Ethical framework for artificial intelligence in healthcare research: A path to integrity. World Journal of Methodology, 14(3), 94071. DOI: 10.5662/wjm.v14.i3.94071.

AI tools, so quality of care may suffer if hospitals and therefore patients have, different levels of access to AI due to a digital divide. Abujaber and Nashwan (2024) identify that without equitably making AI innovations available among many healthcare settings, some groups may benefit from health care improvements while others languish in poorer access. Ethically, AI deployments should consider equity and not just deploy for the sake of introducing AI, including the promise of implementation for poorer settings but ensuring support and programs are in place, and algorithms are adapted or professionally validated for the population being served.

The question of transparency and explainability also has an ethical dimension. In healthcare, if patients are to understand their own treatment and health care options, they must be able to make informed consent decisions and to understand the basis for decisions about their health. If an AI system influences a clinical decision or an administrative action, a lack of transparency might violate those rights. For example, if AI makes a recommendation to prematurely discharge a patient and the physician follows that recommendation, the patient will have a legitimate right to ask either the physician why that recommendation was made. If the physician cannot articulate the underlying assumptions of the AI recommendation, this compromises the informed consent process and the trustworthiness of the patient's care. It has been suggested by Velichko (2021) and Lumenalta (2025) that opacity in AI systems can be ethically problematic with respect to patient consent stating that ethical questions related to patient consent and algorithm ignorance must be explicitly addressed when adopting new technologies. The term algorithmic intolerance here refers to an inability on the part of an algorithm to allow for exceptions or values that lie outside the narrow optimization parameters of algorithmic design, which can be interpreted as an unrespectful approach to individual patient contexts. From an ethical standpoint, there is rising momentum towards explainable AI in medicine, which calls for using AI systems that can provide humans with understandable rationales for their decisions and that allows human decision-makers to validate and interpret AI recommendations consistent with clinical judgment and ethical principles. There is universal agreement from Abujaber and Nashwan (2024) that transparency and explainability of AI decision-making processes are necessary for maintaining trust and accountability in healthcare environments. If clinical decisions and ultimately care recommendations derive from AI-guided patient assessments, then the clinicians and patients directly affected need to understand, fundamentally, how the AI reached its conclusion. Therefore, it follows that pursuing explainable AI (or at the very least providing interpretable outputs regardless of the complexity of the model) is not just technically challenging, it is an ethical challenge that needs to be addressed to maintain the principles of informed consent and shared decision making.

Another main source of ethical and legal ethical challenges is accountability and liability. There remains ambiguity about who is responsible for AI guided decisions when these decisions impact patient outcomes if something goes wrong. For instance, if a patient who is identified as high-risk by the AI algorithm in triage suffers an adverse event, who is responsible? The clinician who used the AI to make a determination about the patient? The hospital that used the AI? The developer who programmed the algorithm? Liability ecosystems for healthcare AI are not fully emerged. Bhagat and Kanyal (2024) and others have highlighted the ambiguity of legal responsibility for AI based decisions, and Dangi et al (2024) call out liability as a prominent identifiable ethical challenge that must be resolved in order to use AI in safe and effective ways (Dangi et al., 2024). Ethically there can be confusion about what to do in the event of an error: patients should not fall into a blame vacuum when an AIs false positive, or false negative, does not mean any accountability. Hospitals must establish protocols that determine who is in control of oversight of AI decisions and, regardless, that a human is held to account for final decisions. The overarching ethical concern is that technology exists under the control of human beings, which is a separate ethical issue. The literature continues to have deep concern about the dilemma of accountability. As Abujaber and Nashwan (2024) point out, the question of who is accountable for AI guided decisions is still difficult to answer, adding to the ethical complexity; Chustecki (2024) observed that who is accountable for the continual failure of AI in making clinically wrong decisions raises ethical issues given that it may be perceived to be unjust to hold a physician responsible for an AI failure, as holding a likely far removed software developer responsible seems impractical; thus ways to shed light on the liability guidelines are still lacking. Experts in this area believe that creating clear liability frameworks will help to address this issue even if accountability frameworks can be created where, for example, clinicians always takes responsibility for decisions while also ensuring that the AI systems can be audited and modified if errors occur.

Patient consent and autonomy also factor into AI. Patients aren't always aware of when AI algorithms are utilized in their care for instance, an AI might sort patients based on urgency predicted when allocating them for surgery, or AI might assist in interpreting their radiology images. Ethical standards would imply patients have a right to understand when significant AI assistance is being utilized in their care, especially when the information is used to influence their care plan. At the least, they should know if their data is being potentially used to train AI systems (although this is typically included in the broad consent for research or analytics consent, it should be transparent). Lumenalta (2025) provided strong guidance on the importance of patient consent in advancing AI, arguing that integration of AI in a way which is responsible requires heightened processes to inform patients and to investigate consent for the purpose of the words and executed processes used in project protocols. If patients are uncomfortable with AI being involved in their care decisions, providers need to take their concerns seriously - whether its through additional human review of data and AI application, or an increased opportunity to ask questions. Indeed, Abujaber and Nashwan (2024) noted how AI in healthcare can create narrowing of, or go beyond traditional frameworks of consent complicating informed consent in a time of AI. They say that consent processes should be revised so that patients can see clearly what they are consenting to with respect to how their data will be used and when AI will help them with their care, and in this way preserve their autonomy with respect to their rights based on informed decisions. Hospitals may need to do modifications in their consent forms and patient communications to ensure patients know when AI is involved in their care so the individuals have been offered the opportunity to ask questions, or opt out if appropriate. Preserving autonomy in this way means giving patients some level of control, or at least knowledge about the digital processes that affect them.

Lastly, it is important to consider how to use AI in a way that embodies the fundamental values of the medical profession, beneficence (doing good), non-maleficence (avoiding harm), autonomy and justice. AI should be designed and used to prefer patients' welfare and safety. In fact, any AI that is introduced into practice, should be tested to ensure it will do more good than harm. For example, an AI tool could make processes more efficient, however if it unintentionally reduced the in-person time doctors could spend with patients, does that success come at an ethical cost? These questions are challenging moral dilemmas. As Forouzanfar and Varnosfaderani (2024) recommend, the ethical integration of AI must ensure that the technology is being used responsibly, preserving patient welfare as the primary concern, with interdisciplinary oversight to examine and assess the ethical dimensions (Forouzanfar & Varnosfaderani, 2024). In practical terms, this could mean having ethics committees or board of governance in hospitals to examine AI related implementations, as well as continuous review of use cases to identify undesirable ethical consequences (such as biased contextual or patient dissatisfied outcomes). Responding to these ethical decisions is not only necessary for being 'on the right side of the law' or avoid the material impact of harm, but a way to earn trust back from the healthcare professionals affected by the changes AI brings, or patients in the future of patient care. Failing to account for ethical considerations of AI workflows may mean that it is possible for AI to stir a backlash of some sort from the general public or government bodies all the way down to accidents or bad consequences from the system you set to use AI. For example, some academic authors have proposed models to formally provide frameworks in the health care where AI would be used ethically. Abujaber and Nashwan (2024) state that the swiftness of AI application in healthcare means there must be an ethical framework that will guide it's use through human processes and offerring cautions that a framework may limit itself which can affect trust, hurting patient privacy, and increasing inequitable consequences. In a current shape of framework in a more ethical way that would flourish otherwise if there would be reflection in someone's practice each time we usually intended not deferent reaping benefits, it would be a future to shredded up as content in someway between and that would carry preserving something we can return to the indices of justice, beneficence and non-maleficence. For that reason as we explore in the final paragraph, it is vitally important to think of AI as something to be integrated intentionally in our responsibly addressing both the technical issues we raise in the previous paragraphs, and the ethical considerations raised.

5. Strategies for Responsible Integration

Based on the range of challenges and ethical issues outlined, what can hospitals and healthcare systems do to ensure the responsible and effective uptake of AI into hospital management? This sub-section makes a number of proposals and recommendations as part of the inquiry's commitment to create a transparent and appropriate path for AI in the health sector. The key premise is that AI should be introduced in a way that is slow, intentional, and human-centered, to enable the delivery of improvements without compromising quality of care, equity, and/or ethics. As Chustecki (2024) points out, striking a balance between innovation and patient care means imagining AI abstraction and then proactively working to overcome and address ethical, regulatory, and safety issues that arise with integrating of AI. In other words, Responsible introduction of AI involves thoughtfully planning for the future to allow for consideration of how to strike a balance between innovation and the protection of patient care.

