INVESTIGATING THE IMPACT OF ARTIFICIAL INTELLIGENCE ON ORGANISATIONAL PERFORMANCE IN THE HEALTHCARE SECTOR: A STUDY OF NIGERIA AND THE UK

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School of Business and Creative Industries

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ABSTRACT

Healthcare systems all over the world encounter challenges in achieving the 'quadruple aim' for healthcare: which is to improve the health of the population, patient experience, healthcare team wellbeing and to reduce the rising cost of healthcare. These aims are all focused on improving performance in healthcare settings. Although there is an abundance of research on AI in healthcare, there exists a lack of understanding of the specific impacts of AI on OP in healthcare. Despite the continued interest of researchers and practitioners, the application, adoption, and implementation of AI to specific elements of organisational performance does not appear to have received much interest. Prior to the Covid-19 pandemic, applications of AI focused more on other business sectors than on the healthcare sector. Recently however, there is increasing interest in how AI can help improve the performance of healthcare organisations. This Research investigated the impact of AI on OP in healthcare with a view to linking AI to specific elements of OP in healthcare. To accomplish this, the Research adopted the exploratory interpretivist paradigm by collecting data from semi-structured interviews with Key informants in diverse healthcare settings. This was achieved by thematic analysis of interviews, which revealed the impacts of AI on OP in healthcare settings, challenges of AI adoption in healthcare and key factors for healthcare AI adoption. The Research concluded that AI potentially improves OP in healthcare; furthermore, a framework (and implementation guidance) to support the adoption of AI to improve OP in healthcare was developed.

Keywords: Artificial intelligence, Organisational performance, AI adoption, Healthcare performance, Healthcare organisation

DECLARATION

I hereby declare that no part of this work has been submitted for any other degree, neither at this university nor at any other institution of learning. As the Research author, I own the copyrights of this dissertation (with the inclusion of appendices) and have given the University of the West of Scotland the right to use such the Copyright, to support research and for administrative purposes. Copies of this research may be made only in accordance with the Copyright, Designs and Patents Act 1988 (as amended) and component regulations, or UWS licensing agreements, as appropriate. Copies of the Research should include this page. I further declare that this research is completely my personal work and is therefore based on my own efforts to conduct the research. I also declare that the process of collecting and presenting information has been conducted in conformity with academic policies and ethical behaviour. Furthermore, I declare that this Research is solely my work. I also declare that all the information used in this Research is consistent with academic regulations and ethical practice.

OPEYEMI SEYI OZIGA

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DEDICATION

This Research is first dedicated to the loving memory of my late Father David Ajiboye Ogunsua. I will forever cherish and remember your love, commitment to family and all your legacies, Rest on!. And to my mother, my number one woman, my jewel of inestimable value, I deeply grateful for your lifelong support. I also dedicate this work to my darling husband Joseph and dear children Jessica and Jane as well as my ever-loving siblings Oluwaseye, Aderonke, Adetutu, Temitope, Akinwale I am thankful for your steadfast love and support through this journey.

ABBREVIATIONS

1. AI- ARTIFICIAL INTELLIGENCE
2. OP- ORGANISATIONAL PERFORMANCE
3. UK-UNITED KINGDOM
4. USA-UNITED STATES OF AMERICA
5. KI- KEY INFORMANTS
6. NN- NEURAL NETWORKS
7. ANN-ARTIFICIAL NEURAL NETWORKS
8. CNN- CONVOLUTIONAL NEURAL NETWORKS
9. DL- DEEP LEARNING
10. ML- MACHINE LEARNING
11. NLP- NATURAL LANGUAGE PROCESSING

PART I

1. CHAPTER ONE: INTRODUCTION

1.1. Introduction

This Chapter provides the background for the thesis. It presents the research background, research problem, research significance, research motivation, the aims and objectives, research questions, research contributions, summary of the literature review, overview of the research methodology, research limitations and the research structure. The Chapter also discusses the concepts of AI and OP in healthcare, the application of AI to OP in the context of Nigerian and the UK healthcare and the management of these two concepts in healthcare.

1.2. Research background

1.2.1. Organisational performance (OP)

Since the inception of the organisation, the concept of organisational performance (OP) has continued to attract the interest of scholars and practitioners alike (Demeke and Tao, 2020). OP has been described as a vital concept of strategic management (Edwards, 2014) and according to some scholars, it is the only sustainable source of competitive advantage (Huang *et al*, 2016; Isorate, 2018). Although organisational performance is both an important and central strategic management concept (Shafter *et al.,* 2016), It is without a universally agreed definition (Leitão, Pereira and Gonçalves, 2019). This may be due to variances in performance elements that are identified as important to the achievement of objectives in an organisation or its wider sector, different approaches to measurement of OP and differences in views regarding what constitutes successful performance (Leitao *et al.,* 2019, Demeke and Tao, 2020; AlShehhi *et al*., 2021).

The responsibility of achieving organisational performance lies with the leadership and management of an organisation who are required to formulate and implement strategies that are expected to culminate in the achievement of organisational goals and objectives (Shafter, Ghnaem and Abdelmotleb, 2016). Consequently, managers are increasingly under pressure to improve organisational performance (Muthuveloo, Shanmugam and Teoh, 2017). This pressure is worsened by factors that affect the global business environment such as the global financial crisis, harsh economic terrain, the constantly evolving needs of customers, technological advancements as well as increased competition (Dirican, 2015). All of which may threaten organisational survival (Wang, Bhanugopan and Lockhart, 2015). The importance of OP stems from the fact that it enables managers to identify the factors that impact the organisations performance (Farooq, 2014) and to develop strategies to enhance performance, competitive advantage, and survival (Oyemomi *et al.*, 2016).

Competitive advantage is thought to be partly due to an organisation's unique set of resources and skills i.e., the Resource Based View RBV theory which proposes that an organisation's resources play a major role in the achievement of organisational performance (Ozcelik, Aybas and Uyargil, 2016). RBV proposes that competitive advantages and OP can be achieved when an organisation has strategic resources (i.e., assets that are valuable, rare, non-substitutable, and difficult to imitate) (D'Oria *et al.*, 2021). These strategic resources may also be in the form of human, physical, technological, or reputational capital and tangible or intangible resources (Walls and Barnard, 2020). Research shows that organisations have previously depended a lot on the traditional factors of production or resources. However, reliance is now shifting towards other resources such as knowledge, information technology, Artificial Intelligence, and others that may have an impact OP. This shift may be due to the decline in the economic development potential of these traditional factors of production (Purdy and Daugherty, 2017).

1.2.2. Artificial Intelligence (AI) as a strategic resource for achieving OP

Globally, organisations continue to rely on the application of strategic resources to improve their performance (Khalifa, 2020). Technology has been cited as one of such strategic resources reshaping organisations, by its potential for improving organisational performance (Jabbouri *et al*., 2016) and improving competitive advantage (Raj and Seamans, 2019). There have been four major revolutions witnessed by humans till date as illustrated below (Figure 1.1). The first being the first industrial revolution that saw the development of the steam engine; this was followed by the second industrial revolution that released electrical-energy based products; computer and internet-based knowledge was introduced in the third industrial revolution in the late 20th century which also conceptualised the first information revolution and lastly the fourth industrial revolution and the second information revolution which released AI to the world along with Big data, IoT and cloud computing systems. This present revolution is characterized by high scale automation for global connectivity that would see AI become an important resource for utilisation by organisations (Ganasegeran and Abdulrahman, 2019).

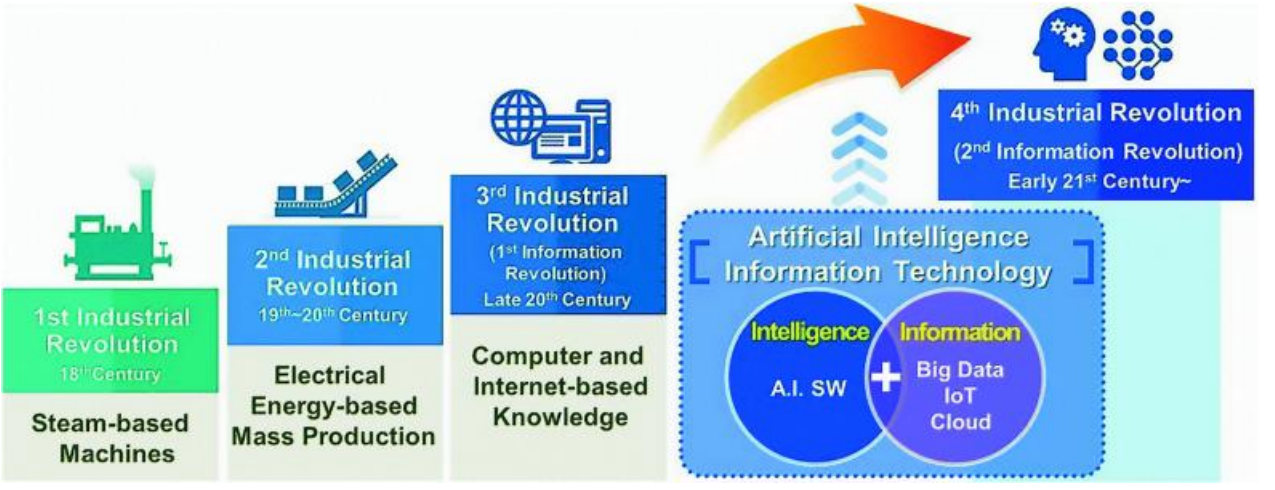

Figure 1.1: The four industrial revolutions showing the entry of AI.

Source: (Ganasegeran and Abdulrahman, 2019).

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The 4th industrial revolution also referred to as the digital transformation era is expected to deliver new economic value that will determine success or failure in many sectors. This on-going industrial and digital revolution is impacting the nations, societies, employment, businesses, healthcare, and life in general. In the business terrain, the digital transformation is enabling business process transformations, competitiveness, productivity, efficiency, and performance (Martinelli, Farioli and Tunisini, 2020). Artificial Intelligence (AI) is one of the digital transformation strategies that are being deployed in various business sectors (Raj and Seamans, 2018). AI is expected to usher in a new revolution into the global business terrain by acting as a new factor of production and therefore a resource that will drive growth and profitability both at the economic and organisational level (Russell, Dewey, and Tegmark, 2016; Felten, Manav, and Robert, 2018). Technological breakthroughs such as image recognition etc. (Felten, Manav, and Robert, 2018) that have occurred in the last decade due to AI performance have been successfully applied to different sectors even though there are arguments as to the limits and boundaries of AI (Raj and Seamans, 2018).

According to industry research by Accenture and Frontier Economics which involved modelling of AI on 12 countries with approximately 50% of global economic output. AI was reported as having the capacity to double the rate of development of the 12 countries researched by the year 2035 by changing the process of work and creating a relationship between people and machines. This UK was one of the countries researched (Purdy and Daugherty, 2017).

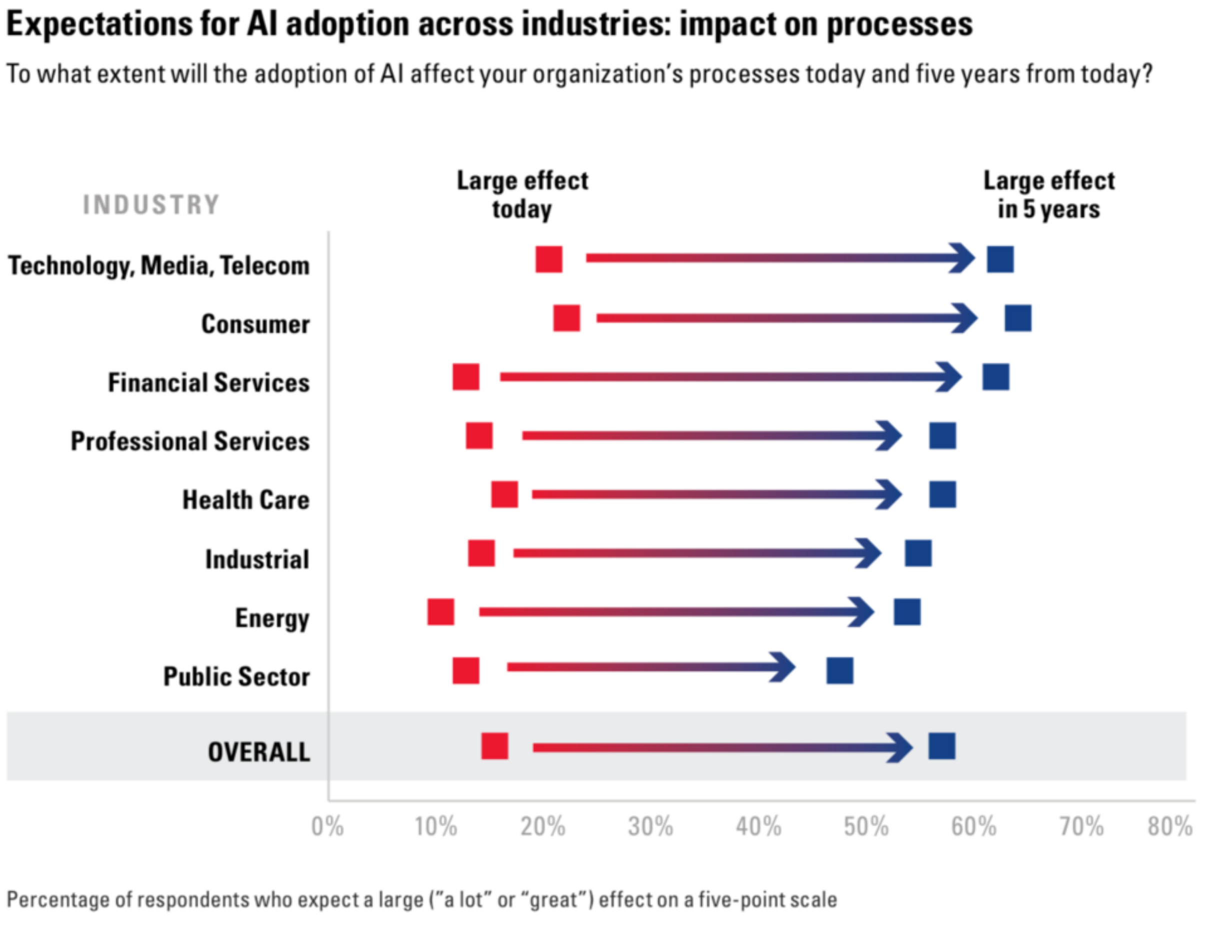

Figure 1.2: Expectation for AI adoption across industries: impact on processes

Percentage of respondents that expect AI to have a great effect across industries.

Source: Ransbotham, (2017)

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Artificial intelligence is expected to have a big impact on organisational processes within the next years including the healthcare sector as illustrated in Figure 1.3 above. This is due to the ability of machines to match and outperform humans in certain activities such as learning, emotion sensing, tacit judgement and more (Ransbotham, 2017). Consequently, organisations in different sectors all over the globe are adopting AI. These early adopters of AI are actively developing AI strategies and utilizing them in enhancing their performance and competitiveness (Kang *et al.*, 2016). Some of the fields where AI has been applied with reported benefits include customer service, medical diagnosis, pharmaceuticals; in drug discovery and production, law, scientific discovery, transportation, education, administration, finance, sales, and marketing, in supply chain and warehousing (Shabbir and Anwer, 2015; Maurer *et al.*, 2016; Agrawal *et al.*, 2017; Aksu *et al.*, 2017; Hamet and Tremblay, 2017; Siau and Yang, 2017; Ma *et al.*, 2018). Of all these sectors, the healthcare sector is one of the lowest and latest adopters of AI as with other technologies even though AI has great benefits for the sector (Loh, 2018). From the discussion above, AI can be applied as a strategic resource for the benefit of business sectors including the healthcare sector.

1.2.3. Sector Overview

The Healthcare sector is made up of all the different organisations that are involved in the provision and coordination of medical and all related goods and services (Scott, 2019). Although there appears to be no agreed classification of the sector, the healthcare sector is composed of industries, sub-industries, and a diverse range of companies. The healthcare sector can be categorised mainly into the following industries pharmaceuticals, biotechnology, equipment, distribution, healthcare facilities, and managed health care (Technofunc.com, 2013; Ledesma *et al.,* 2015). The Pharmaceutical industry is the healthcare sector industry that deals with researching, developing, producing, and distributing medications mainly using chemical processes. While the Biotechnology industry develops, manufactures, and markets novel, patented medicines by using biological processes. The equipment industry deals with the manufacturer of health care equipment and medical devices e.g., diagnostic equipment. The Distribution industry is responsible for the distribution and sales of healthcare products e.g., pharmacies, wholesalers of equipment. Healthcare facilities are responsible for providing healthcare services to those in need of such services and includes a wide range of health and social care services such as hospitals, clinics, surgical centres, nursing homes. The Managed health care or the health insurance industry deals with the provision of variety of techniques aimed at decreasing the cost of healthcare provision and improving quality of care (Ledesma *et al.*, 2015). Healthcare is reported to be one of the most important sectors of any economy (Darvas *et al.,* 2018) majorly because of its crucial role in supporting human health through diagnosis, treatment and prevention of disease, illness, injury, and other physical and mental impairments that occur in humans (Gupta and Rokade, 2016).

The healthcare sector has other crucial roles such as macroeconomic implications which include feedback effect on public revenue and expenditure for instance human health and social work activities contribute 7.4% to value added and 10.6% of overall employment in the EU (Darvas *et al.*, 2018). The pharmaceutical sector is part of the healthcare sector and contributes immensely to revenue through research and development for new drugs and processes; estimated at 1,143.3 billion dollars in 2017. The sector also has direct and indirect impacts on the macro-economy such as its impact on fiscal sustainability and economic development through public spending decisions (Ibid). Furthermore, the sector impacts the labour market with regards to contribution to the labour force, the formation of human capital, productivity, and inequality (McPake *et al.,* 2013), and is therefore unarguably one of the most important sectors of any economy.

1.2.4. Research context Nigeria and UK

1.2.4.1. Nigeria

Nigeria is a country located in the sub-Saharan Africa, with a population of approximately 206 million persons (NPC, 2022). The country has been described as Africa's largest economy with a 2019 GDP estimate of approximately US$ 448 billion (The World Bank, 2022b). In 2019, the Nigerian health expenditure was about 3.03% of the country's GDP Nevertheless, with slight increases in the preceding years (Statista, 2022). The Nigerian Healthcare sector is one that is predominantly driven by the public sector, with the private sector supplementing service provision. The urban areas are served by secondary and tertiary health facilities while the needs of rural areas are serviced by primary health care facilities (WHO, 2017). A large proportion of these facilities are unable to the healthcare needs of the population, especially those located in the rural areas which makes up 53% of the entire population due to reasons such as; shortage of qualified healthcare professionals, inadequate facilities, inadequate supply of essential drugs, poor quality of services, poor infrastructure, mismanagement, political, instability, corruption, high cost of healthcare, lack of funding and other reasons (Aregbeshola and Khan, 2017; Oyekale, 2017; Aregbeshola, 2019).

Nigeria is classified as a developing country: i.e., those countries with Gross National Income per Capita per year of less than or equal to $11,905 (Guo and Li, 2018). In these countries, life expectancy and general healthcare performance is poor due to high incidence and prevalence of both communicable and non-communicable (Oguntimilehin *et al.,* 2014), limited healthcare access, low public health spending, low health insurance coverage, inadequate healthcare facilities, shortage of qualified healthcare professionals diseases as well as low number of healthcare professionals to provide support ultimately resulting in high morbidity and mortality in these populations (Oguntimilehin *et al.,* 2014; Strasser *et al,* 2016). Furthermore, there are inequalities in the distribution of healthcare services between the urban and rural areas due to more adverse economic situations, a dearth of healthcare providers, transportation problems and other issues resulting in even poorer health outcomes and performance in these areas (Strasser *et al.,* 2016; Guo and Li, 2018).

1.2.4.2. United Kingdom (UK)

The United Kingdom is an island country located off the north-western coast of the Europe mainland. It comprises of the island of Great Britain, which is made up of England, Wales, Scotland, and the Northern part of the island of Ireland (Kellner and Briggs, 2019). As of 2019, the UK (United Kingdom) had an estimated population of 66.8 million (ONS, 2019). The UK's healthcare sector is government funded through the universal healthcare system known as the National Health Service (NHS) is made up of a group of publicly funded healthcare services. It consists of the NHS England, NHS Scotland, NHS Wales and Health and Social Care in Northern Ireland. Under this healthcare provision UK residents are entitled to healthcare and have the option to seek private healthcare (Chang *et al.,* 2022).

According to the World bank classification, the UK is a high-income country, these are countries with a GNI per capita of $12,736 or more (Hamadeh, Rompaey and Metreau, 2021). UK healthcare expenditure for 2020 was estimated as 12% of GDP, with a 2.6% increase over spending in 2019 due to increased healthcare needs (Cooper, 2021). The UK's Healthcare system is reported to be in crisis from lack of central funding to keep up with the healthcare demands of the population (Montgomery *et al.,* 2017). The healthcare system is also being affected by the impacts of COVID-19 on the UK population which has resulted in a high level of morbidity and mortality. There is need for interventions that can effectively prevent increases in COVID-19 cases, further pandemics, health sector crisis as this will help improve performance in the healthcare sector. There is need for technological responses that can prevent increases in COVID-19 cases, further pandemics, and health system crisis (Flynn *et al,* 2020).

1.3. Research problem

One of the important aspects of the healthcare sector is the macroeconomic implication of healthcare spending decisions. Healthcare spending is increasing faster than the rest of the global economy and contributes up to 10% of global gross domestic product (GDP), with higher growth observed in the low- and middle-income countries; a 6% annual average compared to 4% in high income countries (WHO, 2019). The healthcare expenditure for Nigeria (Classified as a lower –middle-income country), in 2020 was approximately 3.75% of the country's GDP Nevertheless, the same as the figures for 2018 and 2019 but with slight increases in the preceding years (www.statista.com. 2019; Smith, 2021; WHO, 2021). Although the Nigerian healthcare expenditure is low compared with the global average and that of other African countries (with the same classification) e.g., Kenya, Morocco, Algeria, approximately 5%, 5.31%, and 6.24% respectively (World Bank, 2022a; World Bank 2022b). This may not be the case for long as there are plans underway for foreign investment to supplement the Nigerian healthcare expenditure by about 80 billion US Dollars to help meet the unmet healthcare needs of the population (Smith, 2021). This implies that healthcare spending for Nigeria is likely to increase in the future. For the UK, (Classified as a high-income country) total current healthcare expenditure as a percentage of GDP was estimated at 9.9%, 10.2% and 12% for 2018, 2019 and 2020 respectively. The increased spending in 2020 over 2019 is thought to be due to government spending on the Covid-19 pandemic (Cooper, 2021; ONS, 2021; World Bank, 2022a; World Bank 2022b). Healthcare spending in the high-income countries, is estimated to increase from approximately $5221 per capita in 2014, are expected to increase spending by $9215 (with an uncertainty of [UI] of 3254–4746) between 2014 and 2040 while, lower-middle-income countries, healthcare expenditure is expected to increase to from $267 per capita in 2014, to $844 (UI 472–737). At the global level health care spending is estimated to increase from approximately 9 trillion US Dollars in 2014 to approximately 24 trillion US Dollars in 2040 (UI of 20·47–29·72) (Dieleman *et al.*, 2017). Increases in healthcare expenditure may affect economic growth either positively or negatively. Healthcare expenditure is positively associated with the indicators of labour productivity, personal spending, and GDP, while being negatively associated with multifactor productivity which may lead to sub-optimal healthcare spending, reduced efficiency, and a decrease in economic growth (Raghupathi and Raghupathi, 2020).

The healthcare sector faces numerous issues that prevent optimal performance of organisations in the sector. Research shows there was a decline in global mortality rates from 1960 to 2016 which has resulted in increased life expectancy, ageing population (implying a rise in the incidence and prevalence of chronic illnesses such as Parkinson's, Alzheimer's disease, Cancer etc.) and expansion in the non-fatal burden of disease and injury (Augostovski *et al.,* 2018). Consequently, there is a consistently high global disease burden as evidenced by the DALYS (Disability adjusted life years a measure of disease burden of a population) for the period 2010 and 2015 to 2017 respectively; 2,688,683,014.751, 2,672,541,416.178, 2,668,475,492.634 and 2,499,292,055.68 (Augostovski *et al.*, 2018; GBD 2017 DALYs and HALE collaborators, 2018).

The ageing global population, increased incidence of chronic and non-communicable diseases (Dall *et al.*, 2013) and resultant high burden of disease have culminated into a disproportionate rise in demand for healthcare resulting in high expenditure on healthcare reported globally both in low- and high-income countries (Collier, 2011; Lacobucci, 2017). The sector is also being challenged by other existing and emerging issues in its move to become smarter such as: sustaining a positive margin in an uncertain and changing health economy, making a strategic move from volume to value, responding to health policy and complex regulations, investing in exponential technologies for cost reduction, increased access, more effective processes, improved care, consumer engagement and improvement of patient experience, acute shortage of human resources for health and need to structure the workforce of the future (Miseda *et al.*, 2017, Knight and Sorin, 2016; Sullivan, 2018, Lagasse, 2019, Deloitte, 2018).

As earlier alluded to, technology and innovation are widely acknowledged as important drivers of economic growth applied by organisations to achieve organisational performance in today's business terrain (Acar and Acar, 2012; Khin and Ho, 2019). Scholars have made the case for the application and adoption of AI and digital technologies to the healthcare sector (Desautels *et al*, 2017; Tursunbayeva and Renkema, 2022) as is the case in other business sectors (Manyika *et al.*, 2017; Ma and Siau, 2018). This is due to several expected benefits for healthcare such as improvement of chronic disease management, suggestion of precise therapies for management of complex diseases, reduction in medical errors, improvement of enrolment into clinical trials (Dilsizian and Siegel, 2014; Miller, 2018), improved record keeping, enhanced decision making, enhanced medical diagnosis, reduced costs, promotion of personalized healthcare and enhanced customer experience (Davenport and Kalakuta, 2019; Sunarti *et al,* 2021). Research shows successful application of AI in the business sector and the same positive impact is expected in the healthcare sector for organisational performance elements specific to healthcare such as improved clinical performance, patient satisfaction, increased efficiency, reduced cost per patient and financial performance (Secinaro *et al,* 2021; Ciecierski-Holmes *et al*., 2022). For healthcare sector organisations that adopt AI, it is expected that there will be significant revenue increases and profitability. For instance, the National Bureau of Labour Statistics estimates that there will be about 40% increase in the use of home health appliances over the next 10 years resulting in significant reduction in hospital stay and positively impacting patient outcomes and hospital performance (Wang and Siau, 2017). Although a large segment of corporate organisations (about 90%) are of the opinion that AI will enable them to attain sustained competitive advantage, only a very small segment (5%) has integrated AI into business offerings and processes and less than 40% operate by AI strategies (Ransbotham *et al.,* 2017). These statistics imply that although organisations are aware that AI can help them achieve competitive advantage, they may not actually understand the concept of AI, and the process through which it can result in OP (Fredriksson,2018; Shahid, Rappon, Berta, 2019).

The literature shows that research has been conducted globally on AI and its application to different business sectors including the healthcare sector. However, most research on the healthcare sector are studies of the application of AI to healthcare performance (Singh *et al.,* 2018; Wu *et al.,* 2020a; Ding *et al.,* 2019) that do not investigate performance or assessment of OP elements in healthcare such as cost effectiveness, profitability, quality of care, patient health outcomes, patient satisfaction etc. which are crucial to assess or measure OP in healthcare (Sivathaasan, 2013; Panch, Mattie, and Celi, 2019; Shah, Milstein and Bagley, 2019). Therefore organisations in the healthcare sector may not have sufficient information to apply, adopt and implement AI for OP (Panch, Mattie, and Celi, 2019). AI is described as a disruptive technology in healthcare (Esteva *et al*, 2017), this implies that organisations that do not adopt AI may experience negative effects in their performance and survival in the future (Raj and Seamans, 2019). This makes it pertinent that organisations consider the adoption of AI to gain competitive advantage, survive and improve organisational performance. It is the aim of this research to provide evidence-based information to help solve the healthcare problems discussed above through the effective application, adoption, and implementation of AI.

1.4. Research significance

Healthcare organisations today, are under increasing pressure to account for the development and implementation of actions that are directed towards the improvement of care quality, reduction of associated healthcare costs and the attainment of quality, person-centred care (Backman, Vanderloo, Forster, 2016). Strategies are crucial to the achievement of superior organisational performance (Yanney, Annan-Dennis, and Awuah, 2016) and should be applied to provide directions for organisations to follow to achieve their objectives. It is therefore imperative for organisations in the healthcare sector to identify and apply effective strategies to improve organisational performance. Scholars suggest that strategy should be linked to organisational performance through performance measurement frameworks as these serve as a tool to furnish the requisite information for achieving organisational goals and objectives (Kaplan and Norton, 2008; Haddadi and Yaghoobi, 2014).

Several researchers emphasize that AI can be a strategy for achieving organisational objectives in the general business sector (Nozaki *et al*, 2017; Davenport, and Kalakota, 2019; Huang and Rust, 2018). Organisations in healthcare are also showing similar interest in AI as a strategy to improve OP (Gambhir, Malik, and Kumar, 2016; Bajwa *et al.,* 2021). Literature on the topic shows that AI has been applied to different areas of healthcare both in the Nigeria, UK, and in the global context, but as previously alluded, there is scant literature on the applications of AI to OP elements that have been identified as important indicators of OP in the healthcare sector. Most of the studies have not measured or assessed the actual impact of AI on elements of OP. These studies have also not applied performance frameworks that take into consideration elements of organisational performance that are relevant and important in healthcare (Vainieri *et al.,* 2019) which are linked to AI such that organisations in the healthcare sector can be appropriately guided in adopting and applying AI.

Although exploratory in nature, this research investigates the impact of artificial intelligence on organisational performance in the healthcare sector by analysing elements that have been identified as important for OP in healthcare and those that have been identified for the general business sector. This will make it possible to assess the impact that artificial intelligence has had on organisations that have applied it and provide a framework that is practically applicable by healthcare organisations to apply, adopt and implement AI for OP (Reddy, Fox, and Purohit, 2018; Davenport and Kalakota, 2019). This Research will contribute to the body of knowledge on how AI can be adopted by health sector organizations to achieve OP. The research is significant because it will help in providing solutions to the operational challenges of the health sector towards enhancing performance of organizations in the sector.

1.5. Research motivation

Motivation for this research is drawn mainly from the Researchers desire to apply previous knowledge and experiences in the healthcare sector to solving contemporary and challenging issues that are arising in the general business sector and more specifically in the healthcare sector such as growing population, ageing population, increase in the prevalence of chronic diseases such as cancer, diabetes, cardiac issues, high cost of healthcare services, high burden of healthcare, long waiting times, shortage of healthcare skills, low quality of healthcare services. Also of great interest to the Researcher is the issue of Organisational Performance in the healthcare sector and improved sustainable healthcare for healthcare users. Another motivational factor for this research is the sense of intellectual achievement that the Researcher gets from doing creative work that contributes to the development and functioning of the society. This Research enables the Researcher to discover new facts, verify and test them adding to the body of knowledge in the field of AI and thereby contributing to the enhancement of the health sector both in Nigeria and in general. This Research is a part of the requirements for the conferment of the degree of Doctor of Business Administration on the Researcher. Apart from the Doctoral achievement for the Researcher, other potential benefits include better employment opportunities, promotion, higher remuneration other incentives such as leadership and management opportunities. Healthcare is particularly lacking in consultants within the intersection of technologies such as AI and OP in healthcare. This Research therefore enables the Researcher to gain the knowledge, skills and competencies required to consult in this area of healthcare. Competencies from this area can also be transferred to other business sectors. Overall, the main motivation for this Research stems from a desire to improve healthcare performance both for the benefit of healthcare consumers and the economic growth and survival of healthcare organisations.

1.6. Research Aim and Objectives

Building upon the research problem in Section 1.2 above, the aims of this research are:

1. To investigate the impact of Artificial Intelligence (AI) on Organisational Performance (OP) in the Healthcare sector.
2. To develop a framework for the adoption of AI for OP in the Healthcare sector supported by implementation guidance.

Consequently, the objectives for this research are stated below:

1.6.1. Objectives

1. To critically review the literature on the application of AI to Organisational performance in the General healthcare sector and the Nigerian healthcare sector.

2. To identify the challenges and benefits of artificial intelligence AI for the healthcare sector.
3. To evaluate current frameworks of Artificial intelligence in healthcare.
4. To investigate the impact of AI on OP in the Nigerian and the UK healthcare sectors.
5. To investigate the challenges of AI adoption in the Nigerian and the UK healthcare sectors.
6. To investigate factors for the adoption of Artificial intelligence in the Nigerian and the UK healthcare sectors.

1.7. Research Questions

1. What is the current literature on the application of AI to OP in the general healthcare sector and Nigerian healthcare sector?
2. What are the challenges and benefits of artificial intelligence for the healthcare sector?
3. How effective are current AI frameworks in healthcare?
4. How does Artificial intelligence impact OP in healthcare in the Nigerian and the UK healthcare sector?
5. What are the challenges of AI adoption in healthcare in the Nigerian and the UK healthcare sectors?
6. What are the factors for the adoption of Artificial intelligence in the Nigerian and the UK healthcare sectors?

1.8. Research contribution

This Research contributes in several ways towards achieving a clearer understanding of the application, adoption, and implementation of AI for the enhancement of OP in healthcare. First it adds to the body of knowledge by reviewing and evaluating the adoption of AI for Organisational performance in healthcare. Secondly it contributes to the body of knowledge, by investigating the impact of AI on OP in the healthcare sector. Thirdly, the research makes an original contribution to theory and practice by developing a framework for the adoption of AI in the healthcare sector, Furthermore the study provides implementation guidance for managers in the healthcare sector on how to use the developed AI/OP framework.

1.9. Research structure

This Research is structured into sections, parts, and Chapters, with the following sections: Title page, abstract, dedication page, acknowledgment page, table of contents, body of the thesis, reference list and appendix. As illustrated in figure 1.4 below, the body of the thesis is in two parts; Part 1 is composed of theoretical Chapters or desk research and Part 2 allocated to field research and is composed of Chapters that have a qualitative grounding as illustrated in the figure 1.4 below.

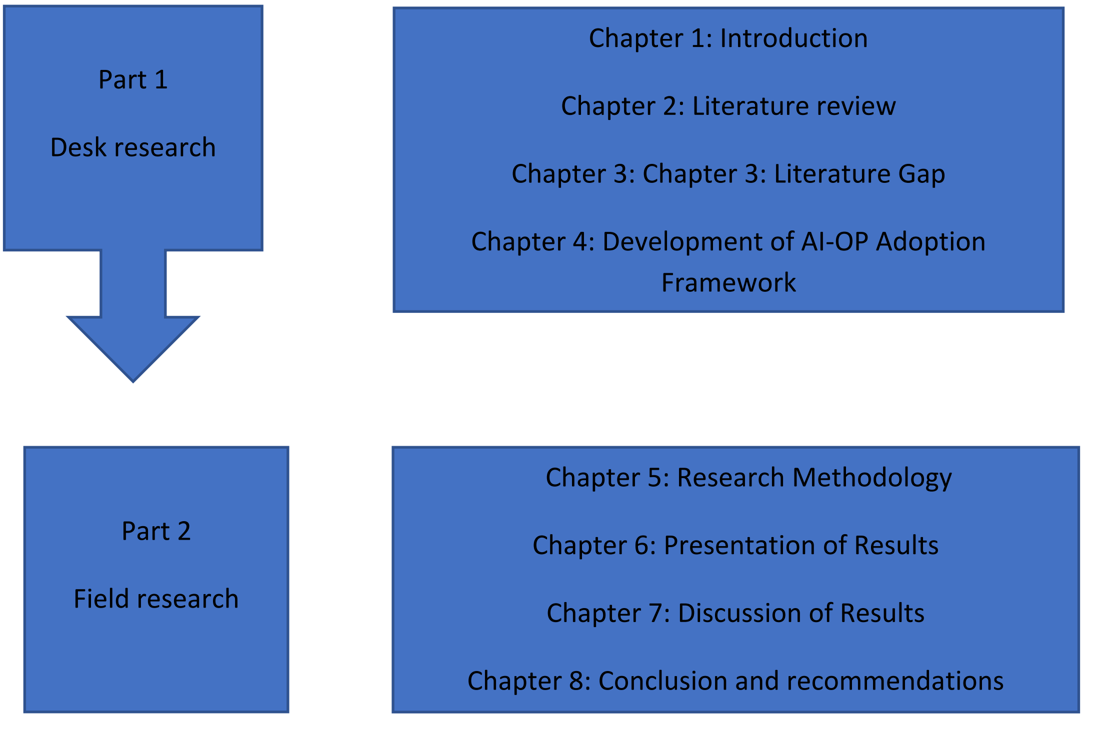

Figure 1.3**:** Research structure

Source: The Researcher

1.9.1. Chapter 1: Introduction

This Chapter is the introductory Chapter and serves as the foundation for the study. It presents the background of the research, the research problem, research significance, research motivation, research aims and objectives, research questions and structure of the research.

1.9.2. Chapter 2: Literature Review

This Chapter is the literature review and features a review of key and relevant literature on the topic, with the aim of identifying gaps.

1.9.3. Chapter 3: Literature Gap

This Chapter presents key deficiencies identified based on in depth review of literature and evaluation of relevant literature.

1.9.4. Chapter 4: Development of AI/OP Adoption Framework

This Chapter is a presentation of theories, models and literature that are relevant to the research for development of the theoretical AI-OP adoption framework.

1.9.5. Chapter 5: Research Methodology

This is the Research methodology Chapter. It outlines the research methodology for the research, the research methods or techniques, methods of data collection and analysis and justification for these methods, how these methods will answer the research questions.

1.9.6. Chapter 6: Presentation of results

This chapter presents the results and findings from the analysis of primary data collected through the semi structured interviews of Key informants in healthcare. This includes responses from interview respondents what they represent.

1.9.7. Chapter 7: Discussion

This Chapter discusses the results of the literature review and analysis of primary data collected in line with the design of the study and the research questions as stated in Chapter one.

1.9.8. Chapter 8: Conclusion and Recommendations

This Chapter concludes the research by discussing the contributions of the research and demonstrating that the research aims, and objectives have been met and the research questions answered.

2. CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

This Chapter of the research focuses on the application and adoption of Artificial intelligence (AI) for Organisational performance (OP) in healthcare sector by reviewing research on the topic by academic scholars. Furthermore, it discusses the evolution of AI and OP, definitions of AI and OP, challenges and benefits of AI and OP in healthcare, and key literature on the application of AI to OP in the healthcare sector. The review and analysis of academic literature enables key contributions on the research topic. This is followed up with a comprehensive literature evaluation which facilitates the establishment of key shortcomings in the application and adoption of AI to OP in the healthcare sector, which is discussed in Chapter 3, the literature review will also reveal the state of the application of AI to OP in the healthcare sector and opportunities for the development of these concepts.

2.2. Artificial Intelligence (AI)

Although Artificial intelligence is not a new concept considering its introduction by academics and scholars since the 1950's, it is a concept that has recently gained more interest and attention by academics, researchers, and industry experts across various fields. The concept appears to have first being introduced by Professor John McCarthy and founded on the claim that 'intelligence' can be described with precision and simulated by machines (McCarthy *et al.*, 1955).The phrase Artificial intelligence (AI) was reported to be first used at the Dartmouth College conference in 1956 (Patel *et al.,* 2009) and can be traced to researchers such as Turing, McCarthy, Minsky (Moor, 2006; Pan, 2016).

2.2.1. The Evolution of AI

Aristotle's approach to understanding human thinking as a type of logic that applies syllogism (a dualistic geometric concept created by Pythagoras to all manner including animate and inanimate) involved the application of the binary system to responses such as Yes/No, Finite/Infinite, Male/Female (Steel, n.d, and Bringsjord and Govindarajul, 2018). This appears to be the foundation that machines can replicate and even replace human intelligence. Renowned Poet and Theologian Llul, publisher of the book -Ars generalis ultima (The Ultimate General Art), combined concepts based on Aristotle's logic to a system for the recreation of the human mind (Sales, 1997). Later in 1666, Leibniz a German mathematician and philosopher published his book titled "Dissertatio de arte combinatoria" (On the Combinatorial Art) in which he suggested that any of man's thoughts is implementable by a non-complex combination of concepts (Leibniz, 1989).

Boole, in 1854 proposed the conduction of logical reasoning in similar pattern as using a set of systems to solve equations, inferring that computing can replace logical thinking (Boole, 1854). This proposal was adopted by Turing who later discovered that Boole's proposition could be applied to computation of numbers (Turing, 1936). Thus, he later applied this to the Turing machine project, development of the concept of the universal computer, AI, and the Turing test in 1950 (Muggleton, 2014). Turing asserted that AI has attained human intelligence when a person does not know whether his or her contact is AI or a human during a conversation (Turing, 1950). By 1956, researchers; McCarthy of Dartmouth University, Minsky of Harvard University, Rochester of IBM, Shanon of the Bell Telephony institute through workshops, birthed the academic specialty of AI (Moor, 2006). McCulloch and Pitts, 1990, presented the idea that neural networks can effectively imitate the human brain (McCulloch and Pitts, 1990). Later in 1951, Minsky and Edmund designed the first neural network technology- the stochastic neural analogue reinforcement calculator (Park and Park, 2018). Nineteen fifty-five, saw the development of the first AI program- "Logic Theorist" by Newell and Simon (Newell and Simon, 1976) and in 1969, Bryson and Ho built the foundation for today's deep learning by the development of the back-propagation algorithm (Bryson and Ho, 1979). In 1972, Stanford University groups researching computational models applicable to clinical decision making and problem-solving, developed an expert system 'MYCIN' for the identification of pathogenic bacteria and suitable antibiotics for treatment (Kulikowski, 2015). As research into the field of AI is increasing so are the applications of AI also increasing and currently, they cut across various spheres of human endeavours including ordinary and professional activities (Guo and Li, 2018). AI has gradually progressed from a phase of simpler applications of binary systems to responses and then on to the replication of human intelligence by machines and currently to the phase of application to more complex cases.

2.2.2. Definition of AI

The concept of AI has been reported as difficult to define by both Practitioners and researchers alike (Coombs *et al.,* 2017; Miaihe and Hodes, 2017) and this may be partly due to the lack of a universal definition of intelligence. Most definitions of AI including earlier, and more recent ones connect the concept to human intelligence. For example, Turing, 1950 asserted that a machine/computer was intelligent if it could imitate human responses under certain conditions: i.e., in a form equivalent or indistinguishable from human intelligence (Turing, 1950). Turing's understanding of AI is one where machines that pass the Turing's test exhibit human level intelligence. McCarthy, 1950 defines AI as the science and engineering by which intelligent machines, and intelligent computer programs are made (McCarthy, 1955). His definition is also alike to Turing's as it views AI as machines and computer programs that are intelligent. Some of the more recent definitions of AI are in congruence with earlier definitions as they define the concept in relation to human intelligence. For instance, Sawrup, (2012) defines AI as the science and engineering of creating intelligent machines, particularly intelligent computer programs to assist in understanding human intelligence (Sawrup, 2012). Sawrup's definition appears to position AI as intelligent machines or intelligent computer programs that exhibit human intelligence. While Jakhar and Kaur, 2019 simply defined AI as ''Incorporation of human intelligence into machines'' (Jakhar and Kaur, 2019), they also make the same connection between machines and human intelligence just like earlier definitions.