Strengthening Technical Infrastructure and Data Governance: First, hospitals need to ensure there are adequate investments made in the infrastructure and data governance space. This means upgrading IT systems, putting in place high-speed networks and possibly cloud-based solutions for the computing demands of AI algorithms. At the same time, it will be important to think about data governance: refinement of data collection protocols, cleaning up existing data and facilitating systems interoperability to combine the data from the various departments (or even different organizations). Many barriers exist due to data quality and the integration of technology, thus making addressing these challenges upfront is the recommended path to creating a base to build AI on (Velichko, 2021). Hospitals may want to explore unified data platforms or data warehouses to collect patient information across the enterprise so that it can be more easily accessed by AI tools. Or, executing on a data stewardship team to monitor and improve data quality will be beneficial. When there is sufficient infrastructure, combined with data quality, the technical barriers to AI adoption will be lessened. Maleki Varnosfaderani and Forouzanfar (2024) suggest that as further computing infrastructure and requisite data governance arrive, where AI is usable in health care and can impact patients' care, will develop. They underscore that readiness translates into improved patient care.

Human-Centered Implementation and Training: To counter act human resistance, developing a change management and training program at the start of the process of deploying the AI is advisable. This means making sure to involve clinicians, nurses, and administrative staff in the earliest stages of the development of the AI project. For example, have representatives from almost future end-users involved in the selection of an AI system or early project phases providing feedback (Dangi et al., 2024). Dangi et al. (2024) recommend co-development methods of AI tools to increase the likelihood that the AI tools will engage with real needs and provide users a sense of ownership over new technology.

Furthermore, hospitals should prepare staff for AI by noting the AI's role: to support human procedures by helping, increasing the capabilities of staff, and not monitoring or replacing them. If AI is framed as a supportive team member, it is more likely fears will be diminished. Training is important: not just a single training course but continued learning opportunities to develop confidence and comfort in using the AI systems. For instance, simulation exercises should allow clinicians to attempt the decision support system in a low-stakes setting before using it with patients. Increased exposure with technology will promote more familiarity and trust with the AI systems. Digital literacy could even be integrated into Medical and Nursing programs so that incoming practitioners have comfort and competence level has improved working with AI tools. Ultimately, an adaptive and continuous learning organizational culture will support staff adaptability and resiliency to technological change. Leadership can support this by publicly acknowledging AI and sharing stories where AI has assisted with time management tasks or improved patient care and normalizing trial and error as viable for exploring new tools.

Ethical and Regulatory Frameworks: First, hospitals should consider developing governance mechanisms for the implementation of AI, to outline ethical practices. The governance mechanisms could include an AI Ethics Committee, or an expanded role for their existing Institutional Review Boards to consider how to assess AI interventions. These committees would review proposed AI tools to ensure ethical consideration (i.e., evaluating bias, gauging privacy protections and whether there are established processes for accountability). They would also create policies on how and when AI can be used in times of patient care. For example, one of the policies might stipulate that any AI-suggested recommendation would require a human clinician to review and agree before any action is taken, suggesting a human is preserving oversight. Interdisciplinary collaboration is an important part of this process, as Forouzanfar and Varnosfaderani (2024) stated- these committees must consist of clinicians and technical experts along with representatives from ethics, law, and the perspective of patients (Forouzanfar & Varnosfaderani, 2024). The inclusion of these repositories helps ensure a variety of opinions inform the governance related to AI. Related to the regulatory perspectives of AI integration into hospitals- hospitals must remain compliant with regulations that relate to the use of patient data (e.g., HIPAA in the US, or GDPR in Europe). Additionally, any data used to train algorithms (which is likely to be de-identified or anonymized) must have protocols in place for de-identification so patient identity is protected. Best practices: There must be transparency with patients: hospitals could revise their consent documents to indicate to patients that their information may be used (anonymously) to improve algorithms that support patient care and possibly offer them an opt-out, if applicable. More broadly, some scholars suggest developing formalized frameworks at the organizational or even national level to establish responsible use of AI more rigorously. Abujaber and Nashwan (2024) propose a rigorous framework for ethicality relative to AI in organizational healthcare initiatives that provide examples of ways to translate ethical principles into practical actions. Their framework ensures that privacy and confidentiality are always most significant (with provisions for explicit data handling and protection) while also improving informed consent processes to ensure participants know how their data can potentially drive AI innovations. The framework equally works to address biases within algorithms by requiring continual bias audits and emphasizing fairness in outcomes while requiring AI systems to provide understandable outputs to support trust and transparency. For example, to operationalize taking up an ethical framework in a hospital context would be to build ethical checkpoints into the AI implementation process - from design, roll out and ongoing use. By institutionalizing policies that require bias reduction, explainability, privacy, and clear accountability, hospitals can then operationalise their commitment to ethically deploying AI. In short, while building ethics and compliance as part of the AI strategy is not optional community, it is an integral part of discrete positional responsibility.

Ensuring Transparency and Accountability: To retain trust almost all proposals have invoked the need for explainable AI solutions for critical applications. When feasible, hospitals should always choose an AI solution that is capable of providing explanations for the decisions it makes (or if vendors can't add this feature). Even if the underlying model is too complicated, the system may still be able to identify which factors were most influential in a particular recommendation. By delegating knowledge and planning around explanations, it will also improve clinicians' ability to validate AI outputs, as well as provide patients with a little more insight into their care decisions process. In situations involving high consequence decisions it may also be wise to use simpler models (which are potentially more interpretable) or to simply complement complex models with a secondary mechanism that can explain the AI decisions. In relation to accountability, hospitals should develop firm guidance e.g. the physician of record is ultimately responsible for clinical decisions that incorporate AI support. These types of guidelines establishes the notion that AI is a tool of these human professions and they are ultimately accountable to their decisions, as are the associated institutions. AI-associated adverse events or errors should be identified and reported like other medical errors in a culture of safety and improvement (e.g. absolute accountability). If there is evidence that an AI system caused or contributed to a mistake then it will also trigger an examination of the system which may lead to some modification or retraining. Being able to set up this feedback will enable continual improved performance of both the AI and the human behaviours surrounding the AI. More importantly, it allows accountability to never be lost there is always a human or human-led committee to translate outcomes of the AI, or make decisions as a result of something potentially adverse.

Stepwise and Pilot Implementation: One viable approach may be a stepwise, phased-in approach to AI implementation using pilot or controlled implementations. Instead of trying to use AI and roll it out across the entire hospital in one step, hospitals may wish to implement a new AI tool in one department or for one purpose. Moreover, this presented the hospital with an opportunity to evaluate the AI tool in practice, identify the challenges presented by the AI, and gather limited but valuable user feedback. As Rong et al. (2020) note, AI applications in medicine are still being considered, and a slow and methodical approach with fluent consequences may be an acceptable rationalization. Early successes (or failures) with a pilot bring a lot of relevant information that can be used to guide the AI approach before the hospital rolls out some version of AI across the whole hospital. For example, a hospital using AI to predict patient admissions would likely first want to use the AI in their emergency department. If this pilot proved to be successful in predicting admissions, and the staff agreed that it was beneficial, then a hospital might expand the project to become part of their hospital-wide bed management plan. These pilots should have some measures of success (e.g., reduction of wait times, reduction of cost, increased user satisfaction), or be observing for (perhaps unintended) effects (e.g., in-film biases or workflow disruption). By using stepwise approaches to piloting AI processes, hospitals will be more agile - they can fix issues early in the AI adoption process, which, will allow them to have, by the time they are ready to use AI more broadly, stakeholder support, their best chances for success, and introduced some successful change to the hospital environment.

Continuous Assessment and Adjustment: Responsible integration is a process, not an event. Even after AI systems have been adopted, they still need to have continuous assessments on their performances, fairness, and impact on the outcomes of health services. Key performance indicators could be based on: the accuracy of AI predictions, frequency of adverse events, patient outcomes, measures of efficiency, and user satisfaction. Regularly auditing also could assist in identifying challenges, such as the emergence of model drift (wherein an AI's accuracy declines over time due to changes in data patterns) or the emergence of biases. AI in health care is seen as an iterative and dynamic process and will require ongoing review because of evolution of ethical and clinical expectations [20](Shiwlani et al. 2024). For example, if an audit identifies that an AI supported scheduling template has gradually started to under-represent certain groups of patients, the hospital must stop using the tool until it can be re-trained, adjusted or redesigned. Robust auditing and performance reviews create a continuous quality review and quality improvement cycle making it easier to adjust AI as an asset rather than a liability. It also communicates to the staff and the patients that the hospital is actively watching over the AI technologies and is responsible for its safe use.

Promoting a Role of AI Complements Human Decision-Making: Lastly, an ethical but important piece of responsible integration should engage defining AI in a role of complementing human professionals. As several authors have alluded, AI should be promoted as a tool to support human decision-making, not replacing it. Embedding this principle into training, policies and communications from leaders in the hospital keeps this clear boundary: AI executes data rich, repetitive, or highly complicated pattern recognition tasks (and does it well), while humans use empathy, ethical judgement, and retain the last word. This prevents machines from relieving human responsibility and allows for a remnant human aspect of healthcare, which is key in creating opportunity for patients and their caregivers. As Prabhod (2024) reminds us, this is indispensable, especially in the context of rising demand and costs deriving from, but not limited to, aging populations and chronic disease; AI can be helpful in this respect to help provide efficiency and potentially improve outcomes, but it should not be so relied upon that we lose the quality of care (for example, while an AI could possibly recommend treatment options, a human clinician should always have the conversation and make the decision).