Table 2.1: Definition table for AI

Author/year	Definition	Main focus
McCarthy, 1950	"The science and engineering of making intelligent machines, especially intelligent computer programs"	Machines that exhibit human level intelligence.
Turing, 1950	A machine/computer was asserted as intelligent if it could imitate human responses under certain conditions: i.e., in a form equivalent or indistinguishable from human intelligence	Machines that exhibit human level intelligence.
Sawrup, 2012	The science and engineering of creating intelligent machines, particularly intelligent computer programs to assist in understanding human intelligence	Intelligent machines and intelligent computer programs
Ginsberg, 2012	"The enterprise of constructing a physical symbol system that can reliably pass the Turing test".	Systems that can pass the Turing test.
Shabbir and Answer, 2015	The characteristic of machines, computer programs and systems to perform the intellectual and creative functions of humans, resulting in independently proffering solutions, drawing conclusions, and making decisions.	Technologies with the capacity to perform different human intellectual functions.
Russel and Norvig, 2016	Artificial intelligence is an extensive term covering an array of technologies (some of which have been under development for several years) which aims to solve problems by application of intelligence which resembles human intelligence.	Technology with the capacity to apply human-like intelligence to problem solving.
Berendt, 2018	AI can be defined as the capacity of a digital computer or robot to conduct functions that are linked to intelligent beings.	Digital computers or robots that can execute intelligent functions.
Sable and Khanvilkar, 2018	Artificial Intelligence as the field that is concerned with the design and application of algorithms for analysing, learning and interpreting data.	Algorithms with the capacity to manage data.
Floridi, 2019	AI is defined on the premise of McCarthy's definition as "making a machine behave in ways that would be called intelligent if a human were so behaving.	Machines with intelligent behaviour.
Jakhar and Kaur, 2020	Artificial intelligence is simply the ''Incorporation of human intelligence into machines''.	Machines with human intelligence.

Source: The Researcher

The Table 2.1 above is a summary of definitions of AI by different AI scholars and researchers starting with McCarthy and Turing the founding fathers of the AI concept. A recurring term used in 80% of the above definitions is ''intelligence'', with most of the definitions implying AI to be the application of human and machine intelligence applied to various functions.

The following working definition of AI has been developed for this Research. AI is: ''***The process by which machines or computers are programmed with information that enables them to provide solution to real world problems with a level of precision that equals or supersedes that of humans***'' (Researcher).

2.2.3. Classifications of Artificial Intelligence

Several classifications of AI have been observed in literature such as on the bases of strength, level of intelligence, type, or organisational application (Alpcan, Erfani, Leckie, 2017; Mialhe and Hodes, 2017; Park and Park, 2018; Garbuio and Lin, 2019). With reference to the subject of discuss and scope of this Research, AI is classified based on organisational application. Garbuio and Lin, 2019 classify AI on the bases of its organisational applications into: Assisted intelligence, augmented intelligence, and autonomous intelligence (Garbuio and Lin, 2019).

2.2.3.1. Assisted Intelligence

Assisted intelligence enhances business by assisting humans in making decisions or taking actions and amplifying the value of current activities, these systems do not learn from their own interactions (Gillham *et al*., 2018). However, they function based on clearly defined rules, repeated tasks involving data verification and tests for simulation to reduce the risks associated with business decisions e.g., medical image classification is an example of assisted intelligence in health care services to improve accuracy over conventional processing techniques (Garbuio and Lin, 2019).

2.2.3.2. Autonomous intelligence

Autonomous intelligence is the advanced stage of AI that is currently in development; this type of AI enables a system to behave within previously set limits as defined by the builder, in such a way that it may adapt to changing situations or act autonomously without the intervention of humans (Gillham *et al*., 2018). In health care, the doctorless hospital is a future application for the autonomous intelligence system. However, this requires not only advances in AI but also the ability to build in enough transparency for humans to trust the technology to act in their best interest (Garbuio and Lin, 2019).

2.2.3.3. Augmented Intelligence

Augmented Intelligence is a subset of Artificial Intelligence technology that augments human decision making and learns continuously from their interactions with humans and the environment (Gillham *et al*., 2018). It emulates and extends human cognitive abilities like memory and sequencing, perception, anticipation, problem solving, and decision making (Garbuio and Lin, 2019). Augmented Intelligence systems use artificial intelligence techniques such as natural language processing, spatial navigation, machine vision, logical reasoning, machine learning, and pattern recognition. These have been applied to various sectors such as Financial Services, Healthcare and Digital commerce (Sabhikhi and Sanchez, 2017). Garbuio and Lin, 2019 classification implies that Assisted intelligence improve services based on clearly defined rules without the ability to learn from their interactions, autonomous intelligence can improve services as well as learn from interactions and adapt to changes in their environment in a transparent manner. Augmented intelligence has the capabilities of assisted and autonomous intelligence of services improvement and interaction with the environment as well as the augmentation of human decision making.

2.2.4. Subfields of AI

2.2.4.1. Artificial Neural Network (ANN)

These are information processing systems that function in a pattern resembling that of biological systems, such as information processing by the brain (Shukla and Jaiswal, 2013). These units are constituted by numerous interconnected processing elements called neurons (mimicking human brain learning) which use a computer model that works synergistically to solve problems through learning by example (Dastres, Roza and Soori, 2021). ANNs have being applied to healthcare areas such as classification of data in medical databases (Mao *et al*., 2020) in diagnosis such as prediction of Type 2 diabetes (Borzouei and Soltanian, 2018).

2.2.4.2. Machine learning

Machine learning (ML) is the scientific study of algorithms and statistical models used by computer systems to perform specific tasks without the need for explicitly programming (Mahesh, 2019). Data analysis is automated by applying algorithms that identify patterns iteratively and learn from them (Wahl *et al,* 2018). Machine learning applications are of three types: Supervised, Unsupervised and Reinforcement-learning (Silver *et al*, 2013). Supervised learning uses identified data patterns, Unsupervised uses, discovers and learns from patterns in data (e.g. data mining) while Reinforcement learning is supervised learning where rewards and penalties are assigned in the course of the applications interaction with a dynamic environment (Wahl *et al,* 2018). Machine learning in healthcare is commonly applied in precision medicine to predict the success of treatments based on patient attributes and treatment context, also in disease prediction (Lee *et a*l, 2018; Davenport and Kalakota, 2019).

2.2.4.3. Automated planning and scheduling

This is an emerging subfield of AI, that is concerned with organising and prioritising the activities required to achieve a specific goal. It is also referred to as AI planning, AI planning applications may be used to improve human efficiency or for optimized processes (Hirschberg and Manning, 2015).

2.2.4.4. Natural language processing (NLP)

NLP bridges the gap between human and computer language by using algorithms that enable the identification of natural language key words and phrases by machines (Wahl *et al.,* 2018). It is mainly applied to understanding and classification of clinical documents and published research (Davenport and Kalakota, 2019).

2.2.4.5. Image and signal processing

This is another subfield of AI that is applied in the processing of large amounts of data from images and signals e.g., motion and sound. The process involves signal feature analysis, data classification by tools e.g., ANNs (Wahl *et al.,* 2018).

2.2.4.6. Expert systems

Expert systems also known as knowledge or reason-based AI programs are interactive computer-based AI systems that have the capacity to replicate the decision-making and/ or problem-solving processes performed by human experts (Tan *et al*., 2022). They operate based on 'if-then' rules and were the dominant AI in the 1980s and have been used commercially during that period and beyond. The drawback with these systems is reduced functionality, conflict, and breakdown with enormous number of rules (usually in thousands). Although they are being applied to the healthcare setting but for the previously mentioned reason, they are being replaced in healthcare by approaches that are based on data and machine learning algorithms (Davenport and Kalakota, 2019).

2.2.4.7. Robotics

Robotics is the field of knowledge and techniques that is applied to creation of robots while Robots can be defined as devices that are programmable, self-controlled, and composed of electronic, electrical, or mechanical units. In more general terms, they are machines that functions in the place of living agents (Mihret, 2020). In healthcare, different types of robots are being applied; Cognitive therapy robots, Companion robots, Humanoids, Robotic limbs and exoskeletons, Telepresence robots (such as screens on wheels), Service robots, Surgical robots (Cresswell, Cunningham-Burley, and Sheikh, 2018).

2.2.4.8. Robotic process automation (RPA)

Robotic process automation is a relatively inexpensive, easily programmable, and transparent technology (Davenport and Kalakota, 2019) that follows defined rule-based functions to perform a set of specified tasks (Wiljer and Hakim, 2019). In Healthcare RPA has been applied to automation of workflow, tasks involving repetition such as prior authorisation (Ratia, Myllärniemi, and Helander, 2018).

2.2.5. Benefits and Challenges of Artificial Intelligence in Healthcare

AI has several benefits for the healthcare sector as discussed below.

2.2.5.1. Benefits of AI

AI has several benefits for the healthcare sector as discussed below.

2.2.5.1 Improvement of medical research

AI is used in analysing and getting inference from large and complex data sets for health research, combing different data types, in drug trials to match studies with suitable individuals (O'Mara-Eves *et al.,* 2015; Al-Lazikani, 2013; NHS, 2016). It can be applied to the processing of massive amounts of data without any negative impacts as observed in humans such as memory lapse or fatigue (Paredes, 2018). This implies that may be able to enhance medical research and at the same time, decreasing research associated workload and time burn out.

2.2.5.1.1. Improvement of resource management

AI can be utilized in the planning and allocating resources in healthcare e.g., Harrow council UK, used the pilot application of IBM Watson care manager system in matching clients with care providers that would meet their needs within specified budget and the development of care plans and optimal use of care management resources (Harrow Council, 2016). Machine learning is being applied to resource planning and allocation in ventilator triage for Covid-19 patients (Grand-Clement *et al.,* 2021). Consequently, AI may be able to enhance efficiency around resource management leading to more cost-effective healthcare.

2.2.5.1.2. Improvement of patient care

Data from digital devices such as fitness devices, smart phone apps, EHRs, can be analysed using machine learning techniques to predict acute disease, and to efficient monitoring of chronic conditions resulting in reduced hospitalization, efficient management e.g. GP at Hand an hospital app that is under trial in some London NHS surgeries (Hamid, 2016; Hall *et al*, 2016; Barret *et al*, 2019; NHS, n.d). This implies that AI can improve healthcare access and the healthcare quality for patients.

2.2.5.1.3. Improvement of clinical processes

AI is being applied to clinical processes in many different healthcare specialties as discussed. Radiology: Machine learning is being applied in radiology, for automated and easier detection of disease (Hosny *et al.*, 2018; Sukegawa *et al.,* 2020). In Neurology AI has been applied to neuroimaging (Fellous *et al.,* 2019), Oncology: for treatment through dermatology, genomics, pathology, and radiology (Cazzato *et al.,* 2021; Shao *et al.,* 2022). Dermatology: for clinical decision making, diagnosis and prevention of the onset of skin disease (Li *et al.,* 2020). Assisted Living: in the health and social care sector to the sick, disabled and elderly (Rong *et al,* 2020), social robots that interact with humans through gestures, speech, facial recognition, movements etc., AI for fall detection, dietary advice, and among others (Scoglio *et al.,* 2019; Rong *et al,* 2020). Cardiology: for prediction, diagnosis of cardiac diseases and provision of support for the cardiologists in choosing the most appropriate treatment alternative (Busnatu *et al*., 2022). Mental health: for predicting, monitoring, tracking and treatment of mental health conditions (Carr, 2020; Lovejoy, 2019), such as anxiety, depression, autism spectrum disorder, post-traumatic stress disorder among and other mental illness (Lovejoy, 2019; Tran *et al.,* 2019) and in treatment of mental illness (Fiske *et al., 2*019). Ophthalmology: for diagnosis of diabetic retinopathy, age-related macular degeneration, glaucoma, and cataracts (Gunasekeran *et al.,* 2020), Critical Care: for disease diagnosis in critical situations (Mlodzinski *et al.,* 2020), prediction of mortality, sepsis onset, hospital length of stay etc. (Shillan *et al.*, 2019). Public health: for the early identification of infectious diseases e.g. in the Covid-19 pandemic to facilitate Covid-19 preparedness, tracking people, forecasting, surveillance (Whitelaw *et al.*, 2020).

2.2.5.1.4 Cost reduction

AI technologies have been described as more cost-effective, faster, and with reduced potential for errors when compared with humans especially with regards to analytical tasks (Canhoto and Clear, 2020). AI in healthcare has led to more efficient disease diagnosis, treatment, and management, decrease in hospital visits and patient length of stay (Garg *et al.,* 2018; Horgan *et al.,* 2019) resulting into significant cost savings for healthcare providers and healthcare users.

From the above discussion it can be concluded that AI can benefit healthcare in many ways such as supporting medical research, enabling better management of healthcare resources, better patient access to care, and higher accuracy of diagnostic processes in many healthcare specialties such as radiology and imaging, genetics and genomics, pathology, dermatology, oncology, neurology, health and social care, ophthalmology, diabetes, critical care, public health resulting in reduced treatment and associated costs, more efficient management of diseases decreased morbidity, mortality and provision of better health outcomes.

2.2.5.2. Challenges of AI in Healthcare

In the same manner that AI has beneficial applications in healthcare, there are also challenges in its application. These are discussed below.

2.2.5.2.1. Reliability and safety issues

Current AI technologies utilize models of their environment that are simpler than human mental models, this will not be the case for future AI technologies which are expected to learn to apply environmental models of higher complexity than human models (Barnes, 2016). This implies that AI technologies could result in high-level destruction if its behaviour cannot be reliably predicted (Shabir and Anwer, 2018) and this could be detrimental to safety. AI technologies have been reported to have reduced accuracy and reliability, providing wrong treatment recommendations based on hypothetical, synthetically generated data, when not pre trained with complex clinical data (Hamid, 2016) resulting in increased patient risk and potential fatalities.

2.2.5.2.2. Legal liability

The issue of legal liability has been raised, for instance in the case of medical errors there is no clear guidance regarding accountability/ responsibility for actions performed by AI/ robots which are not legal entities (Kingston, 2016). As standards are still being developed for AI in healthcare, a case could be made for parties concerned (Coeckelberg, 2019) which include the healthcare professional, the hospital, the manufacturer, the developer of the software and even the data provider (Rowe, 2017). This implies that all these parties are at risk of litigation if things go wrong.

2.2.5.2.3. Lack of transparency and explainability

One of the big challenges for AI is the Black box phenomenon. This refers to difficulty in understanding the process through which AI reaches its decisions (Khoury and Palanica, 2019), this may result in lack of trust for the technology and caution towards its application. The black box challenge is more prevalent in healthcare where there is need to understand the process by which conclusions have been drawn (Bloomberg, 2018) as processes need to be evaluated, monitored, and controlled for errors.

2.2.5.2.4. Data privacy and security issues

Since healthcare AI technologies use information that is private and of both medium, high sensitivity and requiring legal control (Hamid, 2016; Frontier Economics, 2018). Privacy and security breaches may occur (Quartz, 2018; Rajkomar, 2018) and this could lead to unauthorized access to patient information and therefore may be potentially detrimental to patients.

2.2.5.2.5. Unethical and Malicious use

AI is potentially subject to malicious uses through covert surveillance (Analysis of motor behaviour, mobility patterns from smart phones can show health information without person's knowledge) (Yuste, 2017), and cyber-attacks or poisoning whereby data are introduced which may cause learning systems to make mistakes or misclassify medical information (Brundage, *et al*, 2018; Finlayson *et al*, 2019) with potential detrimental effects for patient safety and wellbeing.

2.2.5.2.6. Bias, Equity and Fairness of Data

Data used in training AI may reflect bias and discrimination e.g., on the bases of demographic parameters (which is legally unacceptable). These data are sometimes not representative of the entire population; the algorithms themselves may reflect the ideas of the developers (Ntoutsi *et al.,* 2020). This can lead to health inequalities and poorer health outcomes for minority groups.

2.2.5.2.7. Resistance from Healthcare professionals

There have been questions raised around the reliability and accountability of the decision making of predictive AI (Gille *et al.,* 2020; Parasuraman and Riley, 1997). Healthcare professionals generally believe in tested and trusted methods and have spent several years training to become certified. With AI they may need to scale up their skills set to include AI and they may feel that their expertise is challenged and may be unwilling to accept AI or even resist it (Hamid, 2006; Cohen *et al.,* 2014).

2.2.5.2.8. Profitability issue

Although AI and other digital technologies have been reported to improve productivity, most organisations will only be willing to adopt AI if it will clearly deliver significant profits beyond the cost of adoption (Frontier Economics, 2018). This is especially the case for profit-based private healthcare organisations and sometimes the case for healthcare organisations that may be partly self-funded due to reliance on profits made for funding of certain services.

2.2.5.2.9. Over-reliance

One of the challenges of artificial intelligence is the full dependence of human lives on technology which may eventually result in unemployment problems, social discrimination, and power inequalities within societies (Shabir and Anwer, 2018). AI application and adoption should be managed in a way that over-reliance is prevented.

2.2.5.2.10. Mental health implications

Although AI technologies result in better health outcomes for sufferers of chronic illnesses resulting in greater independence, improved dignity, and quality of life. It has been reported that they may lead to patients de-alienating themselves from health services and family (Sharkey and Sharkey, 2012). Resulting in psychological, physical, and mental health issues (Shabir and Anwer, 2018; Jibril *et al.,* 2018) and poor quality of life and health outcomes.

2.2.5.2.11. Lack of Evidence-base

Another challenge with AI is that most AI are not in line with evidence-based healthcare which requires new interventions or technologies to improve healthcare outcomes by effectiveness in real world settings (Ciecierski-Holmes *et al.,* 2022). AI technologies tend to be implemented on the bases of characteristics and performance of AI such as comparative accuracy between AI and healthcare experts rather than evidence of improvement of health outcomes (Houssami, 2017; Ciecierski-Holmes *et al.,* 2022). This may result in lack of actual achievement of healthcare performance. These challenges reveal that although AI can be applied widely in healthcare, it is still very much in its developmental stages. These challenges can pose barriers for healthcare organisation thereby preventing the application, adoption, and implementation of AI in healthcare. It is necessary to properly understand these challenges and provide solutions to them as this will transform AI into a truly scientific and evidence-based concept that can be effectively applied to solving healthcare issues.

2.3. Application of AI to OP in the Healthcare sector

To support understanding on how AI has been applied to OP in the healthcare sector, it is exigent to undertake a critical review of studies of the application of Artificial intelligence to Organisational performance in healthcare settings as this will inform on the different areas of healthcare to which AI has been applied and how it has impacted OP. It will also reveal research gaps, hence areas of focus for the research which will ultimately result in guidance towards the adoption of AI for improved OP in healthcare. The concepts of AI and OP have been attracting the interest of researchers since the 1950's (Georgopoulos and Tannenbaum, 1957). Although the concept of OP has gradually gained prominence over the years, the concept of AI has continued to evolve since its formal establishment by researchers at the Dartmouth conference in 1956. Following this initial introductory phase, AI has been successfully applied to various fields such as in banking, insurance, administration, transportation, finance, telecommunication, aviation, manufacturing, publishing, music, healthcare, and several others (Shukla and Jaiswal, 2013; Parise *et al.,* 2016; Alzaidi, 2018; Riikkenen, 2018). In healthcare, research on AI is large and emerging, focusing on different areas of healthcare such as services management, predictive medicine, patient data and diagnostics, clinical decision-making, and other areas (Secinaro *et al.,* 2021). Due to this issue of large emerging research and the constraint of research scope, this review of studies is not exhaustive but covers selected primary real world and experimental research identified as central to the application of AI to OP in the general healthcare sector.

Amiri *et al.,* (2013) compared ANNs, Cox and Kaplan-Meier methods to the prediction of gastric cancer patients. Overall, a better accuracy was observed for the ANN and the neural networks over the Cox proportional hazards in the prediction of survival probability of gastric cancer patients (Amiri *et al.,* 2013). This demonstrates that AI (ANNs) can be applied to aspects of OP such as reducing morbidity, mortality and improving health outcomes. In this study AI was not measured or linked to any specific element of OP.

An experimental study in Switzerland by Ciresan *et al.,* (2013) used AI of deep neural networks (DNN) for mitotic detection of breast cancer in histology images. The DNN classifier approach outperformed other approaches (statistical and CNN) in the mitotic detection of breast cancer histology images from the public annotated dataset (Ciresan *et al,* 2013). This demonstrates that AI can be applied to aspects of OP such as improved predictive accuracy and efficiency. The study did not measure or link AI to any specific element of OP.

Another study by Bennet and Hauser, (2013) investigated the impact of an AI framework in simulation of clinical decision making using a Markov decision approach whereby AI thinks like the doctor, considers healthcare policies, payment methods etc. and thinks like the doctor and makes decisions. The AI application was successful and resulted in outperformance of the current treatment as usual (TAU) fee for service healthcare models and achieving over 60% reduction in unit cost and 30-35% rise in patient outcome (Bennet and Hauser, 2013). The results show that AI (Markov decision approach) can be applied to accurate prediction of clinical decision making in clinical settings, thereby improving efficiency and OP. The result of the study is in line with the results from the study of Ciresan *et al,* (2013). The study linked AI to OP and quantitatively measured financial performance which is an element of OP.

A study by Papantonopoulos *et al.,* 2014 investigated AI (ANN) for the diagnosis of aggressive Periodontitis (AGP) trained by immunologic parameters. The ANNs gave 90 to 98% accuracy in classification of patients into AGP or CP when compared with canonical discriminant analysis and binary logistic regression (Papantonopoulos *et al.,* 2014). This implies that ANNs are more effective in diagnosing AGP or CP and can improve efficiency element OP by adaptation of specific treatment protocols. The study did not mention measurement or linking of AI to any element of OP. The result of the study is consistent with results from the study of Ciresan *et al.,* (2013) and Bennet and Hauser, (2013).

An experimental study by Li *et al*., (2014) which investigated application of Deep learning AI; to imaging data for improvement of brain diagnosis reported significantly higher performance of deep learning in diagnosing brain cancer to two other methods of data estimation (Li *et al,* 2014). The results show that AI (Deep learning) can be applied to accurate prediction of brain cancer and therefore the improved efficiency element of OP in healthcare. AI was not measured or linked to any specific element of OP. The result of the study is in line with the results of the study of Ciresan *et al.,* (2013); Bennet and Hauser, (2013) and Li *et al*., (2014); Papantonopoulos *et al.,* (2014).

Another study by Ozden *et al.,* (2015) investigated the use of Support Vector Machine (SVM), Decision Tree (DT), and Artificial Neural Networks (ANNs), for the classification of periodontal diseases. The accuracy of both methods was compared with resolution and working time. SVM and DT outperformed ANN in the prediction of periodontal diseases

(Ozden *et al.,* 2015). The results show that AI (SVM and DT) may improve decision making and therefore the efficiency element of OP. The study did not measure or link AI to any element of OP. The result of the study agrees with the results from the study of Ciresan *et al.,* (2013); Li *et al.,* (2014) and Papantonopoulos *et al.,* (2014).

An experimental study by Ye, (2015) successfully applied AI Secretary-Mimicking Artificial Intelligence (SMILE) for the performance of pathology related tasks such as interpretation of pathology slides, with increased accuracy and speed (Ye, 2015). This shows that AI can be applied to reducing pathologist's workload, increasing productivity, efficiency and improving OP. In this study, there was no link of AI to elements of OP, neither was any form of measurement of OP reported. The results are consistent with the studies of Ciresan *et al.,* (2013); Bennet and Hauser, (2013), Li *et al.*, (2014); Papantonopoulos *et al.,* (2014); Ozden *et al.,* (2015).

Shi *et al.*, (2015) investigated the use of an adaptive Neuro-Fuzzy System with Semi-Supervised Learning as an Approach to improve data classification, as an approach to bad debt recovery in healthcare. Their models successfully classified unknown cases (Shi *et al.,* 2015). The result of the study therefore shows a potential for improving revenue recovery, and the financial performance element of OP. The study did not report measurement of AI or linking to any specific element of OP.

A study by Gonel *et al.,* (2020) used AI with 5 algorithms with rules based clinical validity defined on AI to eliminate ratios of requested unnecessary tests and for cost-effectiveness. There was successful elimination of five hospital tests which resulted in a potential annual test savings of 363710 tests and approximately 4,536 USD (Gonel *et al.,* 2020). The results demonstrate that AI adapted to analysers can potentially save millions of dollars and improve healthcare financial performance. AI was not measured or linked to elements of OP. The result of the study is alike to the study of Shi *et al.,* (2015) for improved OP.

A study by Litjens *et al.,* 2016 investigated the use of CNNs in diagnosing cancer from Histopathology images. AI resulted in increased efficiency and accuracy during histopathology analysis (Litjens *et al.,* 2016), demonstrating improved performance in the efficiency element of OP. However, AI was not measured or linked to any specific element of OP. The result of the study is in line with the results from the study of Ciresan *et al.,* (2013); Li *et al., (*2014); Papantonopoulos *et al.,* (2014) and Ozden *et al.,* (2015).

Razmara *et al., (*2016) applied a multi-layer ANN with back propagation learning algorithm to the prediction of Elderly fall risk. The results showed that (AI) ANN had a higher accuracy than single datasets (Razmara *et al.,* 2016). This implies that ANNs can be applied in healthcare settings to people at risk of falls for better management ultimately improving health outcomes and healthcare performance in line with the study of Amiri *et al.,* (2013). Razmara and colleagues did not directly measure or link AI to any elements of OP.

Kwong *et al.,* (2016) applied an ANN model to predict systolic blood pressure using ANNs. The experiment showed that ANN had a more reliable prediction of systolic blood pressure than stand-alone measurements (Kwong *et al.,* 2018). This infers that ANNs can improve diagnostic efficiency and therefore OP. Kwong and colleagues did not measure or link AI to any specific element of OP. The result of the study is consistent to the results from the study of Ciresan *et al.,* (2013); Li *et al.,* (2014); Papantonopoulos *et al.,* (2014) Ozden *et al.,* (2015) and Litjens *et al.,* (2015).

Ahmed *et al.,* (2017) applied a Neuro-fuzzy based approach to classify Crohn's disease. The study reported that the AI had a classification accuracy of 97.6% and sensitivity, specificity of 96.07% and 100% respectively (Ahmed *et al.,* 2017). There is no single test for the classification of Chron's disease therefore this approach therefore improves healthcare efficiency and therefore OP by accurate diagnosis of Crohn's disease. However, AI was not measured or linked to any specific element of OP. The result is consistent with the studies of Ciresan *et al.,* (2013); Li *et al.,* (2014); Papantonopoulos *et al.,* (2014) Ozden *et al.,* (2015) and Litjens *et al.,* (2015); Kwong *et al*., (2018).

A study by Desautels *et al.,* (2017) studied the prediction of early unplanned intensive unit care unit readmission in a UK tertiary hospital (Cambridge) using a cross-sectional design and AI (ML approach) (Desautels *et al.*, 2017). This implies accurate prediction of unplanned readmission by AI (ML) and can be used for more efficient management of resources and therefore results in improved efficiency and healthcare performance. However, the study did not measure or link AI to any specific element of OP. The result of the study is consistent to the results from the study of Ciresan *et al.,* (2013); Li *et al.,* (2014); Papantonopoulos *et al.,* (2014); Ozden *et al.,* (2015) and Litjens *et al.,* (*2015);* Desautels *et al.,* (2017).

Jahantigh, 2018 investigated the application of AI; Neural networks in diagnosing periodontal disease by clinical indices The AI which used the Levenberg-Marquardet algorithm successfully diagnosed periodontal disease with decrease in time of diagnosis, minimum mean square error, and fewer iterations (Jahantigh, 2018). This infers that the Neural Networks can improve diagnostic efficiency and therefore healthcare performance. There was no measurement or linkage of AI to elements of OP. Study results are consistent with the studies of Ciresan *et al.,* (2013); Li *et al.,* (2014); Papantonopoulos *et al.,* (2014); Ozden *et al.,* (2015); Litjens *et al.,* (*2015) and* Desautels *et al.,* (2017).

Another study by Moyle *et al*, (2018) used a mixed-methods pilot study to investigate the views of older people with dementia, their families, and health professionals on social connection using tele-presence. The study reported positive social presence from using Giraff (Moyle *et al,* 2018), demonstrating that the social robot Giraff can be used to improve social presence and therefore social health outcomes for older people with dementia. This implies improved health outcomes and healthcare performance. However, AI was not measured or linked to any specific element of OP. The result of the study is in line with the study of Amiri *et al,* (2013) and Razmara *et al.,* (2016).

Sara *et al.,* (2020) used an artificial-intelligence-based method to assess service quality in the prosthodontics sector. The evaluation model developed had high versatility in identifying cases that required prosthodontics improvements. Therefore, the AI model successfully supported the improvement of service quality (Sara *et al.*, 2020). The results therefore imply improved healthcare quality and OP. Although there was no measurement of OP or linking of AI to OP elements.

Incze *et al.,* (2021) used a predictive machine learning model to investigate the risk-increasing and risk-mitigating factors associated with missed appointments in the NHS. Results demonstrate that ML successfully identified factors associated with missed appointments and can help inform policies relating to Missed appointments (Incze *et al.*, 2021). This demonstrates that the AI can be applied to improving patient wellbeing, efficiency of resource management, cost savings and OP. However, no element of AI was measured.

Karuvan *et al.,* (2022) investigated a deep learning–based AI supported by CT imaging for detection of COVID-19 pneumonia. The DL system had a high diagnostic efficiency in the detection of Covid-19 pneumonia. Therefore, beneficial in fighting Covid-19 and demonstrates healthcare performance in terms of decreased morbidity, mortality, and improved health outcomes (Karuvan *et al.,* 2022). The results of this research support the findings of Amiri *et al.,* (2013); Razmara *et al.,* (2016) and Moyle *et al.*, (2018) in the improvement of health outcomes.

Consequent to the review of studies of the application of AI to OP in healthcare, it can be inferred that there is a high interest in research to apply AI to different aspects of OP and in different healthcare settings. The studies reviewed have all applied AI to different aspects of OP in healthcare, resulting mainly in positive impacts. There have however been few studies that directly link, measure, or assess elements of OP in healthcare (such as the study of Bennet and Hauser, 2013) such as efficiency, health outcomes, financial performance, improved health outcomes etc. Without specific linking of AI to OP elements in healthcare, the actual impact of AI on OP in healthcare cannot be ascertained. Evidence from this review of studies on the general healthcare sector, warrant the investigation of the application, adoption of AI to OP with consideration of variables or elements of OP specific to healthcare. The studies reviewed on the application of AI in the healthcare sector in general have been summarised in tables 2.2a and 2.2b (please see appendix 5 and 6). The table summaries show that although most of the studies applied AI to different aspects of healthcare performance, most of them did not specifically link AI to elements of OP in healthcare.

2.4. Application of AI in the Nigerian Healthcare Sector

Further to the critical review of studies on the application of AI to OP in the general healthcare sector, this section in the same vein focuses on critically reviewing research identified as central to the application of AI to OP in the Nigerian healthcare sector. Several challenges have been reported within the Nigerian health sector, in the areas of training, funding, employment, and availability of the health workforce (Adeloye *et al.,* 2017).With regards to healthcare professionals' shortage for instance, the country has a medical doctor to patient ratio of 1: 6,800, as against the WHO standard of 1:600, showing that the population is grossly underserved with regards to medical services (Oladipupo *et al.,* 2015). The situation can be described as appalling and calls for robust interventions to address the country's healthcare challenges. Artificial intelligence is already being successfully applied to the healthcare sector in developed countries (Dilsizian and Siegel, 2014; Bini, 2018) and as such appears to be promising in developing countries where there are more challenges. In view of this it is essential to critically review the application of AI in the Nigerian healthcare sector as this will provide a better understanding of the state of research in the sector and inform on areas for the research to focus on. This will support adoption of AI and improved OP in the sector.

An experimental study by Samuel *et al.,* (2013) to investigate the effectiveness of an AI; fuzzy logic driven web-based decision support system (WBDSS) in diagnosing typhoid fever using the medical records from a medical centre in Nigeria over a 6-month period, reported that the results obtained from the tests conducted using the system were within the predefined limits when the results were examined by experts (Samuel *et al.,* 2013). The results of the study demonstrate efficiency and improved healthcare performance. AI was not measured, assessed, or linked to any specific element of OP.

A study in Nigeria by Oguntimilehin *et al.,* (2014) successfully applied Machine Learning Based Clinical Decision Support System in the diagnosis and treatment of Typhoid Fever. The system successfully diagnosed typhoid fever and treatments applied based on the degree of disease severity (Oguntimilehin *et al.,* 2014). This infers that ML can improve diagnostic efficiency and therefore healthcare performance. There was no measurement, assessment of AI or linkage to any specific element of AI. The result of the study is similar to the results from the study of Samuel *et al.*, 2013 in line with achieving diagnostic accuracy and efficiency.

A study by Oyelere *et al.,* (2017) successfully used an AI application; an Intelligent system composed of self-inference mobile system with the capacity to assist health practitioners in the conduction of clinical pre-screening of Ebola virus, and to serve as a platform for the creation of awareness on the dangers of communicable diseases. The results infer that this system can simultaneously support the inadequate medical facility in endemic areas and create awareness on early EVD detection, prevention, and transmission (Oyelere *et al.,* 2017). The study demonstrates that AI can be used to improve health outcomes and healthcare performance. However, AI was not measured, assessed, or linked to any specific element of OP.

In a study to investigate the effectiveness of a decision support model for the evaluation and selection of suppliers in the healthcare services of tertiary institutions Fashoto *et al.,* (2018), The results of the study showed that the hybrid model composed of AHP, and ANN was more effective in the evaluation and selection of suppliers for the hospital and thereby supporting better decision making and higher overall performance of the hospital (Fashoto *et al.,* 2018). This study linked AI to improved decision making.

A study by Otakore and Ojugo, (2018), applied intelligent classification models to the early detection of gestational diabetes in the Nigerian Niger Delta region using a sample of 768 from different hospitals with two thirds negative to diabetes and one third positive. The results show that the unsupervised models had a lower error and better accuracy than the supervised models (Ojugo and Otakore, 2018). This demonstrates that AI can improve diagnostic efficiency and therefore healthcare performance. There was no measurement of AI or linkage to any specific element of AI. The result of the study is in line with the results from the study of Samuel *et al.,* (2014); Oguntimilehin *et al.,* (2014).

Onu *et al.,* (2019) investigated Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia. The study showed that models based on transfer learning approach was resilient to different types and degrees of noise, as well as to signal loss in time and frequency domains. AI was not measured or linked to any specific element of OP. This demonstrates that AI can improve paediatric diagnosis and therefore healthcare performance (Onu *et al.*, 2019).

For the review of studies of the application of AI to OP in the Nigerian healthcare sector, most of the studies apart from Fashoto *et al.,* (2018), did not show any measurement or specific link to factors of OP specific to healthcare e.g., reduced wait times, improved health outcomes, cost reduction etc. Without specific linkage of AI to key OP factors in healthcare, the actual impact of AI in healthcare cannot be determined. This makes it a necessary requirement to introduce key OP in healthcare when applying AI in healthcare. The studies reviewed on the application of AI in the healthcare sector in the Nigerian healthcare sector have been summarised in tables 2.3 (please see appendix 7). The table summary shows that although most of the studies applied AI to different aspects of healthcare performance, most of them did not specifically link AI to elements of OP in healthcare such as reduced wait times, improved health outcomes, cost reduction etc., except for the study of Fashoto *et al*., (2018) which linked AI to elements of OP in healthcare. There is also no information on how to apply or integrate AI into healthcare systems. Without specific linkage of AI to key OP factors in healthcare, the actual impact of AI in healthcare cannot be determined. Evidence from this review of studies on the Nigerian healthcare sector, warrants the investigation of the application, adoption of AI to OP with consideration of variables or elements of OP specific to healthcare.

2.5. Organisational Performance

The concept of Organisational performance is one that has been linked to competitive advantage, according to Chae *et al.*, (2014) an organisation's performance is dependent upon changes in the environment where there exist potential threats and opportunities that may only be available for a limited time (Chae *et al.*, 2014).

This implies subjectivity in an organisation's capacity to respond to changes in the environment, this infers that an organisation can therefore adopt strategies (for example ICT) which they can apply to differentiate their products or services, reduce costs, improve revenue, profits, customer satisfaction and ultimately organisational performance and sustained competitive advantage (Chae *et al.*, 2014; Yunis *et al.,* 2017).

As important as the construct of OP appears to be, researchers in the field of management assert that it is a concept that is difficult to measure and therefore has no operational definition (Delarue *et al.,* 2008; Richard *et al.*, 2009; Jenatabadi, 2015; Ondoro, 2015) this is thought to be due to the multi-dimensionality of the construct (Palacios-Marqués *et al.*, 2019) variances in context (Oyemomi *et al.*, 2019).

2.5.1. Definition of organisational performance (OP)

Due to its subjective nature, the concept of OP has been widely defined in the literature (Criveanu and Ion, 2016). Most definitions including earlier, and more recent ones revolve around achievement of organisational objectives. According to Georgopoulos and Tannenbaum, 1957 Organisational performance is the degree to which social system organisations achieve their objectives (Georgopoulos and Tannenbaum, 1957, pg. 535). In their opinion, is a measure of the extent to which organisational objectives are achieved. Yuchtman and Seashore, 1967 define OP as an organisation's capability to utilize its environment in the acquisition and application of scarce resources (Yuchtman and Seashore, 1967). They view performance from the angle of effective application and management of both external (environmental) and internal (scarce resources). Kaplan and Norton, 1992 in generic terms define OP as a construct that assesses the extent to which an organisation's goals and objectives are achieved based on the application of a range of financial and non-financial indicators (Kaplan and Norton, 1992). This definition is in line with Georgopoulos and Tannenbaum, 1957 definition of the extent of achievement of organisational objectives. Borman and Motowidlo, 1993 define OP as "the actions and behaviours that are pertinent to an organisation's goals" (Borman and Motowidlo, 1993). They appear to view performance not by measurement or relative comparison to organisational objectives achieved, but by execution of specific actions. Sluyter, 1998 defines OP as "an organisation's overall effectiveness in meeting the identified needs of each of its constituent groups through systematic efforts that continually improve its ability to address those needs effectively" (Sluyter, 1998). Sluyter's definition posits OP in line with organisational effectiveness. Conversely, Liptons, 2000 define OP as "an organisation's capability to prevail'' (Liptons, 2003). Lipton opines that an organisation has achieved OP when it is able to survive. In concordance with Borman and Motowidlo, 1993, earlier definition Lebans and Euske, 2006 also define OP based on achievement of organisational objectives as a collection of financial and non-financial indicators that provide information about the extent of achievement of objectives and results (Lebans and Euske, 2006). Chung and Lo, 2007 define Organisational performance as the results of activities conducted by the members of an organisation to measure the degree of achievement of the organisation's objectives (Chung and Lo, 2007). This definition is based on carrying out specific actions and relative achievement of organisational objectives. Randeree and Al Youha, 2009 define OP as an organisation's propensity to implement its strategies effectively resulting in the achievement of organisational objectives (Randeree and Al Youha, 2009). They view OP as based on execution of specific actions and organisational objectives. According to Cho and Dansereau, 2010 Organisational performance is the performance of a company relative to its goals and objectives (Cho and Dansereau, 2010). Their definition is associated with relative achievement of organisational objectives. Tomal and Jones, 2015 define Organisational performance is an organisation's actual outputs as a measure of its proposed outputs (Tomal and Jones, 2015). This definition is based on measurement of organisational outputs. More recent definitions continue to make a connection to relative achievement of organisational objectives; Novak, 2017 define OP as an organisation's performance in relation to their goals and objective while Ali *et al.,* 2019 define OP as the actions and behaviours that are crucial to the achievement of an organisation's goals (Ali *et al.,* 2019). Their definitions are based on achievement of goals and objectives as is the case with most of the earlier definitions. The table 2.4 below is a summary of the definitions of Organisational performance by different authors in the literature. Most of the authors define AI in terms of the extent to which organisational goals and objectives have been achieved.

With regards to the above definitions, the Researcher defines OP as ***''a measure of the extent to which an organisation achieves its goals and objectives while simultaneously ensuring the efficient management of limited resources''.***

Table 2.2: Definitions of Organisational performance

Author/year	Definition	Main focus
Georgopoulos and Tannenbaum, 1957	The degree to which social system organizations achieved their objectives.	Relative achievement of organizational objectives.
Yuchtman and Seashore, 1967	An organization's capability to utilize its environment in the acquisition and application of scarce resources.	Effective management of external and internal resources.
Kaplan and Norton, 1992	A construct that assesses the extent to which an organization's goals and objectives are achieved based on the application of a range of financial and non-financial indicators.	Relative achievement of organizational goals and objectives.
Borman and Motowidlo, 1993	"The actions and behaviours that are pertinent to an organization's goals"	Performance of specific actions.
Sluyter, 1998	"The organization's overall effectiveness in meeting the identified needs of each of its constituent groups through systematic efforts that continually improve its ability to address those needs effectively"	Relative effectiveness
Liptons, 2003	An organization's capability to prevail.	Organizational success.
Lebans and Euske, 2006	OP is a collection of financial and non-financial indicators that provide information about the extent of achievement of objectives and results	Relative achievement of organisational objectives.
Chung and Lo, 2007	Organizational performance is the result of activities conducted by the members of an organization to measure the degree of achievement of the organizations objectives.	Relative achievement of organizational objectives.
Randeree and Al Youha, 2009	An organization's propensity to implement its strategies effectively resulting in the achievement of organizational objectives.	Organizational effectiveness and objectives achievement.
Cho and Dansereau, 2010	Performance of a company relative to its goals and objectives.	Relative achievement of goals and objectives.
Tomal and Jones, 2015	Organization's actual outputs as a measure of its proposed outputs.	Relative measurement of actual versus proposed outputs.
Novak, 2017	An organization's performance in relation to their goals and objective.	Relative achievement of goals and objectives.
Ali *et al.,* 2019	Actions and behaviours that are crucial to the achievement of an organization's goals.	Execution of specific actions and achievement of organisational objectives.

Source: The Researcher

2.5.2. Elements of OP

Researchers in the field of Organisational performance have taken various positions as to the variables/ elements for measuring OP. While some support the use of qualitative and non-financial measures, others suggest that quantitative financial measures be used. Garcia-Sanchez *et al.,* (2018) measured OP by purely quantitative and financial elements ROA, ROE, ROS, Organisation's market share for main products and markets and the Growth of sales in main products and markets (García-Sánchez *et al.*, 2018). Shazali *et al.,* (2013), posit that OP should be viewed from both qualitative and quantitative perspectives using elements such as: financial performance, patient satisfaction, and Employee performance as elements of Organisational performance (Shazali *et al.*, 2013). Similarly, Criveanu and Ion, (2016) in their study, measured OP using a mix of financial and non-financial measures. For qualitative elements: competitiveness, economy, earning capacity, effectiveness, efficiency, and profitability (Criveanu and Ion, 2016). Sheik *et al,* (2016) also support using both financial and nonfinancial measures, financial such as: accounting KPIs; ROA, ROS, EBIT, EVA and non-financial using operational KPIs such as: market share, innovation level, customer satisfaction etc. (Sheik *et al.*, 2016). Palacios-Marques *et al.,* (2019) investigated OP using 4 correlated elements: financial performance, operational efficiency, competitive ability, and stakeholder satisfaction (Palacios-Marques *et al,* 2019). All these further strengthen the motion that OP is a multi-dimensional construct and can be perceived and measured differently.