In conclusion, it is a complex endeavour to enable AI responsibly in hospital management. It requires at least technical readiness, made aware and educated humans, and commitment to a strong ethical and governing framework. By dealing with technical and infrastructural challenges, managing human and organization changes, and vetting and identifying challenges posed by their algorithm, and maintaining ethics, health institutions can assess the challenges posed by AI adoption. The goal is not to just use AI as a useful and powerful tool increasing efficiency, aiding clinical decision making, and optimizing patient care but still maintaining patient trust, safety, and

[20] Shiwlani, A., Khan, M., Sherani, A. M. K., Qayyum, M. U., & Hussain, H. K. (2024). *Revolutionizing healthcare: The impact of artificial intelligence on patient care, diagnosis, and treatment*. JURIHUM: Jurnal Inovasi dan Humaniora, 1(5), 779–790.

humanity. AI can be a strategically indirect efficacious and complementary technology to use in hospitals (yes, where we echo Dangi et al., 2024, and others), and assist health systems in dealing with pressure but not irresponsible ethical abandonments and lose sight of a patient practice. As we have seen in current literature, in a slow, paced, and responsible manner, the literature suggests not disregarding ethics and values guiding practice and care with compassion can see AI being a useful addition to the health system. For instance, Chustecki (2024), acknowledges AI can provide revolutionary advances for healthcare activities; however, along with the benefits of the AI technologies, must be forward-thinking with its ethical, regulations, and safety issues in achieving balanced and responsible integration. Similarly, the ethical frameworks by many (including Abujaber and Nashwan, 2024) suggests that the future of healthcare with AI must be guided by integrity, transparency, and a commitment to create and uphold patient care. Following these strategies will have time promise when hospitals and health systems decide to integrate AI technologies and be prepared for the next stages of this work, which includes case studies when AI acted and delivery systems of the future, built on the premise of understanding the challenges and ways to address them.

VI. Case Studies

Neonatal (or perinatal) asphyxia where a newborn baby has an inability to breathe spontaneously at birth is a significant global health problem. It accounts for approximately one out of three neonatal deaths and long-term disabilities globally. For example, the World Health Organization lists birth asphyxia as one of the top three causes of newborn mortality, accounting for 3 million neonatal deaths worldwide every year and more than 1 million infants are affected by serious long-term impairments every year (e.g. cerebral palsy, deafness). Nigeria has one of the highest rates of neonatal mortality rate globally at approximately 35 deaths per 1,000 live births. With this in mind this startup ubenwa was created case studies in order to solve this. A leading cause of neonatal death is perinatal asphyxia, which is the process where a newborn experiences oxygen deprivation during or immediately after birth. It is critically important to identify the diagnosis and intervene because it prevents irreversible brain injury, however detection of aspehyxia remains a substantial challenge in low-resource settings. Standard diagnostic methods require sophisticated equipment and trained clinical expertise, for example, asphyxia diagnosis requires blood gas analysis (test of new-born blood for oxygen/pH) in adjunct to multiple APGAR scoring. In many areas of developing regions, these two vital diagnostic tools are not readily available which means asphyxia is often undiagnosed until some visible physical signs appear (e.g. blue extremities), by which time, the baby may have already sustained irreversible serious neurological injury. This gap in diagnosis further elucidates the need for more widespread use of an accessible, low-cost, and easy to use diagnostic approach for preliminary identification asphyxia. One possible method for identifying asphyxia during the newborn period is the analysis of the infant's cry with artificial intelligence (AI). Crying and breathing are physiologically related phenomena they are both linked by the same neural pathways, and a functioning respiratory system is necessary to generate an appropriate cry. In fact, there have been clinical observational studies since the 1970s, which report that asphyxiated newborns tend to cry in a different way than normal: their cries tend to be shorter in duration, softer in amplitude, higher in fundamental frequency, and they often exhibit an abnormal rising intonation pattern. This phenomenon suggests that the sound features of a baby's cry (acoustic features) provide valuable information about the infant's physiological status; this includes a range of respiratory distress. Therefore, a machine learning system that can automatically analyze chaos associated with newborn cry sounds could provide a simple, non-invasive alert for asphyxia. This case study provides background on Ubenwa, an AI-based neonatal asphyxia diagnostic system built on that very premise - to use infant cry analysis to promote early and inexpensive detection of asphyxia where traditional resources may not available.

1.Outline of Ubenwa

Ubenwa (meaning baby's cry in the Igbo language of Nigeria) is a project and startup initiative to create an artificial intelligence-driven approach to diagnosing birth asphyxia. The effort began as a collaborative research project involving McGill University (Mila Quebec AI Institute) in Canada, led by Charles Onu and Doina Precup, as well as clinicians and technologists in Canada and Nigeria. The interdisciplinary team is affiliated with McGill's computer science department and hospital (neonatology division), the University of Port Harcourt Teaching Hospital in Nigeria , and Ubenwa Intelligence Solutions Inc., the startup created to commercialize the research into a real-world solution. Ubenwa seeks to create a smartphone-based diagnostic application to identify the signs of birth asphyxia from an audio recording of an infant's cry, thereby dramatically decreasing the time, cost, and specialized skill involved in diagnosis. By leveraging ubiquitous mobile and wearable technology, Ubenwa hopes to deliver lifes aving newborn assessment at the point of care, particularly in resource-limited settings in which traditional diagnostic procedures are not practical.

The idea was conceived in 2017, when the group first presented results at a major machine learning conference (NeurIPS 2017). Early on, the developers realized that to develop a functional system, they would need more than a training algorithm - they would have to make their algorithm clinically useful and usable. They built a prototype Ubenwa mobile application that runs their cry analysis model on a smartphone; this prototype which was named after the project allows the team to think through the end-to-end deployment issues of the technology and gather input by healthcare workers about their experience and perceptions of how useful the technology might be. In short, Ubenwa's development and vision are situated in the interdisciplinary intersection between AI and global health: Ubenwa is seeking to leverage machine learning along with mobile hardware to help solve the important problem of undiagnosed neonatal asphyxia in healthcare systems with scarce resources.

2. Technical Methodology

This thesis pursues a mixed methods approach to examine AI systems in health care. The research does not collect primary data, but it uses both a critical review of the literature and a detailed technical analysis of a representative case, Ubenwa. Also, the processing of information online has facilitated access to a large volume of valid and relevant material related to the research topic. In addition to websites and blogs that are specifically devoted to the research topic, operated by experts in the field of exploration have provided us with valuable information and important points of view. A number of academic articles and reports from sites were found from Google scholar; Pub Med; were found and used. The qualitative analysis considers ethical, organizational, and social concerns about AI in health care and the quantitative analysis investigates the technical considerations, evaluation measures, and models performance published in peer-reviewed scholarly sources. The research does not involve designing or developing a new AI system specifically. The research is a critical analysis of a relevant and representative case, Ubenwa, which is an AI-based system for early detection of neonatal asphyxia utilizing infant cry analysis. Ubenwa is relevant for the technical considerations, but specifically for its socio-clinical health care value in practice in low resource settings.

The aim of this methodology was to gain an understanding of how artificial intelligence when intentionally designed and applied can operate as a technology and a social innovation in a hospital setting. This task used primarily the study and synthesis of peer-reviewed scientific literature, along with the limited technical documentation made publicly available by the Ubenwa development team and their academic collaborators. The Ubenwa project itself follows a technical process, and this technical process serves as the central part of the case study analysis. The authors of this study utilized the Baby Chillanto Infant Cry Database, the only publicly available clinically annotated dataset of infant cries, to extract approximately 1,049 infant cry recordings from healthy newborn infants and 340 from asphyxiated infants. These were processed by standardizing them and converting the samples of about one second in duration to Mel Frequency Cepstral Coefficients (MFCCs), which represent a way for us humans to interpret sound and is a common representation of sound used in speech and audio processing. They then used these features for two modelling strategies. They used a classical Support Vector Machine (SVM) classifier, which was trained from MFCCs. The authors chose this technique because of its robustness with small datasets. The authors then used an advanced Convolutional Neural Network (CNN) model, which they improved with transfer learning on large datasets of adult speech. They pre-trained their deep models on tasks, such as speaker identification, gender classification, and keyword classification, and then fine-tuned their models on infant cries. Personally, the use of transfer learning to enhance their dataset was necessary because the lack of neonatal cry data is often a considerable hurdle for AI in the pediatrics space. The evaluation protocol by the Ubenwa team was consistent with clinical practice and rigorous. The authors did an 80/20 train-test split, while ensuring infant level separation to avoid overfitting or data contamination. They also used sensitivity, specificity, and Unweighted Average Recall (UAR) instead of a simple accuracy measure, given the imbalanced nature of the dataset. They additionally performed testing under simulated realistic conditions that you would find in the clinical environment, including background noise or truncated audio files, to examine how robust their models were in a real clinical environment.

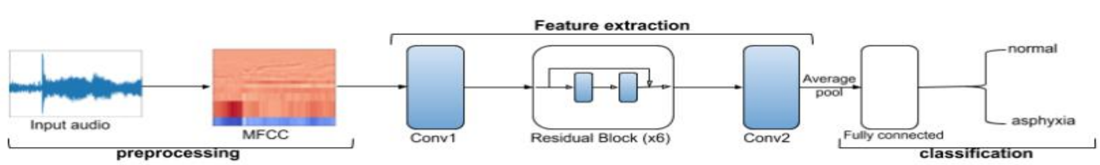

Figure 4. *Processing Pipeline of the Ubenwa Diagnostic System*

From a research perspective, this thesis did nothing to reproduce these experiments, only critically interpret their design, assumptions, and findings. The reasons for taking the Ubenwa case study are based on a recognized application of higher order learning techniques, and the reality of an unmet medical need that merited application of these terms and applied research enterprise. The method taken here is an attempt to minimize and unpack how technical architectures (e.g., MFCCs or residual CNN's) are delivered as a usable clinical tool and more importantly, what can be learned from Ubenwa about broader, AI clinical integrations in our hospitals.

In this context and from a methodological standpoint, this thesis is situated not in code or sampled algorithmic training, but into the deep interpretive exploration of existing frameworks, along with their limitations and implications. Ubenwa allowed this research to explore how AI development for innovation can and perhaps should be thoughtfully directed to address reality, particularly when healthcare resources are compromised, yet high stakes.

3. Outcome and Evaluation

The assessment of the Ubenwa system is encouraging, at least as it relates to automated classifications of infant cries to assist in early identification of neonatal asphyxia. At the beginning, the authors tested the system using Mel-frequency cepstral coefficient (MFCC) audio features and Support Vector Machine (SVM) classifier. As baseline, they achieved a sensitivity of 85% for identifying infants with asphyxia and specificity of 89% for healthy newborns: UAR ~ 87%. Even much simpler forms of machine learning could identify clinically meanings patterns within the acoustic features.

As noted, there were limitations, particularly with the generalizability and robustness of the model under more variable real-world situations. With those limitations in mind, the researchers then began taking the model in a more complicated direction. They ultimately built models from deep learning, specifically convolutional neural networks (CNNs), using transfer learning, with three pretraining methods (task-agnostic pretraining, keyword recognition task, sound classification task). The keyword recognition pretraining method had the best overall performance (UAR: 86.5, sensitivity: 84.1%, specificity: 88.9%). Overall, CNNs that used transfer learning always capture more information than the baseline SVM, and a randomly initialized CNN. The CNNs were also so much more robust, which meant that they were heavy, uttered under noisy conditions. During the experiments where they incorporated background noise to simulate clinical conditions this ranged from sounds of a general hospital to simulated sounds of disturbance who patients' might experience in a clinical situation it was observed that the overall performance of the Deep Learning (DL) models consistently exceed that of the SVM classifier and they degraded more gracefully with lessened signal-to-noise corresponding to real life conditions associated with clinical practice, which is especially important since auditory noise is unavoidable in hospital and low-resource settings, and in order for diagnostic systems to work as clinical viable predictions they need to be unconfounded by noise. A second interesting note related to the ability of the model to still classify signals with very short audio inputs. The best-performing CNN, managed to accurately classify infant cries with clips as short as 0.5 seconds. This kind of rapid detection can be invaluable in a clinical environment when optimal recording conditions can be rare, and time is usually limited.

Finally, a frequency sensitivity test indicated that most models used information primarily in lower frequency bands (<500 Hz), which corresponded to the fundamental frequency range commonly seen in neonatal vocalizations. In contrast, as discussed in the reports regarding transfer learning, the CNN model in general appeared to be making good use of a larger frequency band. Moreover, all confirmed species of cry could be classified appropriately even when certain frequency bands effects were masked, suggesting a more sophisticated internal representation (i.e., enabling detection to occur well before the spectrum of infant cries first entered sound-silent areas of the audio feature dimension space). Taken all together these results demonstrate the potential for the Ubenwa system a reliable supportive diagnosis of neonatal asphyxia, perhaps under optimal conditions, and challenging conditions. That said, a UAR total of approximately 86% represents very promising performance and may approximate clinically actionable standards. Next, there is a need for wide real-world validation, which will include prospective trials across range of realistic clinical environments, continued evaluation of system according to multiple noise conditions, and variations in population demographic characteristics and including integration of interpretability approaches improve confidence and make the path to clinical implementation easier.

In short, the Ubenwa evaluation protocol is an evolution from that of a similar trajectory of AI innovations in medicine, while they may be technically promising, we must loyally scrutinize real-world complexities, and much work remains to ensure that AI developers can successfully make the bridge from state-of-the-art model performance to clinically meaningful issues. Along the way, current best practices for the use of AI in medicine will exist in enabling the iterative use of the model, transparency about data, performance indicators, and improvement gained, and in collaborative outputs to work shapes with clinical collaboratively validated practice points to enable safe and efficacious innovations.

4. Deployment and Clinical Testing

One of the central considerations of the project from early on has been moving from a research prototype to a usable tool in real-world clinical settings. The team recognized from the outset that machine learning is only part of the solution, indicating that they recognized a need for robust deployment planning and consideration for the end-user. To facilitate testing in real-world settings, the Ubenwa cry analysis algorithm was integrated into a mobile application. The Ubenwa app, which will be released on popular application stores, is designed to provide end users with an intuitive interface to record a newborn's cry, and then run the asphyxia diagnosis algorithm on the mobile device. By deploying the machine learning model on a readily available hardware platform (i.e., a mobile device), the developers could ensure that the solution could be easily distributed and used at the point of care without specialized equipment. The app also enabled the team to commence engaging clinicians and caregivers for feedback in terms of usability early demonstrations and pilot usage provided input that allowed the system to be iteratively improved to best fit the workflows of clinicians and display output in an understandable way. In terms of clinical validation, the Ubenwa developers planned and started to test in real-world settings through it being implemented in collaborative studies taking place in hospital settings. Some of the major steps taken towards deployment include:

Prototype Mobile App Development: The team built a fully usable smartphone application that incorporated the cry-based asphyxia detection model and provide end users (e.g., nurses or midwives) the ability to record newborn cries and receive diagnostics results at the point of care. This prototype became a means of iterative improvement, while also validating that the application, and the algorithm, could run efficiently on mobile hardware.

Hospital Partnership and Data Acquisition: Ubenwa started a prospective data collection and validation campaign across two clinical locations one in West Africa and one in North America. In early 2018, they planned to adopt data collection for a year to collect new infant cry recordings, and other clinical data, from the University of Port Harcourt Teaching Hospital (UPTH) in Nigeria, and from the McGill University Health Centre (MUHC) in Montreal, Canada. The aim of this study was twofold: to create a larger dataset for training to increase the number of asphyxia cases, but also to evaluate the clinical performance of the system in a real-world clinical setting. This cross-cultural work demonstrates a commitment to validate the technology against non-Western cultures and within other healthcare systems. Of note, Ubenwa was able to confirm ethics approval from the institutional review board (IRB) of UPTH to be able to conduct the research study (the approval process from MUHC was ongoing at the time of writing), this illustrates the intent of the implementation team to comply with regulatory and ethical principles involved in clinical research Field Testing and User Feedback: Deploying the system to both maternity wards, and neonatal units, found the implementation team able to observe how the tool works in practice for example, determining how easy it would be for a nurse to obtain a clean cry audio file from a busy delivery room, or how well the algorithm is able to manage background noise and multiple crying types. The participation of practicing clinicians allowed for feedback regarding user friendliness, any usability issues, and circumstances where the model's predictions coincided, or did not coincide, with clinical evaluations. Feedback loops were an important iterative process to improve the tool before use by wider audience.

Designed for the Real World: As the Ubenwa algorithm was improved, the implementation team wanted to adapt to real world restrictions when in the deployed setting. The technical developers have focused on training the model to become more robust to environmental noise, to ensure high predictive accuracy while recording in conditions such as a noisy ward that weren't ideal. The implementation team also wanted to learn about the minimum time duration required to establish a reliable diagnosis, to allow clinicians to spend as little time capturing an audio file, yet still obtain enough time to be accurate. Ongoing improvements are also being sought to ensure the model is efficient and with a small memory footprint on mobile systems. This includes reducing the complexity of the model or the use of efficient versions of neural network libraries. This would enable low-end smartphones (particularly in developing regions) to run the app efficiently without the use of internet connectivity or cloud computing approaches. The technical optimizations will represent an important support step towards the conversion of the AI model into a viable medical device in low-resource healthcare conditions.