2.5.3. Benefits of OP

Organisational performance has several benefits as evident in literature; the process of measuring organisational performance enables the application of effective strategic analysis tools which support the formulation and implementation of the organisation's strategy (Rose, 1995; CIMA, 2008). OP enables the classification of current and future performance status, facilitating the achievement of set goals and identification of shortfalls (Shazali *et al,* 2013; Jenatabadi, 2015). When shortfalls are identified, organisations can improve business processes and value to stakeholders by the transformation of resources into quality products and services (Okwo and Marire, 2012), thereby improving value for stakeholders and enhancing organisational effectiveness and sustaining competitive advantage (Kairu *et al,* 2013; Okwo and Marire, 2012). Organisational performance can be used to determine the competitiveness of an organisation; if an organisation is doing well based on analysis using standard performance measures and in comparison, to its competitors then it will have a competitive advantage over its competitors (Felizardo, Félix, and Thomaz, 2017). In terms of productivity, OP benefits organisations by supporting increased productivity via enhancement of employee motivation, teamwork, competency, clarification of job roles which result in higher employee performance (Aguinis, 2013; Kazimoto, 2016). OP reflects achievement of organisational goals and objectives and therefore growth and development of the organisation (Qureshi and Hassan, 2013). This performance is not limited to the organisation but translates to the national level as improved OP in organisations supports the social, economic, and political growth and therefore development at the national level (Gavrea *et al.,* 2011). Furthermore, studies on the impact of OP on innovation report that OP has a positive relationship with innovation therefore it supports the development of innovative practices through organisational learning, knowledge management and transformational leadership (Mafini, 2015).

2.5.4. Challenges of OP

Certain challenges of OP have been identified in literature, some of which are briefly discussed below. Researchers argue that there is a lack theoretical foundation for Organizational performance as most developments in the field are thought to have emanated from practice rather than research (Goshu and Kitaw, 2017; Bourne, Melnyk, and Bititci, 2018; Bititci *et al*, 2018). While these developments are important and support performance, they do not explain causality especially regarding the dynamism of today's business (Nudurupait *et al*., 2016; Bourne, Melnyk, and Bititci, 2018). Another important issue is the lack of consensus in the literature as to the definition of OP, its uniformity, and the application of OP measures (Khan, 2014; Oncioiu *et al*., 2021), Reviewing the OP literature, reflects greater tendency for application of traditional approaches (objective, mainly financial measures) to the measurement of OP than newer approaches (subjective, mainly non-financial measures) and lack of adoption of multiple dimensions or perspectives of OP (CIMA, 2008; Singh, Darwish and Potočnik, 2015). Even when researched frameworks are applied, they may be lacking in certain critical performance elements that are required or important for OP in the context of the specific organisations (CIMA, 2008; Singh, Darwish and Potočnik, 2015; Alves and Lourenço, 2021) and this may not allow robust measurement of OP, and identification of areas that require improvement.

2.6. Organisational Performance in Healthcare sector

2.6.1. Managing OP in the Healthcare sector

Although the concept of organisational performance has become an important concept in health sector management, it was ideally designed to cater to the for-profit sector, due to its multi-dimensional nature not covered by traditional performance measurement. It has however been widely adopted by not-for-profit sectors or those not entirely profit oriented such as universities, hospitals, and other health sector organisations (Dimitropoulos, 2017).

The healthcare sector is a critical sector, due to its role in the health and welfare of communities (Bartram and Dowling, 2013) is faced with several challenges including but not limited to demographic factors such as ageing population, increased incidence of chronic diseases, increasing healthcare costs, imbalanced access to care due to employee shortages, limited infrastructure, increasing expectations on the quality of care, change in life styles, better-informed and more demanding healthcare customers, medical and technological advances, rapidly changing operational environment (Elg *et al.,* 2011; Shazali, *et al.,* 2013; Delloitte, 2018). To respond effectively to these challenges and provide solutions, international organizations such as the WHO and OECD emphasize the need for the demonstration of good performance by the application of holistic approach health system performance measurement and management such that performance mirrors the context of the health sector and results are measurable (WHO, 2008; OECD, 2010; OECD, 2021). This implies that the management of healthcare organizations as a matter of necessity are required to evaluate and manage their organizational systems and performance (Elg *et al,* 2013) by designing and implementing effective strategies (Abubakar *et al,* 2019).

The management and measurement of performance in the healthcare sector varies from the general business sector due to its multiple, complex products that are value-focused due to person-centred nature, unknown causalities, a high level of process-orientation; involving many co-producers, performance indicators that are difficult to define, and unstable, highly-dynamic environment (Klazinga, 2010) as well as crucial objectives peculiar to health sector organizations known as the ‘quadruple aim’ for healthcare: which is to reduce costs, improve the health of the population, patient experience and team well-being and productivity (Arnetz *et al*., 2020). To achieve these objectives of the sector and achieve OP, the management of health sector organizations must measure, assess, and improve elements of OP that are important in the healthcare sector and specific to the organisations strategic objectives (O'Boyle and Hassan, 2014; Song and Tucker, 2016; Al-hamadi and Hussein, 2018).

The concept of OP in healthcare has been measured based on different healthcare elements; with researchers appearing to combine healthcare performance elements and with more general elements of performance. Acharyulu and Shekhar, (2012) applied both healthcare specific and general elements of OP such as assets, costs, customer /patient satisfaction, revenue, reliability, responsiveness, sustainability, and safety (Acharyulu and Shekhar, 2012). Similarly, Kim *et al,* (2015) measures performance using general performance elements such as income, operating margin, return on assets (ROA) and return on investment (ROI) which are crucial to the survival of organizations as well as other more specific measures such as cost per patient, cost per inpatient (Kim *et al,* 2015).

2.6.2 Managing OP in the Nigerian Healthcare sector

Studies on organisational performance in the Nigerian healthcare sector have described performance in the sector as low; Adeyi, (2016) investigated the performance of the healthcare sector based on the country's health outcomes indicators and based on scope of healthcare services in absolute terms and in comparison, to other countries. Performance was reported as low (Adeyi, 2016). Another study based on comparative analysis with another developing country Ghana, reported that the Nigerian Health System has a lower performance than that of Ghana, a neighbouring country (Ogaji and Brisibe, 2015).

Kress *et al.*, (2016) investigated the Nigerian Primary health care (PHC) system using the Primary Health Care Performance Indicator conceptual framework and facility information from the World Bank Service Indicator Survey. The study reported the Nigerian PHC system's performance is low and negatively impacted by segmented supply chains; inadequate funding; inadequate infrastructure, medication, equipment, and low employee performance (Kress *et al.,* 2016). The earlier introduction to the Nigerian Health sector, as well as the studies above reflect that the sector is characterized by several challenges and low performance, this makes a case for identification of areas that require improvement and effective management of organisational performance and performance improvement in the sector (Klazinga, 2010; Liu, 2013; Gu and Itoh, 2016; Si *et al.,* 2017). In order to ensure effective management of OP in the Nigerian healthcare sector just like in other sectors, it is imperative to put in place an effective performance management system, composed of appropriate performance elements that reflect performance (Lin *et al.,* 2013; Rahman *et al.,* 2019).

2.6.2. AI and OP in the Healthcare sector and Nigeria

AI has been applied to different areas of healthcare such as in clinical decision making by using machine learning and natural language processing to successfully analyse patient's EHR, search and analyse publications and guidelines (Guo and Li, 2018); in collection, recording, processing, re-processing, clinical data, personalized assessments and plans (Deliberato *et al.,* 2017), in various fields of diagnostics for the diagnosis of cancers, pulmonary hypertension, stroke with comparable and in some cases higher performance than experts (Ciresan *et al.,* 2013; Esteva *et al.,* 2017; Liu, 2017; Dawes *et al.*, 2017; Prescot, 2019) in robotics to assist in surgical procedures, in care to support patient with companionship, falls prevention, movement etc. (Goher *et al,* 2017). AI has also been applied to precision or personalized medicine a healthcare model where treatment and prevention is based on a person's health condition, genetics, psychosocial, environmental and life-style characteristics. It has been applied to the management of the healthcare system to reduce over-diagnosis, over prescription, healthcare costs and thereby presenting meaningful results and improving quality, effectiveness, and health outcomes (Moss *et al.,* 2017).

In reviewing the literature on the application of AI to OP in the general Healthcare sector and in Nigerian healthcare sector, it has been observed that the concept of AI is not new and has been applied to different areas of healthcare OP and in different settings. Furthermore, the critical review of studies on the application of AI to OP in the general healthcare sector and in a resource constrained setting (Nigeria) suggests that AI can assist in bridging the wide OP divide in resource constrained settings (Djam *et al.*, 2011; Ekong *et al.,* 2012; Williams and Olatunji, 2013) and in more resourceful/ resource-sufficient settings. There is therefore a strong case to research into the adoption of AI technologies in these settings to generate evidence for OP in healthcare. With regards to Management of OP in the healthcare sector it can be concluded that although OP has been long applied in the healthcare sectors, there appear to be inconsistencies in measuring and assessing the concept due to reasons including but not limited to the lack of an operational definition, conceptualizations issues, diversity of organisations in healthcare with diverse objectives, contexts, outcomes, and therefore numerous and varying OP elements among other reasons. These factors make the measurement and assessment of OP in the healthcare sector of higher complexity than in the general business sector. In the general healthcare sector, several robust studies have investigated OP using various performance elements and frameworks while in the Nigerian health there is a scarcity of good quality studies that have investigated the concept of OP using OP elements or variables.

In critically reviewing the application of AI to OP in the healthcare sector, primary studies were included for the general health sector and the Nigerian healthcare sector Table 2.2a, 2.2b and 2. 3. The studies reviewed reveal that AI has been applied to OP in the healthcare sector however this has been done in a generic manner whereby different types of AI have been applied to OP with little focus on linking AI to elements of OP that evidence OP in the healthcare sector. Evidence of the application of AI technologies to elements of OP in healthcare and in different healthcare settings can inform healthcare organisations on how to effectively apply, adopt AI to achieve OP.

2.7. Evaluation of AI Frameworks

Based on the critical review of literature in section 2.3 and section 2.4, it appears that there is a scarcity of frameworks in literature to support the application of AI from the organisational performance in healthcare point of view. This section further reviews the literature by evaluating AI frameworks that have been applied to OP related issues in different healthcare settings. It is important to evaluate AI frameworks in healthcare to assess whether they are linked to OP, or measure and or assess OP as this will help inform and build knowledge towards the application, adoption, and implementation of AI in healthcare. Linking AI to OP and measurement or assessment of OP will also help ascertain the actual impact of AI on OP in healthcare. Another purpose of this evaluation is to identify from these frameworks, factors for the application, adoption of AI in healthcare settings.

Several studies demonstrate the application of different types of AI frameworks both in non-healthcare and healthcare settings such. Examples of these types of frameworks include general (Mohapatra and Kumar, 2019), security and privacy (Lu, *et al.,* 2013), governance (Reddy *et al.,* 2019), development (Higgins and Madai, 2020), evaluative (Park *et al.,* 2020) frameworks etc. These frameworks though developed for specific contexts and may inform the application, adoption of AI in the specific contexts for which they have been designed and they may also inform or support development of AI frameworks in other contexts.

A study by Chen *et al.*, (2020) developed a fusion framework (based on multi-view similarity network fusion (SNF) method) to extract typical treatment patterns from electronic medical records which contain temporal and varying doctor information that can inform treatment pattern. The multi-view SNF framework outperformed the single-view similarity methods in extracting typical treatment patterns. Chen *et al*., (2020) have stated that the extracted patterns can be combined with order content, sequence, and duration views to provide data-focused guidelines in medicine which can aid better clinical decision making (Chen *et al.,* 2020). As there is no visible link to clinical decision making in the framework (Figure 2.1), the study did not directly link AI to OP elements. Also, the figure 2.1 shows that data is incorporated but otherwise does not identify any other information e.g., factors that can support application or adoption of the AI framework.

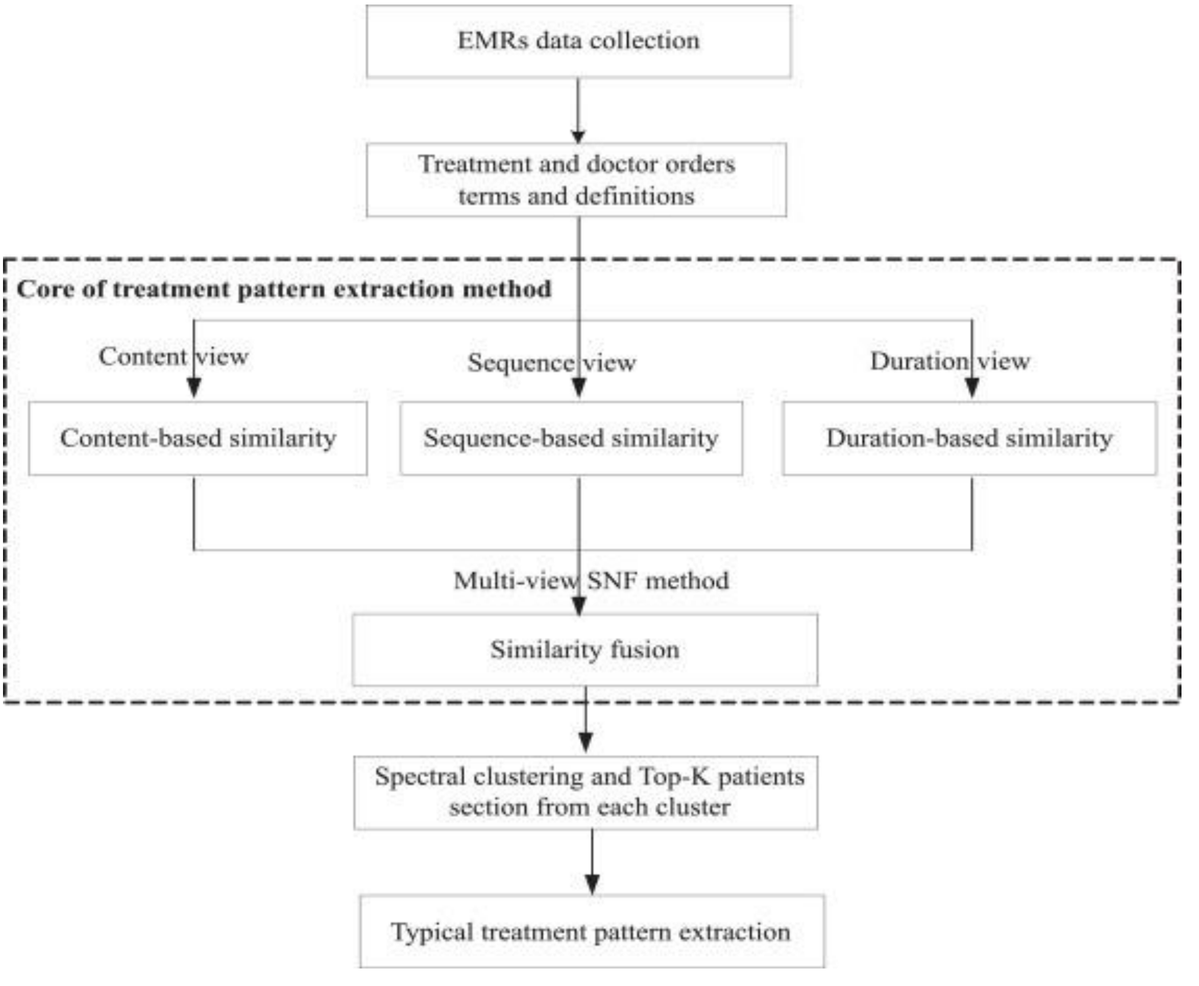

Figure 2.1: Fusion framework for the extraction of treatment patterns from EMRs

Source: Chen *et al.,* (2020).

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Lou *et al.,* (2019) developed an image-based learning framework for individualising radiotherapy dose by a retrospective analysis of outcome prediction. The framework aimed to use lung CT feature to identify radiation sensitivity parameters for the prediction of treatment failure and guidance of individual radiotherapy dose. Patients (n=944) with lung cancer undergoing lung stereotactic body therapy were identified, the internal cohort was composed of patients undergoing treatment at the mainland campus of the Cleveland clinic, OH, USA while the independent validation cohort were receiving treatment from seven affiliate regional or national sites. The results showed that radiation treatment in patients with high Deep Profiler scores failed at a significantly higher rate than in patients with low scores. The results show that Deep Profiler can accurately predict treatment failures and *i*Gray can be safely applied to delivering an optimised personalised radiation dose (Lou *et al.,* 2019). The framework can be used to predict treatment failure and therefore can be linked to the efficiency aspect of OP. It is however not directly linked to OP elements. Although the framework illustrates that different types of patient data are processed and incorporated. Apart from technical components of AI shown, no further information or factors that support application or adoption of the framework are shown.

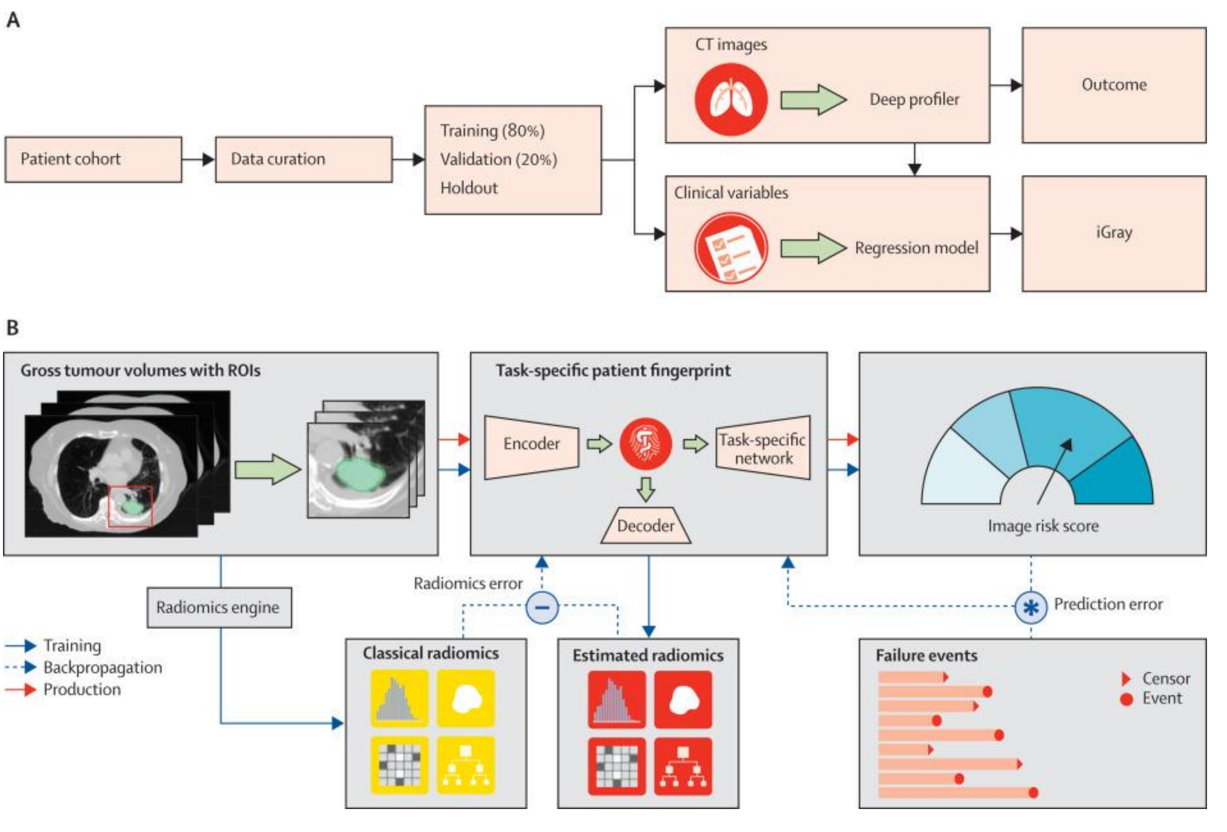


Figure 2.2: Study design and neural network architecture

Source: Lou *et al.*, (2019)

Bargshady *et al.*, (2020) developed an enhanced deep learning algorithm framework for the detection of pain intensity from facial expression images using a study data set composed 200 sequences of 25 subjects and total of 10,783 images applied. The resultant EJH-CNN-BiLSTM classification model, which was tested on four different pain levels, showed a relatively high accuracy compared to other techniques (Bargshady *et al.*, 2020). This indicates that the enhanced EJH-CNN-BiLSTM classification algorithm can be applied as an AI framework for automatically and medically diagnosing and managing pain in patients. Although the framework accurately diagnosed pain in patients, demonstrating potential to improve efficiency and OP in healthcare, it did not show any link to OP or any measurement or assessment of OP. The Figure 2.3 below shows that patients' data in form of images are processed and incorporated but does not identify any other information or factors for applying or adopting the AI framework.