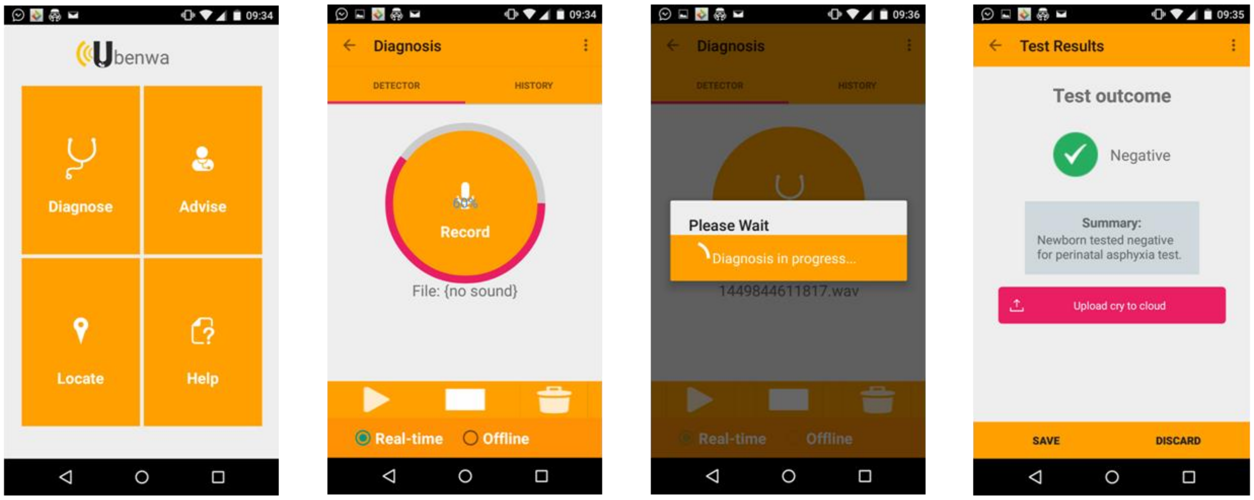

Figure 5. User Interface of the Ubenwa Mobile Application Demonstrating Automated Diagnosis of Perinatal Asphyxia Using Newborn Cry Analysis

From this course of action, Ubenwa has reached a point of actual clinical implementation. According to the latest updates in the above documents, Ubenwa was at the prototype phase, and the system was undergoing hospital trials. The data and feedback from these hospital trials will show whether the Ubenwa system requires improvements before it can be certified or approved for hospital or clinic use. The demonstration of consistent real-world performance, or positive health outcomes of the system (e.g. timely referral of asphyxiated infants leading to appropriate management), will be the method that solidifies the Ubenwa system within the hospital or clinic.

5. Limitations and Consideration

Although the Ubenwa case study reveals important implications for the role of artificial intelligence in neonatal screening, it is imperative to consider several important limitations and practical considerations that are relevant at the present stage of development and for future consideration.

The most significant limitations identified by the Ubenwa team is that of the limited access to clinically annotated infant cry databases. For example, the well-known Baby Chillanto dataset consists of only 69 infants, which is considered small by modern machine learning measures inhibiting the variability and representation of cries that the models can learn from, significantly so for distinguishable population differences, acoustic environments, and variation in respected medical conditions. The research group attempted to counter this with transfer-learning, but even the most sophisticated methods will ultimately be limited by the foundational dataset size and quality. Future development is reliant on cooperative data collection across multiple hospitals, and for instances of neonatal asphyxia, this may involve access to an adequate size for a single dataset.

Retrospective Data and Generalizability: The Ubenwa system initially validated its models using primarily retrospective cry data. While this initial data may represent a promising initial dataset, the validation of infants' cries, and how they reflect the performance of the models in controlled datasets, they do not accurately represent how this will reflect on the performance of the Ubenwa models in clinical contexts. Sources of variability that would affect the diagnostic accuracy when implemented outside of laboratory conditions would surround recording devices, ambient noise, or infant behaviours. The authors themselves note that performance measures like the ~85% unweighted average recall reported in this work will not immediately apply to numerous clinical contexts without additional model adjustments. Prospective, multi-site studies will be necessary to provide generalizability and inform model modifications.

Noise and Recording Conditions: The successful application of Ubenwa in clinical practice is further complicated by the noisy and unpredictable recording conditions usually present in hospital and community settings. Researchers have used simulated noise in their primary experiments to examine their models' robustness to different noise levels; however, real-world factors, such as background voices, hospital machine sounds, and different room acoustics, could still impede accuracy and exacerbate false positives or negatives. Ongoing development will need to focus on the real-world constraints on sound recordings, for example, how to record and process in an optimal setting, and/or incorporating noise-filtering or real-time noise-filtering options. If the model does not produce practical reliability in a clinical setting, all components of the device become irrelevant.

Complexity of Models and Mobile Deployment: There is a fundamental trade-off in design: using deep learning models that are highly accurate but also require real-time energy-efficient deployment on low-power mobile devices. The initial use of MFCC/SVM networks were based on the fact that they could be easily tuned on mobile devices, and used less energy. As the team ultimately pursues a more accurate deep learning (CNN) model, time will need to be devoted towards model-optimizing (e.g. compressing, quantization, and/or hardware accelerating) to ensure the application can be used in real-time, is optimized for speed, and is usable on inexpensive smartphones. Failure to find an effective balance between performance and practicality may preclude any use of analogous solutions, especially in instances where resources are restricted.

Clinical validation and acceptable adoption thresholds: For any AI-supported diagnostic tool to be effectively utilized in clinical workflows, it must perform at or above the accuracy of currently existing gold-standard methodologies and regulatory approvals need to be obtained. While Ubenwa's benchmarks are promising and substantial, in many neonatal screening situations sufficient sensitivity and specificity are require before consideration for implementation in routine practice. The system, as it stands now is more effectively employed as a screening adjunct enabling practitioners to make informed assessments of high-risk infants and take appropriate next steps in evaluation. If more data is obtained and more advanced algorithms developed, this may provide a mechanism to close the performance gap and build a stronger case for clinical acceptance. Situational clinical validation in a medically contextualized neonatal population is fickle, and simply distinguishing crying (i.e. similar to Ubenwa) from other risk levels (that is in practice existing diagnosis would usually be confirmed within crying) is problematic. Currently, Ubenwa's identification of asphyxia and healthy crying, while promising, is limited; crying considered in a neonate broadly to indicate or discriminate many other contextual situations (e.g., hunger, pain or other specific illness), as well as many common pathologies that may provide other identifiable phonation features in presentation. While a binary model, particularly for screening, is helpful, it measurably restricts the clinical detectability and applicability of the tool. The Ubenwa team might wish to consider, for future iteration, an identification-based approach for a multi-class classification approach, or conjunction with other medical assessment approaches to support detection of a wider range of pathologies. In the meantime, clinicians should interpret results with contextually awareness considering the emphasis on diagnostics and possible overlaps with other more established abnormal conditions.

Model interpretability and building clinical trust: A common issue with machine learning models, especially deep neural networks, presents some hurdles for researchers and clinicians interpretability. In particular, it is important that clinicians are offered reasoning and certainty within their decision making involving AI analyses and recommendations. Classical models, such as black box support vector machines, indicate decision borders that may convey digestible clinical decision reasoning, but impose restrictions compared with deep learning based models as a model's operation isn't able to have a human-like operator black box interaction. The Ubenwa team has begun to address this in that they have included reasonable measures of confidence and aspects of model embedding, but there is still considerable work to provide reliable and convincing reasoning and clinical acceptance of Ubenwa's evidence and practices. Therefore, if the aim is to achieve clinician uptake and trust for AI-based algorithms and to subsequently operationalise those into real world practice with clinical acceptance, this could include obtaining fitness for model ensembles with confidence estimates and expert demonstrations visualising the reasoning of the model. Despite some existing limits to operationalising the Ubenwa platform which presents respectable potential, those limits clearly demonstrate the potential need for a further extensive research agenda including larger scale and more representative datasets, medically contextualised clinical validation, and technical enhancements. The authors' candid acceptance of these limitations, and their commitment to ongoing development for future assessments outlines responsible science and puts the team in an excellent position to make iterative progressive improvements in search of reliable, equitable, and scalable neonatal care.

6. Integration into Low-resource Healthcare Systems

A major reason for Ubenwa's potential is its integration into health care delivery in low-resource settings where there is often no diagnostic infrastructure. The specification of the system and its deployment strategy account for access and scalability. Onu et al. specifically acknowledges that, relative to the standard blood gas analyzer method, a cry-based diagnosis approach like that of Ubenwa offers a few significant benefits that make it ideal for a resource-constrained environment.

Non-invasive: It requires an infant's cry as input and not a blood sample. Therefore, the test is free of harm and pain for the newborn, and it requires no lab consumables or biochemical analysis equipment. This is important to consider in this context because sterile blood-draw supplies or trained phlebotomists may not be readily available.

Low-cost: The hardware is effectively a mobile phone or a similar recording device, which is widely available to health workers or clinics and does not create a substantial cost burden. There is no reliance on expensive machines or reagents. With the recent spread of smartphones in even the poorest regions of the world, taking advantage of them for diagnostics can significantly reduce the cost per test (for practical purposes, if someone has a phone, the marginal cost of running the app is zero). Little training needed: The Ubenwa app is intended to be easy to use so that community health workers, midwives, or even parents could use it with very little training. Unlike interpreting an APGAR score or using a blood gas machine, which requires clinical training, the cry diagnostic is just pressing a record button and reading the result. This is particularly important in rural areas where few specialists doctors practice - the fact that it can be used by a lower-level provider or by the caregiver themself frees them to act urgently.

Fast results: The analysis is completed in less than 20 seconds. This is a very fast turnaround which means you get a status of the baby almost immediately. In a setting where every moment counts (for example, a baby who is asphyxiated must be resuscitated within minutes of birth to prevent organ damage), this is extremely important. Fast turnaround also means that the test can be used as a point-of-care screening tool - the baby can be tested at birth or as soon as there is any sign of trouble, and if the test shows asphyxia, the provider can intervene, provide oxygen support or transfer to a higher-level facility immediately without delay.

These features make Ubenwa an attractive neonatal health technology that is suitable for LMICs. As an example, in a clinic with few resources in a rural area, the midwife simply records the cry of a newborn after birth on her smart-phone. The Ubenwa app analyzes the cry and within seconds can let the midwife know if the newborn shows signs of asphyxia. This could provide a very effective early-warning system: if the app shows the baby is showing signs of asphyxia, the midwife could start resuscitation (if she is trained) or transfer/refer the baby to a hospital to get advanced care. In circumstances when there are referrals decisions often made late due to uncertainty, this app can provide objective evidence for making this critical decision sooner i.e., an evidence tool can save the child's life. Even in cases where the delivery occurs at home or in the community, a health worker or family could complete the Ubenwa cry analysis as a first assessment, with a level of diagnostic sophistication right at the bedside which was not possible without admission to the hospital.

Implementing Ubenwa into health systems will likely involve partnerships with ministries of health, NGOs or international health programs that work on maternal-newborn health. The advantage of an app-based approach is obvious for scale this could be as simple as distributing the app and offering some brief training. If the app was implemented at scale, the historic use would provide information and data (which could be updated) to improve the app over time, and also be useful to health systems to collect epidemiological data (e.g., determining asphyxia hotspots, understanding the impact of interventions, etc.). More importantly, because the tool is non-invasive, it could be integrated into routine newborn assessments with minimal concern for risks: for example, along with the routine (hospital and community) APGAR assessment at 1 and 5 minutes after birth, a cry analysis could be an adjunct screening. In low resource hospitals, it could contribute to triage of newborn babies in case where there is no pediatrician immediately available i.e., a nurse could use the app on any crying baby (abdominally) or babies that had borderline oxygen readings, the app would inform them whether urgent care was needed or not.

To properly achieve this integration, Ubenwa must first gain the trust of the healthcare providers and prove itself reliable, which is where the continued clinical validation will aid in the process. Assuming the results continue to be positive, one can imagine a pilot program where Ubenwa is introduced into specific hospitals or community health centres with training for the staff to facilitate rites of passage into a new working tool. Pilot feedback will help redefine the workflow or app interface. For example, the health system may decide to incorporate the app data into the patient records, or create protocols for when the app identifies a baby as high-risk. As Ubenwa works offline (on-device), it is perfectly suited to low-resource settings, even if connectivity is contended; it functions anywhere a phone can be charged. In summary, there is potential for Ubenwa integration into low-resource healthcare systems is tremendous: it utilizes existing technology (phones), it fits into existing practice (listening to a baby's cry is already a natural part of care), and it fills an important gap by providing a diagnostic function to practitioners that previously did not have it. In doing so, it has the potential, to close the inequity gap in neonatal care to care for newborns who are potentially asphyxiated so that they are diagnosed as early as possible, no matter how poor of communities are here is a chance for these newborns to get timely intervention, for a chance at life.

The Ubenwa case that we study illustrates one way in which artificial intelligence can help solve critical issues in healthcare in contexts where conventional solutions are not possible. Ubenwa is an example of how an everyday signal a baby crying can be creatively reconceptualized and analyzed using machine learning, and can be a cost-effective, accessible way to enable an AI-driven medical diagnosis. The evolution of the project illustrates many larger themes regarding AI and health. First, it demonstrates the benefit of collaboration across disciplines: the combined knowledge of computer science, medicine and engineering created a tool that no single discipline could have developed alone. Second, it highlights the necessity of data and representation in healthcare AI: the team used transfer learning from other areas of knowledge (given their limited clinical data), and that there is value in smart use of data that is already available (even if in a different domain) to spur solutions to data-poor challenges. Third, Ubenwa demonstrates the advantage of utilizing a lens of impact for low-resource contexts in this case: rather than implying that more sophisticated technology must be found within a higher capacity hospital, they are focusing on stakeholder engagement of AI at the point of care (where it can have the maximum benefit incrementally in terms of saving lives that would be normally lost due to gaps in expertise/equipment). The embryonic pathway taken by the system, from idea generation, to algorithm development, to mobile smartphone app, and to clinical testing, shows the entire pipeline required for turning AI research into meaningful health intervention, while paying close attention to usability, validity, and system attainment and integration with existing health systems.

Though there are been some challenges (as will be the case with any new technology in medicine), the results so far are promising. The work of Onu and colleagues has supported the capacity of deep learning models to detect fine-grained differences in physiological data (e.g. cry acoustics) which humans may not have the ability to consistently discriminate. Further, it has shown that transfer learning is also a decent way to deal with limited biomedical data, something we discover applies broadly across many more AI-for-health projects where obtaining large labelled dataset is scarce. And most importantly, Ubenwa is also addressing a critical relevance issue: the accessibility of pediatric diagnostics in the very environments that need this type of improved accessibility the most. Additionally, Ubenwa is part of a wider ethical trend that has aligned to use AI as an equalizer in health to bridge the disparity in how we use health services within a well-resourced context, and an under resourced context. The Ubenwa case study as an AI-based neonatal asphyxia diagnostic tool is a practical demonstration of how contemporary AI algorithms (from traditional SVM to current neural-networking) could be used for health globally. It warrants a sense of optimism that this area of AI research will continue to evolve, inciluding how we implement AI into our health systems as a proof of an emergent tool in our healthcare toolkit, to support clinicians save lives in even the most marginal groups.

VII. Emerging Technologies and Recommendations for the Future of Artificial Intelligence in Healthcare

The healthcare landscape is rapidly evolving due to new technologies and advancements in artificial intelligence (AI). Healthcare leaders find themselves increasingly challenged by hospital administration and patient care, and new trending AI technologies can potentially change the game. The anticipated improvement in efficiency, accuracy and accessibility from artificial intelligence will be transformational. This section highlights new trends and will conclude with recommendations for future research and applications of AI in healthcare, with a focus on building and maintaining partnerships; opportunities for innovation; and ethical considerations.

1.Emerging Technologies for the Future of Artificial Intelligence in Healthcare

Robotics and Automation in Care Delivery: Robotics and AI technologies are beginning to change hospital-based care delivery systems from the operating room to rehabilitation, and daily logistics. When guided by AI, surgical robots now help surgeons perform delicate procedures with higher accuracy and lower invasiveness. These technologies are able to eliminate hand tremors and achieve superhuman steadiness that reduces tissue damage from surgery, ultimately increasing patient recovery time . In this perspective, we will see more autonomous surgical robots in the future, capable of regularly performing certain parts of surgical procedures under human supervision. We will also see the emergence of AI-based rehabilitation robots, which will offer personalized therapeutic exercises to patients. Beyond surgery, hospitals use smart robots to perform tasks that include disinfecting patient rooms, delivering medication or transporting supplies, which may help ease the burden of staff workload and human error. Robotics in patient care is still early, but preliminary performance results have produced better outcomes (like shorter rehab times) and perhaps cost savings . The trend points towards a future in which humans and intelligent robots work side-by-side in hospitals – with AI robots completing repetitive or precise behaviors, while clinicians focus on complex decision-making, and patient interaction.