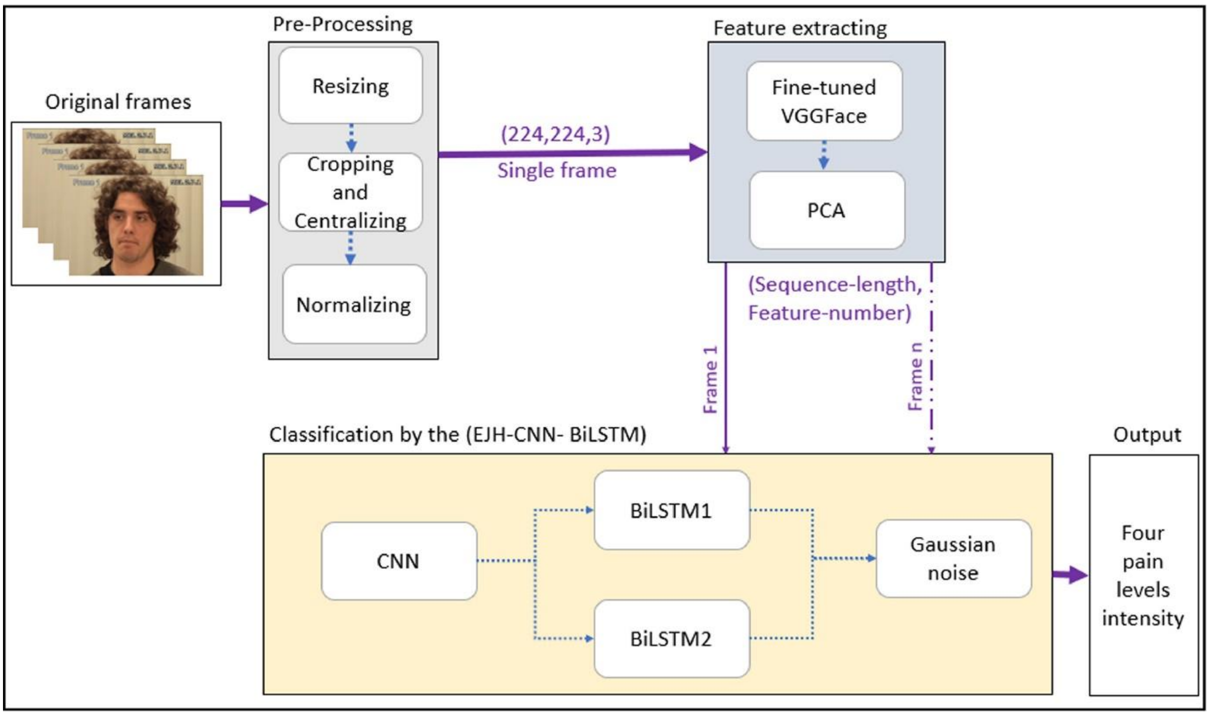


Figure 2.3: Proposed EJH-CNN-BiLSTM framework for the detection of pain from facial expression image database.

Source: Bargshady *et al.,* (2019)

Permission to reproduce material granted by Springer Nature.

Ashfaq *et al.,* (2019), developed a deep learning framework for prediction 30-day unscheduled re-admission using real data (structured) from a Swedish population of over 7500 CHF (Chronic Heart Failure) hospitalised patients between 2012 and 2016. The study focused on key elements of an Electronic Health Record (EHR) prediction model in one framework, using expert and machine-based features while combining sequential patterns and addressing the problem of class imbalance. Features included Human-derived features: D, Machine-derived features E, Visit representation, and Patient representation. The contribution of each element towards prediction performance (ROC-AUC, F1-measure) and cost-savings was analysed. The AI framework and its key components had higher discrimination power and showed a higher performance than the reduced models over a minimum of two evaluation parameters (Li *et al.,* 2019), patients with a high readmission risk may benefit from person-centred discharge plans, care counselling, nurse home visits and other interventions to prevent readmission. The framework demonstrated maximum cost savings of 22% for the study; when such a framework is applied in hospital settings there may be economic benefits as more true positives and less false positives will result in significant cost savings if interventions prove to be effective. The Figure 2.4 below illustrates the incorporation of different features into the framework.

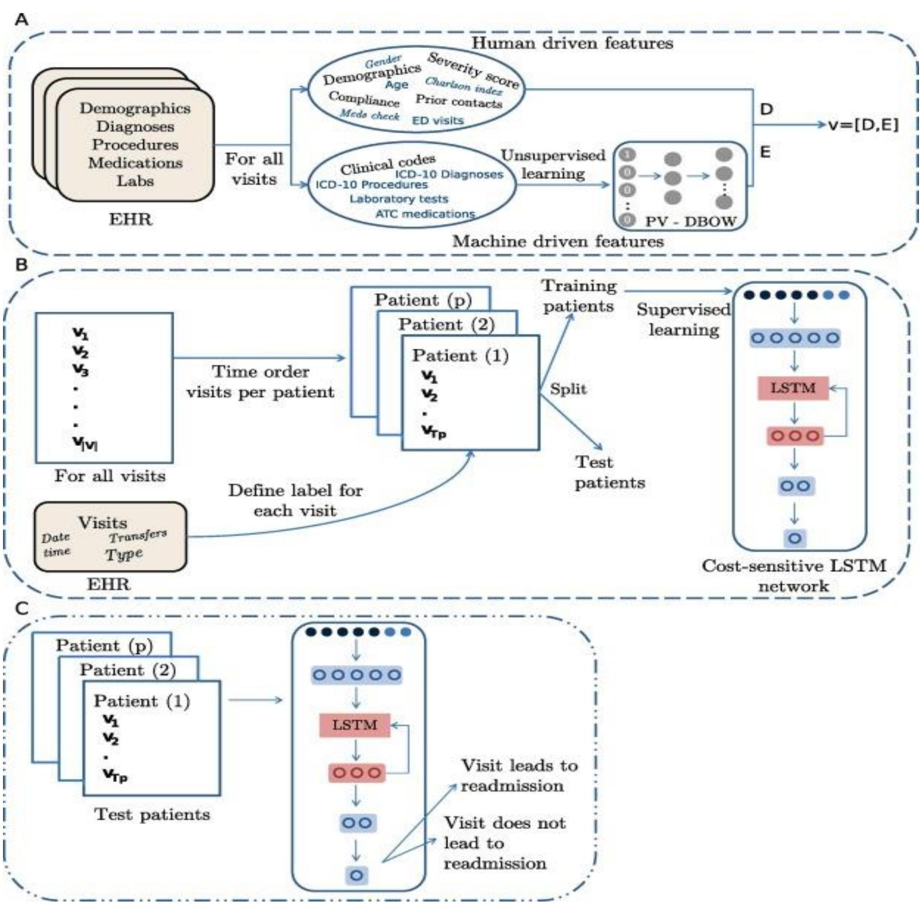
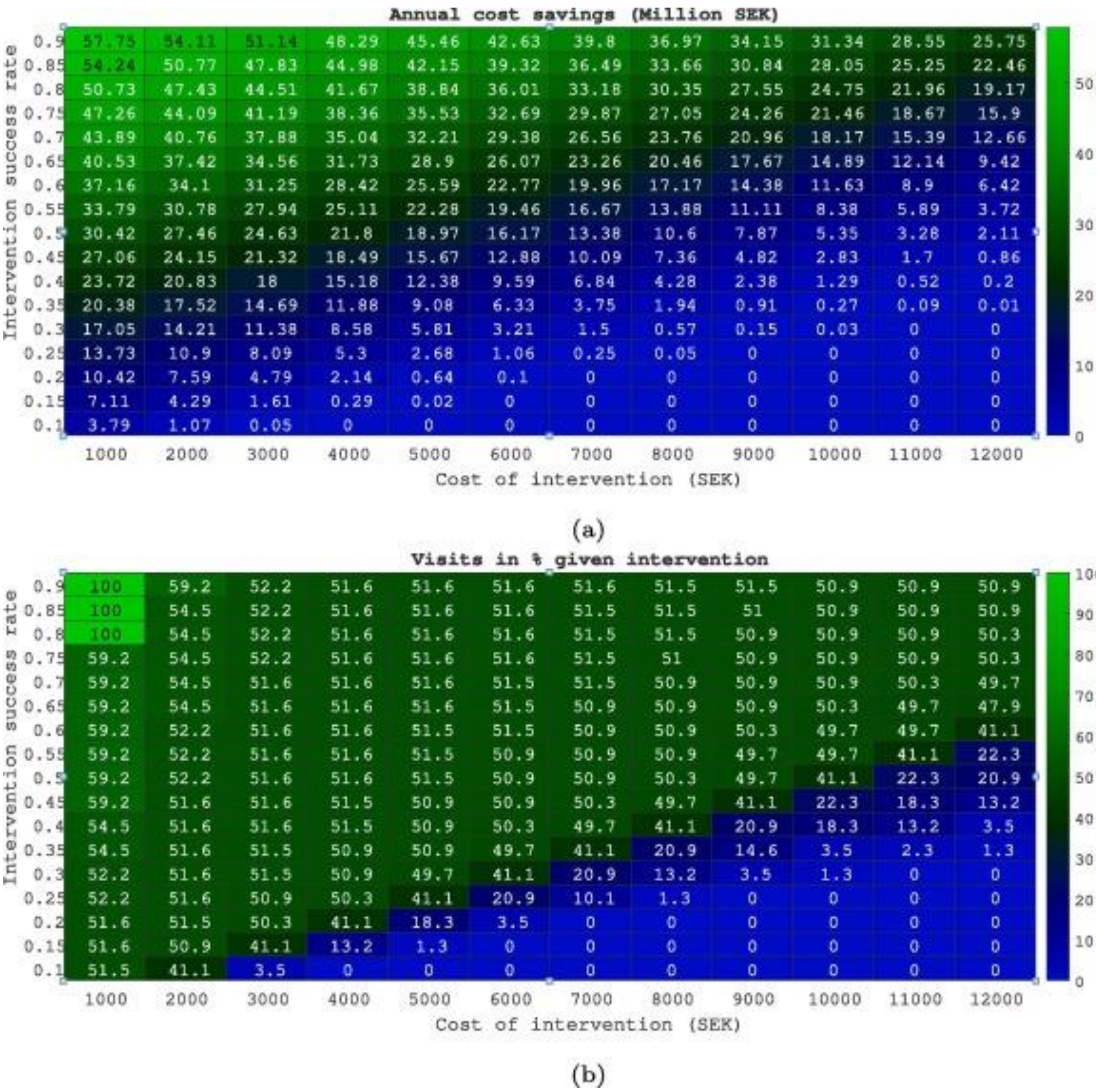


Figure 2.4: Deep learning prediction framework

Source: Ashfaq *et al.,* (2019)



(a) Estimated annual savings (in Million SEK) for different intervention costs and success rates. (b) Total visit in percentage based on specific readmission-preventing intervention of the model output.

Figure 2.5: Framework Economic Impact

Source: Ashfaq *et al.,* (2019)

The framework can accurately predict readmission risk; therefore, which implies that it may improve efficiency and OP in healthcare. Additionally, it linked AI to OP by quantitatively measuring cost savings. Figure 2.5 shows the processing, input of patients' data such as demographics, diagnosis, procedures, and lab data but does not provide other information for applying or adopting the framework.

Hadley *et al.*, (2020) proposed an AI framework to support sustainable AI-driven global health initiatives. The framework factors/ factor includes type of healthcare problem, type of intervention, the appropriateness of individual AI model types may be considered and targeted towards an optimized model fit. When an AI model is chosen, sustainability of resources is considered (e.g., routine maintenance, higher oversight). A synergistic program is then founded upon the resource-conscious strategy which supports adjustment from a vertical program to a program with optimised horizontal components. The framework is illustrated in Figure 1 with four main components for the sustainable AI-driven GHI: Intervention, AI Application, Resource Sustainability Factor, and Synergistic Program Design while figure 2 is a guide for development of a pre-implementation strategy for synergistic AI-driven GHI. When the AI application appropriate for a specific GHI is determined, the resource required can be accounted and pre-deployed. Proposed resource factors are Model, Personnel, Infrastructure, and Process (Hadley *et al.*, 2020). As presented in Figure 2.6, the framework presents important factors for AI adoption in global health initiatives vaccine delivery and community healthcare worker routes (which can be transitioned to local public health settings). The factors identified include the type of AI models, processes, personnel, and infrastructure. In addition, as seen in Figure 2.7 a potential guide is presented to support development of a pre-implementation strategy.

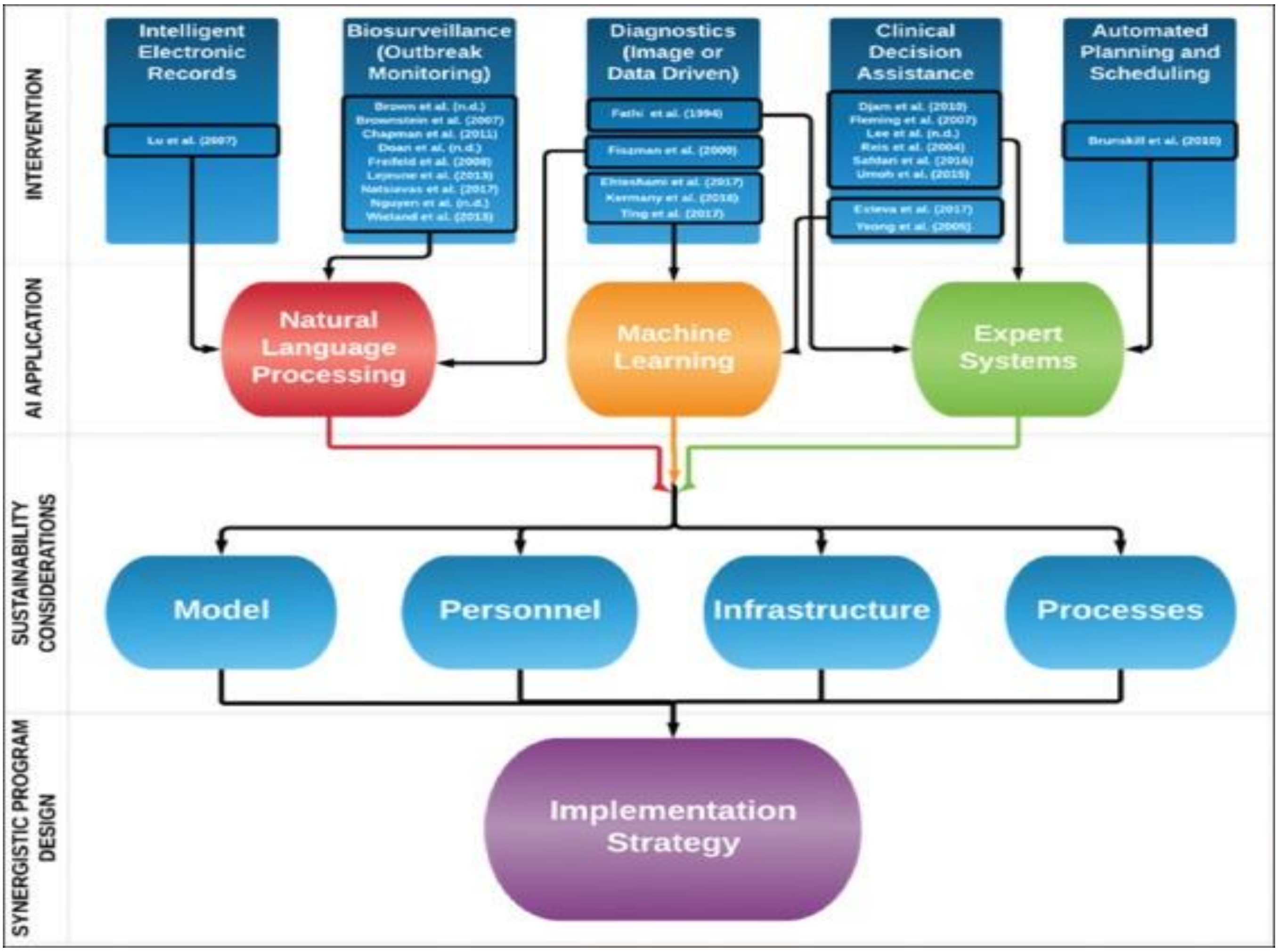


Figure 2.6: A process for development of an artificial intelligence driven global health initiative.

Source: Hadley *et al.,* (2020)

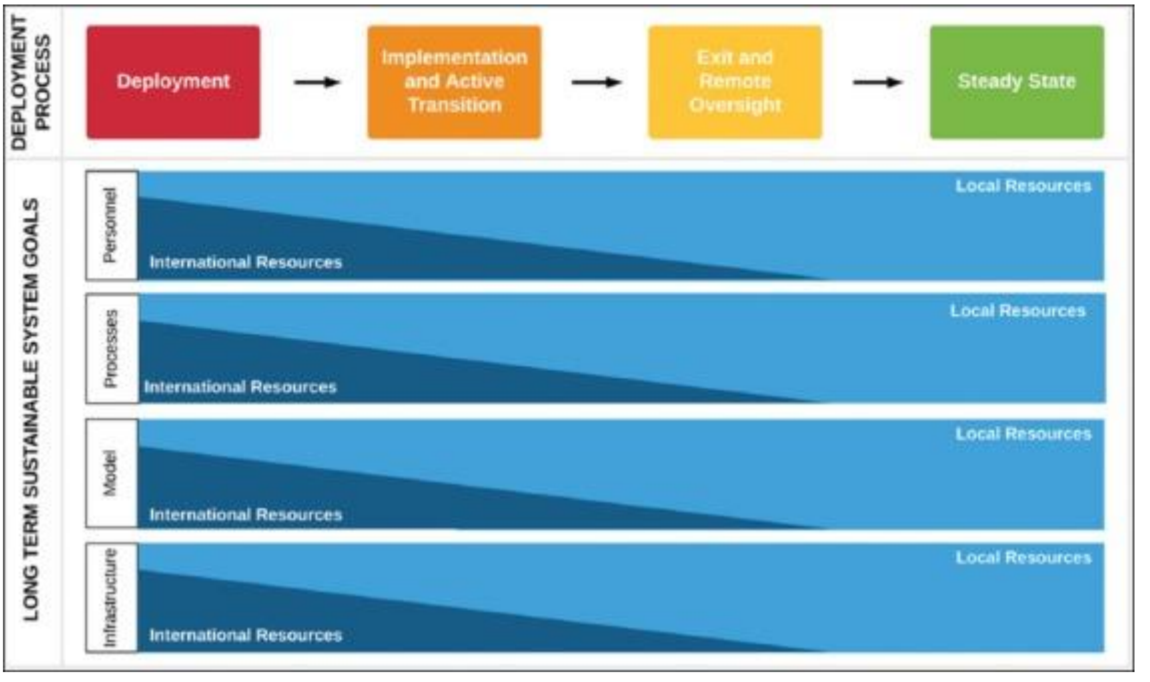


Figure 2.7: A potential strategy for implementation of a synergistic artificial intelligence driven global health initiative.

Source: Hadley *et al.,* (2020)

Having reviewed the above healthcare AI frameworks it can be concluded that most of them focused on the technical side of AI technologies, describing their components and the performance. There was little focus on the information or factors to support adoption of AI (apart from data). One of the frameworks reviewed (Hadley *et al.,* 2020) identified all the factors required to apply the framework and provided implementation guidance. For healthcare organisations to apply and adopt AI for OP, there is need to not only for research that ensures the performance of the AI but there is also need for research to identify the key factors and other to support AI adoption. This calls for a framework that identifies key factors for AI adoption and links them to OP in healthcare and provides supportive information for adoption. The table 2.3 below is a summary of the strengths and weaknesses of the different healthcare AI frameworks evaluated, showing that most of the frameworks are applied to areas of OP in healthcare but with no direct links to elements of OP.

Table 2.3: Summary of AI frameworks evaluated.

Framework	Author	Strength	Weakness
Fusion framework	Chen *et al.*, 2020	AI applied to clinical decision making	No direct link to elements of OP and factors for AI adoption not identified.
Image-based learning framework	Lou *et al.,* 2019	AI applied to predict treatment failure	No direct link to elements of OP and factors for AI adoption not identified.
Enhanced deep learning algorithm framework	Bargshady *et al.*, 2020	AI applied to detection of facial pain and clinical decision making	No direct link to elements of OP and factors for AI adoption not identified.
Deep learning prediction framework	Ashfqal *et al.*, 2019	AI applied to prediction of hospital readmission, clinical decision making, and cost savings.	No link to other factors in the healthcare setting.
Sustainable AI-driven global health initiatives	Hadley *et al.,* 2020	AI can be applied to monitoring outbreaks, diagnostics, clinical decision making and planning and scheduling in public health settings.	The framework shows links to elements of OP and factors for AI adoption such as the type of AI models, processes, personnel and infrastructure are also identified.

Source: The Researcher

2.8. Literature evaluation using the four-quadrant framework

This section aims to further identify gaps in the literature by applying the Four-Quadrant Framework in categorising contributions to the AI-OP adoption literature. According to Althonayan, 2003 the Four-Quadrant Framework is a comprehensive literature evaluation framework that classifies the literature into different research areas on the premise of purpose, into descriptive or prescriptive and outcomes into visionary or implementational. One of the benefits of this classification is that it is outcome and implementation based (Althonayan, 2003). This classification is therefore beneficial to this research because it facilitates the classification of the AI-OP literature on the premise of those that are descriptive or prescriptive in terms of describing the adoption or implementation of AI to improve general aspects of OP and those that are visionary or implementational in terms of those that have implemented AI with evidence of improving specific aspects of organisational performance.