Connected Care via IoT and Wearables: Another prominent trend is the combination of AI with the Internet of Things (IoT) in healthcare. Smart wearables that include sensors (on everything from vital sign monitors to smart hospital beds) are generating continuous data streams. AI algorithms are analyzing and using this data in real time to support proactive health management. For instance, with artificial intelligence (AI) embedded into wearable ECG patches that can identify arrhythmias or indicators of cardiac stress and notify clinicians before any heart attack, imagine the ability to link a web of devices in a smart hospital that alerts a nurse to a change in a patient's health condition, recognizes when IV infusions can be continuously adjusted, or predicts which patients are most likely to deteriorate during the night. This brand-new melding of AI with IoT provides the possibility to deliver personalized health recommendations and reveal trends before they become serious emergency events. It will extend care beyond the walls of the hospital patients at home will likely have smart devices that send data to hospitals AI systems, which will help facilitate optimal follow-up care to prevent re-admissions all together (Forouzanfar, M., & Varnosfaderani, S. M. 2024). As an explosion of connected health devices appear in the marketplace, interoperability and security of data will continue to be two of the most significant challenges to meet, however, the goal will be seamless continuous monitoring of patients, which leads to safer and more efficient care.

Generative AI and virtual assistants: Powerful large language models (e.g., GPT-4) are leading to the development of a new type of AI assistants to help with elements of healthcare. Hospitals are currently piloting generative AI products in an attempt to support administrative and clinical working processes in tasks, such as productivity writing clinical notes, summarizing a patient's history, or with the help of a chatbot, leveled information for a patient's common questions. These AI systems use natural language processing, paired with their fast document creation potential that has the ability to vastly reduce a clinician's documentation burden by freeing up time to spend with patients. An example might be having an AI assistant listen to a patient visit (using voice recognition), summarize the patient visit in real-time, or perhaps even produce discharge instructions (Tripathi, S., Sukumaran, R., & Cook, T. S. 2024)[21]. Having AI powered virtual agents assist with appointment scheduling or online triaging of patient reported symptoms might help guide the patient to the right level of care and improve patient experience once in care. Early indications suggest that LLM-based tools can even provide personal patient scheduling and increase paperwork accuracy. These tools will require a reasonable degree of oversight and governance to ensure the information is reliable, adequate patient privacy is upheld and protection is established. With the right checks and balances, generative AI could be a significant driver of increased efficiency and engagement, in hospital environments .

Personalized Medicine and Predictive Care: AI is supporting a broader shift toward personalized, more proactive patient care that is individualized. There are Machine Learning models, some even with predictive capability, that can sift through large datasets (from genomic data to lifestyle factors) to develop the treatment plans that are right for each patient. AI-enabled personalized medicine will change treatment processes, potentially connecting patients with the most effective therapies for their unique genetic profile and/or health history. The future of AI is to identify disease far sooner, enabling use of predictive care to intercede as a preventive measure, rather than waiting to intervene reactively. Algorithms for early detection from imaging and other types of data analysis of lab data can help detect minute signs of things like cancer or heart disease long before the disease would present with symptoms. This affords timely care and enables timely interventions when there is the most likelihood of improving patient outcomes. Predictive care enabled by personalized and data-driven AI technology improvements in factors directly influencing not only recovery time but also cost - specifically the avoidance of unplanned generic treatments. Both care quality and efficiency will benefit from the favorable aspects across the realm of personalized and individualized care enabled by AI-driven care.

AI for Early Diagnostics and Intervention: And if we look to the arena of diagnostic medicine, AI systems and processes are an emerging area of new tools for medical diagnostics. Advanced machine learning with imaging AI is now able to provide medical diagnoses faster than a clinician with a diagnostic accuracy that sometimes enters the realm of human diagnostic accuracy. For example, AI in software has evaluated thousands of very images looking for things like fractures,

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[21] Tripathi, S., Sukumaran, R., & Cook, T. S. (2024). Efficient healthcare with large language models: Optimizing clinical workflow and enhancing patient care. *Journal of the American Medical Informatics Association*, 31(6), 1436–1440. https://pmc.ncbi.nlm.nih.gov/articles/PMC11105142/

tumors, or neurological issues in real-time for immediate and reliable interaction for the clinician. What is more important is the AI software matured enough to evaluate distant structures, not just the immediate evaluation and visibly show there was a clot and when the stroke occurred – as above, there are measures of time that will ultimately determine the care pathways for early intervention. AI can use imaging to do triaged care and then also analyze whole and partial images from pathology slides to first identify findings that are emergent then notify, ideally assign, a staff member, to respond sooner than later. AI cannot only algorithmically triage imaging but AI computer algorithms like we have already seen will also study vital statistics and selected lab results as they are being monitored and they will also be able to, not readily predict, notice trends that requires staff attention to issue a warning, potentially, of an abnormality from the patient's status or an increased suspicion of sepsis, but the AI timeframe maybe hours sooner than right now. All of these possibilities will hopefully allow hospitals to be in a position to intervene in the care pathway sooner rather than later before serious complications develop.

As a note, AI may soon have the capacity to maneuver through the patterns which are hidden and concealed within the thousands of data points of patients, and potentially identify disease states before a patient even exhibits signs of disease (indeed, a recent model also produced a model for more than 1,000 different conditions). AI will likely enable a more proactive and predictive identification of potential problems and may even improve the outcome of care and patient safety.

2.Recommendations

To take full advantage of possible benefits AI may offer to hospital management and care delivery, stakeholders need to begin to think proactively. Several valuable recommendations emerge from the assessments in the previous sections and our current analysis.

Facilitate Consistent Collaboration: To achieve the goal of developing an AI enabled health care system requires collaboration among stakeholders is an ongoing concern. Co-designing and implementing AI solutions involves multiple stakeholders which includes hospital facility leadership, clinicians, AI developers and maybe policymakers and the patient population, but collaboration requires continual inclusion of this interdisciplinary stakeholder group so as to foster imaginative ideas that appropriately account for the realities of practice and the needs of clinicians and patients using the AI system. Collaboration will need to be ongoing not only during the development stages, but during deployment and monitoring so that the issues encountered by users and patients continually inform how the AI tools are enhanced and adapted. This is the only way we can foster trust, and leverage partnership with clinicians and patients to inform innovations related to AI, mission of healthcare and improving quality health outcomes. As the experts have asserted, bringing AI approaches that are premised on the needs of health care organizations and that can accommodate those needs requires long-term collaborative processes between data scientists, health care professionals, social scientists and ethicists. The collaborative process will produce opportunities to instantiate structured research processes to build deliberate conditions and the collaborative approach can begin to break down high-performance silos to generate collective awareness of AI systems organizational capacities and limitations.

Invest in education and capacity development: Enabling the healthcare workforce with knowledge about AI rationales is an important investment for workforce development. Hospitals and medical schools need to support professional development opportunities for the healthcare workforce to promote AI literacy, while committing to help institute training programs. If healthcare workers have some understanding how AI tools work (and more importantly, where it could fail), they can use this understanding to create safer and effective teams to use AI. Similarly, having the opportunity for data scientists to experience clinical workflows will inform the AI systems design processes more holistically accommodate clinicians practice. Ongoing education programs can take many forms, including workshops that offer guidance about interpreting AI-generated recommendations, and hands-on training with new AI software. The pressing need is to ensure that staff feel comfortable working with AI thinking of it as an efficient helper, rather than as a mysterious black box. Developing human capital around this investment will ultimately yield dividends by facilitating AI use and allowing clinicians to rightly use technology to improve patient care. As one review indicates, education and training for healthcare personnel around the complex range of AI technologies will ensure comprehension of how to apply AI observations to patient care. In short, generating a culture around AI as part of a learning health system will help put the full power of AI to work.

Prioritize Ethical Guidelines and Oversight: Entering an era with AI embedded in healthcare orchestrates strong ethical oversight. Hospitals and health systems, especially at the regional level, need to develop explicit ethical guidelines governing AI development and employment that emphasize patient safety, fairness, transparency, and accountability . This process should involve setting up governance committees or oversight boards to review AI algorithms for bias or risk before deployment. Continuous monitoring is essential AI systems must be audited regularly to ensure that they produce the intended outcomes to avoid or reduce unintentional harms . In addition, ensuring frameworks such as Explainable AI (XAI) are embraced can enhance the transparency of decisions made by AI to clinicians and patients, which helps improve trust . For instance, if an AI feed identifies a patient as high-risk, it must describe in layperson terms, why that patient was deemed high-risk, or the salient risk factors. Ethical oversight involves consent and autonomy considerations: patients should be aware if AI is present in their care and have the ability to ask questions, refuse, or consent. There are real ways organizations have begun exert AI ethics governance in healthcare systems such as the World Health Organization, and their professional associations, so we can all be secure in the knowledge that our ability to innovate will never exceed our ability to be harm free and protect patients rights. By embedding ethics into all phases, design to deployment hospitals are able to retain public confidence and so deploy AI ethically over the long-term.