By applying the specifications of each quadrant, the different approaches to the adoption of AI to OP in the healthcare sector can be evaluated. Research contributions on the application of AI to OP have been reviewed earlier in Chapter 2 (Section 2.3, 2.4 and 2.6); in this section, research on the adoption of AI for improved OP are evaluated and allocated to the quadrant that best describes them. This approach to evaluation has been chosen because it facilitates identification of the literature gap with regards to the research area by showcasing the quadrant with the least research literature. The table 2.6 below shows the Four Quadrant Framework adapted from the study Althonayan, (2003) to suit the healthcare setting by evaluating relevant research on AI frameworks applied in healthcare. Research is classified into quadrants based on approaches of the frameworks to AI application, adoption, and implementation into visionary descriptive; visionary prescriptive, implementational descriptive and implementational prescriptive.

Table 2.4: Four Quadrant Framework

<table>
<tr><td rowspan="6">Research outcomes</td><td rowspan="3">Descriptive</td><td colspan="2">Research philosophy</td></tr>
<tr><td>Visionary</td><td>Implementational</td></tr>
<tr><td>Quadrant 1
Visionary-Descriptive Approaches</td><td>Quadrant 3
Implementational-Descriptive Approaches</td></tr>
<tr><td></td><td>Propose a model or framework of AI for OP in healthcare setting.
Describe theoretical AI framework or model.
Describes accuracy of AI model or framework</td><td>Describes theoretical AI/OP framework or model
Provide a model or framework for adopting or applying AI to improve OP in healthcare setting.
Actual application of AI to OP in a real-world setting.
May describe how to adopt AI model or framework for OP.</td></tr>
<tr><td rowspan="2">Prescriptive</td><td>Quadrant 2
Visionary-Prescriptive Approaches</td><td>Quadrant 4
Implementational-Prescriptive Approaches</td></tr>
<tr><td>Propose a model or framework of AI for OP in healthcare setting.
Describes theoretical AI/OP framework or model.
Provide solution to OP issue in healthcare setting
May direct on the application AI to improve OP in healthcare setting.</td><td>May be an actual application of AI to OP in a real-world setting.
Describes theoretical AI/OP framework or model.
Provide a clear model or framework for adopting and implementing AI to improve OP in healthcare setting.
Provides practical steps and guidelines on how to adopt AI to improve OP in healthcare setting.</td></tr>
</table>

Source: Adapted from Althonayan, (2003)

2.8.1. Visionary-descriptive

Research in Quadrant 1 are those that are mainly theoretical, they propose a framework or model of AI applied in a healthcare setting. They are visionary in the sense that they are proposed for future application to OP in healthcare settings. They describe the AI model and its performance, its accuracy and how AI is applied to performance, there is however little or no discussion on how these models can be incorporated or integrated into healthcare settings in terms of framework or guidelines for implementation, as these support the adoption of technology.

Navarro *et al.,* (2018) describes a predictive naïve Bayesian model used to develop a machine learning algorithm for the prediction of patient length of stay in the hospital (LOS) after primary total knee arthroplasty (TKA) and proposed a tiered patient-specific payment model that takes into consideration patient complexity for reimbursement. The machine-learning algorithm accurately predicted LOS and costs prior to primary TKA (Navarro *et al,* 2018). The Bayesian model can improve OP by improving value-based care and patient centred care.

Gholipour, (2015) used a Neuro-Solution software (NS), ANN model and data to accurately predict traumatic outcome, and length of LOS in ICU using primary data (Gholipour, 2015). When traumatic outcomes are predicted accurately, it is expected that OP will improve as there will be more proactive and faster management of health conditions which can result in better healthcare outcomes. Accurate prediction of LOS can help with more effective hospital resource management.

Balyan *et al., (*2019), in their study used NLP and ML to generate three literacy profiles using data from 283,216 secure messages sent from 6,941 patients to primary care physicians. The results revealed that the combined AI model effectively and economically classified patients into literacy profiles (Balyan *et al.,* 2019). The study describes a theoretical AI model and proposes it for the improvement of health literacy and health outcomes in patients in a healthcare setting.

In their study, Liu *et al.,* (2020) compared four prediction models including AI (ANN models) in the prediction of 30-day readmission after acute myocardial infarction (AMI). The combined ANN model when compared with logistic regression had a higher prediction accuracy for prediction of 30-day readmissions. The ANN model also reclassified risk-standardized hospital readmission rates to 10% of hospitals across hospital performance categories (Liu *et al.,* 2020). The study suggests that AI can improve OP in hospital settings by offering a better approach for the prediction of readmission and generation of risk-standardised hospital readmission rates.

Awan *et al.,* (2019) applied ML techniques to prediction of readmission or death due to heart failure (HF) using data for those aged 65 years and above diagnosed with HF. They reported that ML accurately predicted readmission or death post hospital discharge for heart failure (HF) (Awan *et al.,* 2019). Awan and colleagues suggest that described ML techniques can improve predictability of readmission/ death in heart failure, mitigation of associated risks, therefore improvement of health outcomes and OP in healthcare settings.

Viscaino *et al.,* (2020) study investigated the diagnosis of external and middle ear conditions by applying a combined computer and ML technique. The system was capable to highlight the area under medical suspicion if the system response was any of the ear conditions, except in normal case (Viscaino *et al.*, 2020). The system is proposed for application of AI to achieve OP in general practice settings by improving the accuracy and cost effectiveness of diagnosing and managing the specified ear conditions and potentially other ear conditions before specialist referral. This is particularly useful in resource poor settings where patients may approach general practitioners for medical attention rather than otolaryngologists.

Carson *et al.*, (2019) applied ML and NLP to the identification of suicidal behaviour in psychiatric hospitalized adolescents (n=73) using data from EHR. This model was modestly successful in identifying suicide attempt among a small sample of hospitalized adolescents in a psychiatric setting (Carson *et al.*, 2019). The model describes the development and evaluation of an AI model and proposes it for the detection of suicidal behaviour in adolescents in psychiatric resulting in improved health outcomes in the management of suicidal and psychiatric behaviour in adolescents.

Sunny *et al.,* (2019) successfully applied a combined a tele-cytology model with ANN-based risk-stratification for early diagnosis of oral potentially malignant (OPML)/malignant lesion.) The study describes the tele-cytology integrated ANN model as an AI model that can be used in detecting oral cancer at an early stage (Sunny *et al.,* 2019). The study results suggests that the model can improve health outcomes for OPML. This can be especially beneficial in resource limited settings where there is no skilled Cyto-pathologist.

Zhou *et al.,* (2016) applied ML techniques to investigate defining phenotypes for Rheumatoid arthritis in a primary care EHR. The proposed model had a similar performance to the knowledge-based models (Zhou *et al.,* 2016). The model provides a cost-effective, rapid, accurate and reliable method of classifying rheumatoid arthritis and other complex medical conditions presenting in primary care settings, thereby improving OP in this setting.

A study by Meiring *et al.*, (2018) effectively applied ML to assessing the predictability of ICU (Intensive Care Unit) mortality as a function of time, facilitating the reduction of high complexity of data from ICU admissions. This may prove challenging to capture by linear techniques, improving prognostication, decision making and performance evaluation and performance improvement in ICU (Meiring *et al.*, 2018). The study describes the AI model and proposes its future application to the accurate prediction of ICU prognosis over time.

Yu *et al.,* 2018 investigated the early diagnosis of Acral melanoma and benign nevi of the hands and feet from dermoscopy images using convolutional NN. The CNN model displayed higher accuracy than the expert and non-expert evaluations (Yu *et al.,* 2018). The described model is proposed as a useful technique for accurate detection of acral melanoma, and improvement of prognosis and outcomes during management of the disease.

2.8.2. Visionary-prescriptive

Visionary-prescriptive studies are those that propose a model or framework of AI for OP in healthcare setting, these studies practically apply AI to solving an OP issue.

A study by Hu *et al.*, 2012 using a sample of 1099 patients proposed and demonstrated the use of machine learning combined with data mining techniques in predicting analgesic requirements and PCA (Patient Controlled Analgesia) readjustment in the management of post-operative pain. The ML and decision tree system accurately predicted total analgesic consumption (continuous dose and PCA dose) and PCA analgesic requirement (PCA dose only) outperforming the analgesic prediction consumption of Artificial Neural Network, Support Vector Machine, Random Forest, Rotation Forest, and Naïve Bayesian classifiers in analgesic consumption prediction (Hu *et al.*, 2012). The study proposes and practically demonstrates the application of ML and data mining to improving performance in anaesthesiology through effective post-operative pain management resulting in patient mobilization, shorter hospital stays and decreased financial costs.

Kim *et al.*, 2014 applied a natural language processing program to the extraction of select and organised pathologic findings from EMR reports of radical prostatectomy specimen. This method using NLP, showed high accuracy and efficiency in identifying key pathologic details from the prostatectomy report within an EMR system (Kim *et al.,* 2014). Therefore AI (NLP) can be used by urologists to accurately and efficiently summarize and highlight important information from verbose pathology reports, thereby improving OP more accurate diagnosis and treatment of Urology cases and in provision of data for future urology research.

Grover, Bauhoff and Friedman, in their 2019 study qualitatively applied supervised learning to selection of audit targets for performance-based health financing in Zambia. According to their results, the ML methods, specifically Random Forest had the highest performance. Improved prediction accuracy results in significant cost savings, income from detected cases for cover verification costs, expected decrease in over-reporting, decrease in avoidable time spent on reporting to support verification, increased acceptance of PBF by health facilities and policymakers (Grover and Friedman, 2019). The proposed method can be applied in healthcare facilities that have a routine electronic reporting system, to improve the performance of PBF verification as well as improve the efficiency in the management of financial resources and therefore OP in the healthcare facilities.

Adikari *et al.,* 2020 applied a framework of AI model (PRIME) (validated on a dataset of 277,805 conversations from 18,496 PCa patients from ten international OCSG. When pre-treatment and post-treatment groups of PCa were compared the emotions of the pre-treatment were significantly lower than post-treatment ($p<0.05$) after 12 months indicating that patients who joined at the pre-treatment phase had improved emotions while those who participated long-term, had increased emotional wellbeing (Adikari *et al.,* 2020). This demonstrates that AI can be used to empower patients in OCSG as early psychological intervention in combination with formal intervention processes thereby improving health outcomes in PCa patients. The study describes, proposes and prescribes a practical AI model which can be applied to improving OP in the healthcare setting although implementation is not discussed.

Chiu *et al.,* (2019) effectively used ML techniques, to develop a brief questionnaire to assist neurologists and neuropsychologists in the detection of mild cognitive impairment (MCI) and dementia (Chiu *et al.,* 2019). The study describes, proposes and prescribes a clinically practical AI; the NMD-12 model based on ML techniques applied to detection of MCI and dementia, thereby improving predictive accuracy and OP in the mental health setting derived from machine learning is a simple and effective screening tool for discriminating NC, MCI, and dementia.

2.8.3. Implementational-descriptive

Implementational-descriptive studies are those that describe a practical implementation of AI to OP in healthcare setting. Karhade *et al.*, (2018) used algorithms for the prediction of intermediate (30 day) and long-term (90 day) mortality post- surgery to (improve outcomes) for spinal metastatic disease. The study developed five models (neural network, support vector machine, penalized logistic regression, random forest, stochastic gradient boosting). The final models were incorporated into web applications which can be used for the prediction of intermediate and long-term mortality in spinal metastatic disease and to provide patient-specific explanations (Karhade *et al.*, 2018). These explanations of predictions can be applied by practicing clinicians and patients to understand the determinations required in specific cases, thereby enhancing patient care and shared decision making in the management of spinal metastatic disease. The study also describes incorporation of the resultant AI model into web application applicable for use by clinician for improving management of spinal metastatic disease and therefore OP in healthcare setting. The study provides web access of the framework for clinicians to use.

Wang *et al.*, (2019) applied IILS (Intelligent imaging layout system) to automatic imaging report standardization and the optimization of intra-interdisciplinary clinical workflow optimization for a clinical decision support system-based ubiquitous healthcare service, a lung nodule management system using medical images (Wang *et al.,* 2019). The AI was effective in identification of lung nodules, standardising images and making them more reliable and interpretable, reducing the CT process and providing film reports efficiently and accurately to both radiologists and physicians, improving clinical decision making and therefore OP in radiology and respiratory departments. The study is implementational descriptive as it develops the AI models and proposes that the model can detect lung nodules in clinical radiology and respiratory settings. The study also describes the incorporation or integration into the clinical decision support system.

Zhou *et al.,* 2012 applied a Mapping Partners Master Drug Dictionary based on NLP (AI) the creation and maintenance of RxNorm a local medication terminology that can be used for interoperability. This combined approach of NLP and human expert review is more effective in overcoming the challenge of user uniqueness and application requirement of drug concepts and modelling approaches for terminologies when mapping as it reduces the time and effort required to reasonably generate and maintain a map between terminologies (Zhou *et al.,* 2012). The study provides guidance on how the challenge of changes in the RxNorm model and content can be captured and consistently synchronized and integrated into local clinical terminology and data and the use of change management at organisational level in maintaining and updating mappings and the automation tool to ensure that they are current.

2.8.4. Implementational-prescriptive

Implementational prescriptive studies are mainly real-world implementations of AI to achieve OP in healthcare. Jamei and colleagues 2017 study applied ANN (Artificial Neural Networks to prediction of 30-day hospital readmission. The ANN model showed higher precision than the industry standard LACE (Jamei *et al,* 2017). The study is implementational prescriptive because the AI model applies real-time data from EHR to predict patients with a high risk of hospital readmission, thereby facilitating the mitigation of risks, reducing the high costs of avoidable hospital readmissions and improving patient's quality of care. The neural network model is made available to healthcare organisations and can be retrained on a variety of hospital systems to achieve performance. The study provides guidance on implementing valuable and cost-effective post-discharge interventions by designing a cost-saving analysis which can be used by decision makers to effectively plan and make optimal use of hospital resources.

Araujo *et al.,* 2018, applied TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) in combination with NN to estimating the hospital services in Brazil and the impact of socioeconomic, demographic, and institutional variables as predictors of the performance level observed. The combined model predicted a slight performance increase and identified demographic and socioeconomic status and the juridical nature and type of ownership of the healthcare facilities (i.e. federal and private hospitals) as important predictors (Araujo *et al.,* 2018). The combined TOPSIS and NN model is a practical model that can be applied to evaluating the performance of hospitals and the impact of public health policies provides opportunities for more integrative health policies, better allocation of resources, efficiency, and improved OP. The NN model was not described or explained but it was more prescriptive and implementational as it was applied to prediction of Organisational performance in a public health setting.

Li *et al.,* 2019 used Recurrent Neural Networks to analyse and predict unplanned intensive care unit readmission. The model can help to achieve OP in clinical settings by serving as an efficient decision-making support system for physicians and ICU specialists during discharge (Li *et al.*, 2019). It can also reduce patient's risk exposure to morbidity and mortality, waste of medical resources, financial resources, unplanned readmission to the hospital and ICU and improve person-centred care. The study prescribes a real-world implementation of AI to OP.

Table 2.5: Literature evaluation using Four quadrant framework.

		Research philosophy	
		Visionary	**Implementational**
Research outcomes	Descriptive	**Quadrant 1** **Visionary-Descriptive Approaches**	**Quadrant 3** **Implementational-Descriptive Approaches**
		Gholipur, 2015 Zhou *et al*., 2016 Yu *et al*, 2018, Sergio *et al*, 2018, Meiring *et al*., 2018, Ramkumar *et al*., 2019, Awan *et al,* 2019, Balyan *et al.*, 2019, Carson *et al*, 2019, Sunny *et al.,* 2019 Lou *et al*, 2019, Viscaino *et al*., 2020	Zhou *et al.,* 2012 Karhade *et al.,* 2019 Wang *et al.,* 2019
	Prescriptive	**Quadrant 2** **Visionary-Prescriptive Approaches**	**Quadrant 4** **Implementational-Prescriptive Approaches**
		Hu *et al.,* 2012, Shi *et al.*, 2012 Kim *et al.,* 2014 Grover and Friedman, 2019, Chiu *et al.,* 2019 Adikari *et al*., 2020	Jamei *et al*., 2017 Li *et al*., 2019 Araujo *et al*, 2019

Source: The Researcher

The literature evaluation conducted using the Four quadrant framework is summarised in the above Table 2.7 showing the different studies evaluated and the quadrants they fall into. The table shows that most of the studies on AI adoption or implementation fall into the Visionary-descriptive quadrant, and these are mainly theoretical applications of AI to OP in healthcare. These studies present theoretical or technically focused AI frameworks but no frameworks to support the actual adoption or implementation of AI and integration of AI into healthcare.

Visionary-prescriptive studies are those that present a theoretical AI framework practically applied to solving an OP issue in healthcare. Implementational-descriptive studies are those studies with practical adoption of AI to OP issues in a real-world setting. These studies describe or provide guidelines on how to adopt or implement AI. Lastly the Implementational-prescriptive studies are those with a practical implementation of AI to solve an OP issue in real-world settings. Some of the studies in this category also provide a framework of AI that is linked to elements of OP. The number of studies in the implementation descriptive and the implementational prescriptive quadrants are fewer than the visionary descriptive and visionary prescriptive approaches. The literature evaluation based on the Four quadrant framework revealed some more gaps in the literature. There were few studies in the Implementational-descriptive quadrant, implying a scarcity of AI studies that apply AI to solving an OP issue in a real-world setting that describe or provide guidelines on how to adopt or implement AI. There were even fewer studies in the Implementational-prescriptive quadrant, implying a scarcity of studies that provide practical implementation of AI to solve an OP issue in real-world settings and provide a framework of AI that links AI to elements of OP. Therefore, it can be implied that there is a scarcity of studies with a focus on practical guidelines adoption and implementation of AI in the healthcare sector.

Conclusion

The Chapter reviewed the literature on AI and OP, by first conducting a review of the application of AI to OP in the healthcare sector which involved reviewing selected studies from the general healthcare sector and the Nigerian healthcare sector. Next the topic was further reviewed by evaluating current frameworks that applied AI to OP in healthcare. In addition to the literature review of studies, evaluation of frameworks, an additional literature evaluation was conducted using the Four quadrant framework. This involved evaluating research on the adoption of AI for improved OP and subsequent allocation to the appropriate quadrant for identification of literature gap. Based on the literature review conducted, it can be concluded that the application of AI to OP in the healthcare sector is a well-researched topic. It however appears that there is a lack of appropriately designed studies with reference to OP that can be relied upon as evidence of the application of AI to OP. Most of the studies have not considered or linked, measured, or assessed elements or variables of OP that indicate performance in the healthcare sector. Studies with frameworks have mostly not specified key factors for AI adoption in the frameworks. Lastly there is a scarcity of studies that provide clear guidance on the adoption and implementation of AI to OP in healthcare. The gaps identified are presented in the next Chapter.

3. CHAPTER 3: LITERATURE GAP

3.1. Introduction

Consequent upon the review of literature in Chapter 2, and deficiencies in the AI frameworks evaluated, the Researcher identifies key deficiencies and presents the literature gap and research direction as summarized in Figure 3.1.

3.2. Literature outcome and gaps in the literature

The literature review of studies that have applied, adopted AI for OP in the healthcare sector highlights gaps in the research as presented below.

I. Most of the studies reviewed in Chapter 2 section 2.3 and 2.4 did not link AI to elements of OP in the healthcare sector e.g., quality of care, efficiency, productivity, cost reduction, access to healthcare, healthcare practice and patient outcomes etc. although these studies demonstrated that AI on OP. These studies focused on describing the performance and accuracy of AI more than focus on OP in healthcare. Without directly linking AI to OP elements in healthcare, the actual impact of AI on OP in healthcare cannot be truly ascertained. This may hinder the improvement of OP in the healthcare sector. It is therefore necessary to link AI to OP in healthcare elements identified as relevant when applying AI to OP in the healthcare sector.

II. Most of the AI frameworks evaluated in Chapter 2, section 2.6 did not also directly link AI to OP. In a few cases where AI was linked to OP, there was little consideration for strategic factors that affect the application, adoption of AI in the healthcare sector. Only a very few of the AI frameworks linked AI to OP or approached AI adoption from the strategic point of view. For healthcare organisations to apply and adopt AI for OP firstly, there is need to ensure the performance of the AI, secondly there is greater need to ensure that the key and relevant factors for AI adoption are identified and thirdly there is need to link AI to OP in healthcare so that the aims, objectives and goals of the healthcare organisation can be achieved. This warrants the development of an AI-OP framework that supports identification of key factors for AI adoption and links them to elements of OP in healthcare.

III. The literature evaluation in Chapter 2, section 2.7 reveals that most of the studies on AI adoption or implementation are mainly theoretical applications of AI to OP in healthcare that do not link AI to OP. Most of these studies are not practical adoptions or implementation of AI to solve OP issues in real-world settings and provide no guidelines for adoption or implementation AI for OP. Lastly there is a scarcity of studies that apply AI to solving an OP issue in a real-world setting that describe or provide guidelines on how to adopt or implement AI.

Bringing gaps, I, II, III together it can be inferred that there is a scarcity of AI studies with a focus on practical adoption and implementation of AI in the healthcare sector and with linkage to elements or variables of OP. These gaps have highlighted the need for a new AI-OP adoption framework for the healthcare sector. The methodology to be applied in achieving this is presented in the following Chapter. The Table 3.1 shows the literature gaps identified and which have informed and directed the Research.