Enhance Data Privacy and Security: The appetite for data for AI presumes patient privacy will not be lost sight of. Future iterations of research and implementation will need to advance the means for AI models to learn from data while preserving privacy. Hospitals should invest in privacy protected methods along with strong cyber-protection from data breaches. It is always advisable for anonymization and encryption of patient data when utilizing the patient data for development of AI whenever feasible. Regulatory organizations and hospital compliance teams will need to continuously update guidelines associated with new privacy issues that arise such as how to manage AI models that might accidentally store sensitive information. By integrating privacy and security standards into AI projects from the outset, healthcare organizations can make sure developments do not weaken public confidence. In other words, data utility and strict privacy protections should serve as a fundamental requirement as new healthcare AI projects arise.

Inspire a Culture of Innovation with Responsible Governance: Healthcare organizations need to foster an environment of AI innovation with responsible governance. This includes the willingness to implement small pilot projects for new AI solutions, analyze their effectiveness, and iterate based on results. Leadership should be supportive of creative methods of experimentation for example, AI innovation teams or collaborations with startups or research laboratories for the organization to stay close to the forefront of technology. Simultaneously, a fail-fast, learn-fast model may be appropriate, where implementations are tracked closely, and any emerging issues are resolved immediately or the project is redirected.

Most significantly, innovation needs to be tempered with responsible governance. Experts universally recommend stakeholders advocate for responsible regulation and standard setting that keeps pace with advances in AI. By proactively working with policymakers, healthcare leaders can manage and create their governance standards and produce responsible, effective regulation that protect the safety of patients and the efficacy of AI tools for undefined examples, ensuring clear approval processes provide certainty for AI-based medical devices or algorithms. In addition, healthcare organizations can create internal review boards to evaluate and validate AI deployments to ensure new innovations meet quality and ethical thresholds before being more broadly implemented. In summary, healthcare should continue to encourage innovation but foster it with appropriate evaluation and controls. By experimenting with new concepts while retaining high standards, the sector can adapt and evolve alongside AI in a more equitable and sustainable fashion.

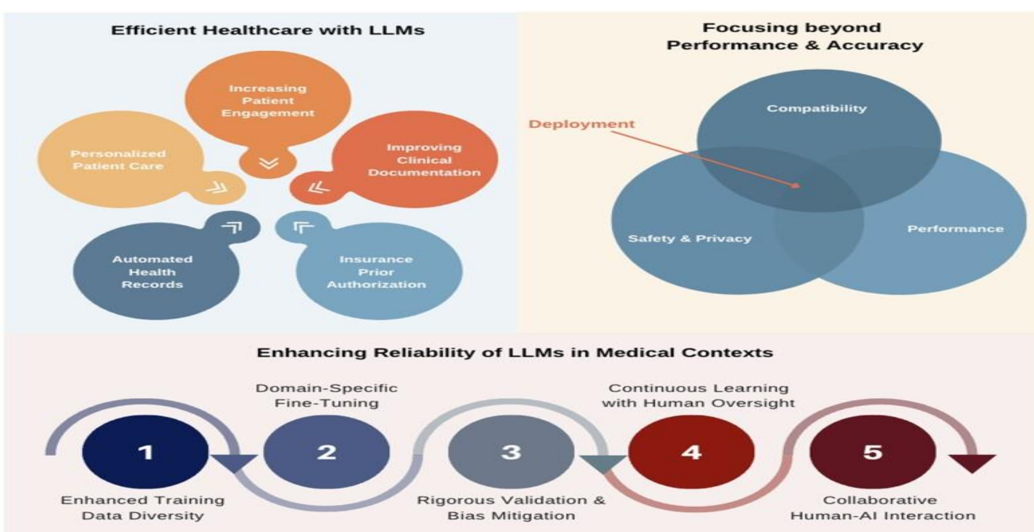

Figure 6. Potential uses of large language models across the clinical workflow (from Tripathi, S., Sukumaran, R., & Cook, T. S. 2024).

The recent developments in large language models (LLMs) are providing new opportunities to improve clinical workflows and the delivery of care. Tripathi, Sukumaran, and Cook (2024) describe how LLMs can automate and augment many forms of administrative and clinical tasks in healthcare practices, including documentation, triage and patient communications. These models have demonstrated great feats of communicating and processing information about often complex medical information while limiting cognitive and administrative load on providers in the clinical space, plus generating concise and accurate summaries of information. The authors argue that if utilized with intention to train staff on their use, LLMs can provide better resource efficiency, speed up patient throughput, and provide better care. LLMs can facilitate clinical workflows through all aspects of clinical activity including if consent is provided, assisting providers with drafting clinical notes, extracting information from electronic health records (EHRs), generating evidence-based recommendations in real time, and developing list of Recall Actions for next steps clinically. The authors provide cautions for readers to remain mindful of the necessary validations and surveillance on these technologies to account for ethical and safety issues. Evidence behind the use of patient data privacy, model bias, and oversight by appropriate clinicians is possible to navigate together and overcoming some of these issues may align things with improving the benefits of the technology in a health care setting.

Conclusion

This thesis has conducted a thorough analysis of the degree to which artificial intelligence can change hospital management and improve healthcare provision. Through a critical review of the literature, the contrast of traditional versus AI methods, and a case study of the Ubenwa project, it has been shown that AI is much more than just a new way of delivering technological progress. AI could become a fundamental force for change in health systems in the modern age.

The findings indicate that artificial intelligence can improve operational effectiveness, increase accuracy of diagnostic information, and extend accessibility to care. Based on the critical analysis of the literature, AI systems tend to be more positively performing than traditional methods in term of diagnostic information accuracy, with sensitivity and specificity levels often reaching 85 to 90 percent in both serious and vital areas of healthcare delivery like medical imaging or early disease detection. The Ubenwa case study highlights this very capacity of AI to be adaptable to lower resource situations to alleviate some of the urgent threats to public health like neonatal asphyxia detection. Furthermore, the findings show the effect of AI on smoothing workforce or hospital workflow, improving resource allocation, and enhancing the patient journey through reducing or eliminating repetition of administrative duties to healthcare professionals and administrators letting them spend more time caring for patients while providing clinical decision makers accurate predictive and resource allocation information.

There are limits to the potential to improve the integration of AI into clinical settings, including barriers such as technical, infrastructure, and data quality issues, system interoperability and cost. Organizational and human resistance, including anxieties about job security and acceptance of new technologies, will be a challenge in its own right. Ethics also play a pivotal role in this transition. Governance structures and ongoing oversight will be needed to address ethical issues around data privacy, algorithmic bias, transparency, and accountability. The future success of AI in healthcare systems will depend on managing AI technologies responsibly and ethically and on technical success of the technology itself. AI in health care is heading towards the development of more explainable, inclusive, and accessible systems. We believe a higher degree of explainable AI, the use of federated learning, and a greater multi-modal use of technologies will create pathways to overcome the limitations of AI systems, as well as the ability to expand the reach of AI technologies across more populations. Based on the research we have conducted, many recommendations arise like, facilitate collaborative interdisciplinary groups of clinicians, data scientists, ethicists, and policy makers to develop ethical AI solutions that are relevant to the context that they are developed to solve. Support educational investment in developing digital literacy and principled approaches to using AI tools that impacts growth and problem solving by health care professionals. To realize this transition in a socially responsible manner, it is important to provide shifting regulatory and ethical positions in conjunction with technology, to ensure the ethical and equitable use of AI.

Use phased implementation strategies through pilots and iterative assessments that manage risk and enhance learning and organizational learning. This research suggests that AI is not a rival to health professionals. Rather, AI is a major enabler of health professionals by offloading standardized and time consuming tasks and amplifying clinical insight for diagnosis. Therefore, the clinician can do what we value most: listen, care, clinical reasoning, and therapeutic relationships. The health environment into the future may represent a hybrid state, where the work of humans and artificial intelligence will be integrated in order to deliver health that is more accurate and efficient but also responds with compassion. Achieving this aim requires nothing less than a wholesale change, not just in learning how to manage technology within our current practices but also how to engender the professional values that are the foundation of medicine. This dissertation provides evidence to suggest that artificial intelligence represents an opportunity for the transformation of hospital systems and health system delivery. While AI systems encounter technical, human, and ethical challenges, we must not overlook their potential to transform health care in many areas including, enhancing diagnostic certainty and efficiency, resource use, expense, and access to health care. The Ubenwa case illustrates how AI can enhance health equity through interventions like those described in Ubenwa, particularly in many resource limited environments. Our ambition in the description for this case study, is for social impact to remain a central tenant for the development of AI in health care. The future must be directed towards creating synergies between human capabilities and machines, enabling technologies to enhance rather than replace human potential, in order to establish pathways toward a streamlined health system with health equity as an outcome. The success of this transformation depends on our capacity to see, think, and act on issues with foresight, ethical considerations and the implications for patients and communities well-being. This dissertation has generated opportunities for future research in investigating the intended and unintended long-term implications of the transformation of health systems through the use of AI technology, the evolution of health professionals roles, and new emergence of care designed for a very different health care stage in a digital era.

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