Table 3.1 Literature gaps and Research direction

Table 3.1 Literature gaps and Research direction

S/ No	Description of current research	Literature Gap/ Issue	Direction of this Research
I	Literature is dominated by application of AI to diverse OP related issues in the healthcare sector.	Scarcity of research that directly link AI to relevant elements of Organisational performance (OP) in the healthcare sector.	Linking of AI to relevant elements of OP in the healthcare sector.
	Description of AI performance/ accuracy with comparison to human performance/ other technologies.	Scarcity of research that simultaneously apply AI and measure/ assess the impact of AI on elements of OP relevant to the healthcare sector.	Measurement/ assessment of the impact of AI on OP by elements of OP relevant to the healthcare sector.
II	Literature is dominated by the description of AI frameworks.	Scarcity of literature that report frameworks with strategic, factors for the adoption/ implementation of AI in the healthcare sector. Scarcity of literature that link AI frameworks to elements of OP in healthcare.	Development of an AI-OP framework that supports the adoption of AI with identification of strategic, key factors for AI adoption and simultaneous linkage to elements of OP in the healthcare sector.
III	The literature is dominated by theoretical applications of AI to diverse OP related issues	Scarcity of studies on practical adoption/ implementations of AI for OP in real-world healthcare settings.	Development of a strategic AI-OP framework for the adoption/ implementation of AI

Table 3.1

Source: Researcher

3.3. Conclusion:

The Chapter brought together key deficiencies identified through the literature review, framework evaluation and literature evaluation conducted in Chapter 2 (Section 2.3, 2.4, 2.6 and 2.7). These were combined to form the literature gap which serves as the rationale for the development of the theoretical AI-OP adoption framework, discussed in Chapter 4 (Figure 4.1). This theoretical framework is conceptually underpinned by existing theories presented in the literature, concepts of AI and OP discussed in Chapter 2 and the literature gap analysed in Chapter 3.

4. CHAPTER 4: DEVELOPMENT OF AI-OP ADOPTION FRAMEWORK

4.1. Introduction

This Chapter is a presentation of theories, models and literature that are relevant to the research development of the theoretical AI-OP Framework. Firstly, the theoretical foundations of AI are discussed and then the technology acceptance theory and model are presented as a baseline for AI adoption. Next the Balanced score card is adopted for OP in the healthcare context. Finally, factors identified as pertinent are incorporated to develop the AI-OP adoption framework.

4.2. Relevant Theories and Models

4.2.1. Artificial Intelligence theoretical foundation

Although most fields of science are guided by theories, the field of AI appears to be an exception; AI has no generally accepted theories even after over half a century of its development (Wang, 2012). This may be due to the failure of attempts to make computers work similarly to the human mind (even though this is explicitly impossible as the computer is not a biological system), on this basis therefore there are a variety of proposals of AI paradigms along with different objectives, methodologies, and applications (Wang *et al.*, 2018). Realistically however the difficulty may rest in the complexities in developing such a theory which should be both descriptive and normative as is the case with Computer science and physics respectively, make connections between the brain and the computer because the brain's functions are expectedly taken over by the computer in certain situations; it should also be centred on the Human intelligence, Computer intelligence and General intelligence (common to both computers and humans) (Wang, 2012).

4.2.2. Symbolism

One of the most widely accepted views on the theory of AI is the Physical symbol system hypothesis by Newell and Simon, 1980. They proposed that a physical symbol system composed of mathematical symbols and formulas can be sufficiently used in the representation and application of intellectual behaviours (Newell and Simon, 1980). Based on this view, a complete symbol system or an intelligent system uses rule-based memory to search, acquire and control knowledge and operators to develop solutions to general problems (Vernon and Furlong, 2007). The system is required to be able to perform 6 basic functions: symbol inputting, symbol outputting, symbol storing, symbol duplication, symbol structure creation by identifying the relationship between symbols, conditional migration based on existing symbols (Li and Du, 2017).

4.2.3. Connectivism

The Connectivism approach was first put forward by McCulloch and Pitts, (1943) who proposed a mathematical model for neurons, integrated into a multilayer model referred to as a neural network (McCulloch and Pitts, 1943). The research however became stagnated and was re-established by Hopefield's proposal of the Hopefield neural network which successfully provided a solution to the salesman problem by the calculation of a complex NP (Nondeterministic Polynomial) (Hopefield, 1982). This view argues that neural cells are the basic unit of human thinking, and the human brain cannot be equated to a computer, a bionic brain model is requisite to simulating human intelligence which occurs as a result of competition and coordination between neural cells of the brain. In the ANN approach, the neuron network is represented by the value of weights in the interconnection between units, with the weights being sometimes continuous. The learning rule of the ANN is dependent upon basic varying discrete sub-symbol values which serve as basic units of cognitive and intellectual activity. This approach has provided a more biologically relevant model compared to the abstract concept of symbolism and has been applied to many specialist areas such as pattern recognition, automatic control, and optimization (Li and Du, 2017).

4.2.4. Behaviourism

Behaviourism is based on the intellectual behaviour described by the perception-behaviour model, this approach also referred to as the black box approach, was concerned with studying the objective measures of animal stimuli and the resultant responses devoid of considering internal processes of systems (Zhong, 2008). Its development started between 1940's to 1960's with the classical control theory which used frequency analysis to study linear invariant time systems. The modern control theory from the 1960s to the 1970s which used the state-space method was used to solve multi-input/ multi-output problem thereby transforming a steady-state linear system into a time-varied nonlinear system. The generalized control system theory was developed in the 1970s, focused on using control and information to coordinate a generalised system, simulation of human perception processes and behaviours and biotical functions control. The 1980s ushered in the birth of intelligent control systems and intelligent robots (Li and Du, 2017). Behaviourism successfully simulated lower-level intelligence in animals by studying animals such as rats and pigeons, resulting into several discoveries but encountered less success with humans (Zhong, 2008). Some important contributions are the six-legged walking robot developed by (Raibert, 1986), mobile robot with the capability of retrieving objects (Conell, 1989) and multi-robot systems by (Mataric, 1997). These three approaches have unique challenges; while symbolism has challenges in the designing of expert systems, Connectivism has problems with structural complexity relating to neuron connectivity and behaviourism is limited to low level intelligence.

4.2.5. Technology Adoption

Technology adoption takes place when an individual, firm, or other agent initially uses a new technology. In this setting, technology may be a new product, service, or innovation (Forman, Goldfarb, and Greenstein, 2018). Technology Adoption has been classified into three stages namely initiation, adoption decision and implementation (Damanpour and Schneider, 2006; Pichlak, 2016). The initiation stage is the pre-adaptation stage which involves all activities towards adoption such as need identification, solution finding, gaining knowledge about existing technologies, opinion seeking and preparation for implementation. The second stage which is the adoption decision stage is when management makes the decision to adopt and involves acceptance of proposed idea, practical, strategic, financial technological evaluation of the technology (Ober, 2020). Technology adoption has been further classified into levels mainly the individual and organisational level of adoption (Kyratsis *et al,* 2012; Miranda *et al*, 2016). Although healthcare organisations take the first step in organisational technology adoption, the success of technology adoption majorly relies on the end users (Hostgaard *et al*, 2017; Ruiz-Morilla *et al*, 2017) in this case the healthcare professionals adopting the technology. When organizations decide to invest in new technology, they are adopting technology at primary level and when they install the technology, and individuals in the organisation apply it then then technology adoption is at secondary level (Talukder, 2012). Based on this perspective, it can be implied that secondary adoption by individuals in the organisation is contingent upon primary adoption decision by the organisation and secondary adoption is requisite to improved organisational performance via the technology.

4.2.6. The Technology Acceptance Model (TAM)

Technology acceptance has been cited by several researchers as an important concept for the acceptance, adoption, and use of technology in healthcare as well as in other fields (Brock and Khan, 2017; Dwivedi et al, 2017; Ehteshami, 2017; Granić and Marangunić, 2019; Ahmad et al., 2020). Technology acceptance theories are therefore significant in understanding the factors that affect adoption and use of technology in healthcare (Beldad and Hergner, 2017). Technology acceptance model, Theory of planned behaviour, Unified theory of acceptance and use of technology, Value-based adoption model among others are some of the technology acceptance theories that have been applied to technology adoption (Taherdoost, 2018). This Research will focus on evaluating the TAM, for a better understanding of important factors for the adoption and implementation of AI technologies at the healthcare organisational level. The TAM which was developed from the Theory of Reasoned Action by Davis in 1989, is reported to be one of the most influential models of technology acceptance (Charness and Boot, 2016), It is also the first model to include psychological factors as having a significant impact on technology acceptance (Samaradiwakara and Gunawardena, 2014). In contrast to theories like the innovation resistance theory, the technology acceptance model, and related theories can be used to predict and explain the adoption of technology. It has also been applied to healthcare settings (Nguyen et al, 2020; Klaic and Galea, 2020). The model proposes two primary factors as important influencers of an individual's intention to use new technology: Perceived Ease of Use (PEU) and Perceived Usefulness (PU) (Tsai, 2014). While PEU is the degree of effortlessness an individual expects to have when using a specific technology, PU is the degree to which an individual believes that his or her job will be enhanced by using a specific technology (Diop et al, 2019). The TAM was developed on the premise that employees reflected low use of technologies made available for their use (David, 1989; Davis, Bagozzi and Warshaw, 1989). The TAM developers proposed that addressing these factors during the developmental stage of a technology would help increase user acceptance, impact behavioural intention to use and actual use of technology (Portz et al., 2019). The TAM 2 which is an extension of the TAM by Vankatesh, and Davis was developed to provide a better understanding of the PU and PEU from the social influence and cognitive perspective (Vankatesh and Davis, 2000). This model has the attitude (ATT) variable removed from the model (ATT originally mediated the impact of PU and PEOU) and replaced by another variable to reflect social influence (for instance from colleagues or superiors) denoted by Subjective Norm (SN) from the TRA and TPB models which enables users undergo a positive evaluation of IT and accept it (Momani and Jamous, 2017).

Although the TAM has been criticized, it is still considered to be one of the most useful frameworks for investigating the factors that impact new technology use (Al-Mamary et al, 2016). The TAM has been supported for having the advantage of ease of application across different settings related to technology adoption as well as more cost-effective application (Kurniabudi, Sharipuddin and Assegaf, 2014). As well as being a strong predictor of attitude towards using technology and intention to adopt technology (Lai and Ahmad, 2015). Also based on its original design the TAM can address the problem of user's lack of acceptance of technology by taking up suitable measures to support technology adoption (Lai, 2017). The TAM has been criticized based on studies that have found no significant results for the variables identified as strong predictors of intention to use technology (Surendran, 2012; Scherer et al, 2018). It has also been criticized on its generalized approach to the information systems field which does not take into consideration factors of importance in other settings (Lai, 2017). The TAM has been applied to provide a better understanding of technology adoption in different areas of healthcare such as in intelligent health care systems (Chen et al, 2017), intelligent health monitoring systems (Tseng et al, 2013) and Health informatics, (Ammenwerth, 2019) and is therefore applicable to understanding and predicting AI adoption in healthcare.

4.3. Key Factors for AI adoption

Various factors for adoption of AI have been identified from literature. Bukowski *et al.*, (2020) identified the digital infrastructure, interoperability, education, security, privacy, ethics, and legal factor as critical factors for the implementation of AI in healthcare settings (Bukowski *et al.*, 2020). Ruiz-morilla and colleagues identified the following factors identified as barriers are; legal and regulatory issues, impact on quality of care and patient outcomes (Ruiz-morilla *et al.*, 2017), potential dangers of AI algorithms such as data set shifts, accidental fitting of confounders, discriminatory bias errors, problems with generalizability (Kelly *et al.*, 2019). Factors identified in other studies include political and economic factors (such as regulatory, financial, market issues), healthcare practice norms that affect service delivery in the healthcare sector (Khan and Hashmani, 2018; Panch, Mattie, and Celi, 2019). To support the development of a framework for the adoption of AI for OP in healthcare, the literature was reviewed to identify key factors for AI adoption in healthcare. The factors identified from technology and AI literature as important in adoption of technology have been classified as internal and external factors. Internal factors are the influences within organizations that can affect AI adoption while external factors are those influences outside organization's that affect the organization (Chairoel and Riski, 2018) in this case with regards to AI adoption, the Internal factors are Data, Education and training, Acceptance, Organizational, and Technological factor while external factors are legal, ethical, regulatory, and environmental.

4.3.1. Data

Data is one of the key requirements for evidence based and effective AI in Healthcare (Shin, 2018; Davenport and Kalakota, 2019; Kelly *et al.,* 2019). The type of data that a healthcare organisation requires is determined based on factors such as the type of healthcare needs of users (Hosny *et al.,* 2018, Davenport and Kalakota, 2019) as well as its the strategic priorities (DalleMule and Davenport, 2017). Not only is data required for AI to function, but the performance of AI is also as good as the data it uses. Therefore, data type, data collection, data quality, data quantity, data security and financial implications of data must be put into consideration and controlled for (Park and Shin, 2017; Shin, 2018; Troung *et al.*, 2019; Forcier, 2019; Li, Yang and Lin, 2021). Data collection mainly involves data acquisition, data labelling and existing model improvement. Data acquisition to find data sets for model training is one of the most challenging aspects of data collection. It follows three approaches: data discovery, data augmentation and data generation. Data discovery is used when new data sets are required for instance from the web or corporate data lakes, while data augmentation involves improvement of existing data by the addition of external data. Data generation involves using crowd-sourced or synthetic data when there is no available external data set (Roh *et al.,* 2018). After data acquisition, due to the diversity of data streams which may be structured, semi-structured or unstructured, the data may require processing, standardization, and integration (Miotto *et al.*, 2018). Another point of importance is the quality of healthcare data, although large quantity of training and test data are required for the development of AI technologies. To ensure that AI is reliable and performs well, data must not be incomplete or erroneous and must also have high quality along many dimensions such as accuracy, completeness, diversity, consistency, and uniformity (Hosny *et al*, 2018; Shin, 2018; Budach *et al,* 2022). AI technologies in healthcare require vast amounts of data to train them with data generated from healthcare activities e.g., clinical activities such as screening, disease diagnosis, allocation of treatment etc. This facilitates the learning of identical group of subjects, interconnections between subject characteristics and outcomes of interest

(Najafabadi *et al.,* 2015; Wang and Alexander, 2016; Jiang *et al.*, 2017). Data security can be defined as the confidentiality, integrity, availability of data (Jain *et al*, 2019). According to Data security should encompass data security, control of access and information security (Kim *et al.*, 2014). Moreso the sensitive nature of individual data in healthcare requires security and privacy of data (Abouelmehdi *et al.,* 2018).This may pose a challenge considering that healthcare AI data come from a range of different sources. The issue of data access has also been cited as important in AI design and implementation (Van de Sande *et al*., 2022). Therefore, healthcare organisations should research approaches to accessing data if required.

4.3.2. Education and training

As the application of AI to different areas of healthcare continues to rise it has become necessary for healthcare professionals to be adequately exposed to AI education/ training through courses in mathematics, AI fundamentals, data science, ethical and legal issue (Paranjape *et al.,* 2019). They should also be aware of its benefits to healthcare such as improved health outcomes (Weng, Reps, and Kai, 2017) faster and more accurate diagnosis (Dreyer and Geis, 2017), cost, quality, access to healthcare, improved health outcomes and the challenging aspects such as transparency and liability (Paranjape *et al.,* 2019). The healthcare profession consists of different classes of professionals working together to achieve health outcomes, oftentimes these are highly skilled professionals (Morley and Cashell, 2017) with their knowledge based predominantly on their area of medical specialisation. Medical doctors for instance have a great proportion of their medical training focused on memorising as much information as possible and applying it to patient care, with less time allocated to new technologies such as AI (Wartman and Combs, 2018). These and other healthcare professionals should act as collaborators by understanding that the increasing trend of AI applications to healthcare is accompanied by increased access to knowledge by other professionals and service users, who may question healthcare professionals' status as holders of exclusive knowledge in healthcare, and this implies that they must be knowledgeable in AI (Rampton *et al.,* 2020). Therefore, AI education and training should not be restricted to core healthcare professionals such as clinicians but should cut across multiple disciplines relevant to AI healthcare such as Managers, Administrators in healthcare etc. (Reed, 2018; Fountaine *et al.,* 2019). This will support the use of data from different sources, supervision of AI tools and detection of algorithm inaccuracies (Park *et al.*, 2019). Another important reason why education and training are critical for AI adoption and effectiveness is that it will help healthcare professionals better understand and trust AI. This is because many AI technologies applied in healthcare have the black box challenge which may be a barrier to the effectiveness of AI in healthcare settings, for example in a clinical setting where an AI – a CDSSs (Clinical Decision Support System) is introduced, the clinicians will be more trusting of the decisions of the system if they understand the mental model by which the algorithms use data to make decisions, on the other hand a lack of understanding of how the system works could lead to over-reliance on the technology, decrease in clinical decision making skills and poorer health outcomes for service users (Lysaght *et al.*, 2019; Sutton *et al*., 2020).

4.3.3. Acceptance

Acceptance of AI by professionals appears to be an important yet challenging aspect of AI adoption and implementation (Papadopoulos, Koulouglioti and Ali, 2018). Distrust and lack of acceptance for AI is due to various reasons such as the fact that AI technologies are not human entities like healthcare professionals and therefore cannot be trusted (trust implies in healthcare requires placing life in the hands of healthcare professionals in situations of vulnerability), AI technologies lack capacity to meet healthcare needs, they lack transparency due to the black box issue, they are also characterised by safety issues like knocking over; safety; privacy and several other issues (Decamp and Tilburt, 2019; Kelly, 2019;Longoni, Bonezi and Morewedge, 2019; Laï, Brian, and Mamzer, 2020). Despite the apparent lack of AI acceptance by healthcare professionals the healthcare sector continues to experience increasing disease burden, ageing global population and healthcare workforce shortage and crisis all of which may have a negative impact on health outcomes (Meskó, Hetényi and Győrffy, 2018; WHO, 2020; Papadopoulos, Koulouglioti and Ali, 2018) especially in the absence of effective interventions.

4.3.4. Organisational

One of the factors identified as key in the adoption of technology is the organisational factor (Zhen *et al,* 2012; Tan *et al,* 2015). It refers to the specific characteristics of an organisation that may significantly affect its decision to adopt technologies such as AI (Alkhater *et al*, 2014). In order, to provide a better understanding of the organisational factors that affect the adoption of AI, it is expedient to evaluate the factors that affect the adoption of technology in general as well adoption of AI. Studies have cited various organisational factors such as top management and leadership support, decision-making support, organisational size, organisational structure, strategic positioning, organisational climate, inter-organisational links, technology readiness, organisational readiness, benefits for the organisation, organisational processes, user involvement, culture, cost, attitude towards innovation, standards, staff relationship (Cresswell and Sheikh, 2018; Alkhater *et al*, 2014; Yao *et al*, 2016; Varabyova *et al,* 2017; Jöhnk *et al*, 2020; McAleenan, 2020; Chatterjee *et al,* 2020).

4.3.5. Technological

Technological factors are characteristics of a technology that affects an organisations decision to adopt a technology such as computer hardware, data, networking (Alkhater *et al*, 2014; Alsheibani *et al.*, 2018), a lack of technology resources is reported to potentially result in lack of value addition to organisations as well as destruction of value (Goldstein *et al.*, 2011; Benaroch and Chernobai, 2017). Models such as the technology acceptance model and the innovation diffusion theory focus on technological factors, suggesting that these factors are determinants of successful technology adoption (Taherdoost, 2018). Various other technology factors have also been identified as important in AI adoption; technology infrastructure, human capital with knowledge of ICTs (Garcia-Moreno *et al.*, 2018).

4.3.6. Ethical

Many AI applications such as the independent therapist Tess, a psychological AI chatbot (developed by X2AI Inc to provide integrative mental health support, psychoeducation, and reminders via brief conversations) used as an adjunct therapeutic resource to support an integrative approach with therapists (Fulmer *et al*, 2018), Social robots used in dementia and autism care, robots for sexual disorders among many others (Fiske, Henningsen and Buyx, 2019) imply potential risks to users, developers, and the government, which has remained largely unsolved (Siau and Wang, 2018; Rigby, 2019). Some of the ethical issues in healthcare include threat to privacy and confidentiality, informed consent, and patient autonomy; medical errors, the issue of control of outcomes when AI makes decisions, incorrect treatment recommendations the issue of human bias which could be gender, racial etc.; malicious use, accountability, quality control, lack of transparency (Mahomed, 2018; Wang and Siau, 2018, Coeckelbergh, 2020). A fatal example is the Therac-25 Cancer-zapper that contained defective software resulting to the death of 4 patients and life-long injury for two others (Leveson and Turner, 1993). It is necessary to define the ethics around AI and the allocation of responsibility to enable proper management of mistakes and undesirable outcomes of AI in healthcare (Kelly *et al*, 2019).

4.3.7. Legal

Legal factors in healthcare are concerned with laws that govern the health of individuals and populations, healthcare provision and operations within the healthcare system (Weiner and Wettstein, 2013; WHO, 2020). The release of AI into healthcare has been exponential, consequently there is a lag of legal frameworks to guide its regulation (McCartney, 2018) Or laws to guide its use and application just as is the case with most scientific and technological developments (Mahomed, 2018). AI technologies use large amounts of high-quality data for training and validation, making the issue of data ownership, data consent and data protection of high priority (Carter *et al.*, 2019) An example of data breach is the provision of Data by the University of Chicago Health Centre to Google for the development of a predictive-AI EHR system which has led to litigation for both organisations (Cohen and Mello, 2019). Such issues could result in litigation for the different healthcare stakeholders which include individuals, Healthcare professionals, public sector organisations, private sector organisations, academic institutions (Forcier *et al.*, 2019; Vogel, 2019).

4.3.8. Regulation

The delay in lack of regulation in the field of AI may be linked to the lack of definition for the concept of AI even amongst researchers and experts there is also the issue of the frequently changing dynamics of AI and its technologies (Scherer, 2016). Regardless of the lack of consensus, the urgent need for regulation of AI appears to have led to different approaches towards regulation of AI. While some have developed policies covering regulation e.g., China, France others currently regulate AI within existing data frameworks as they gather more information on these dynamic technologies before developing specific regulations, others are the General Data Protection Regulation (GDPR) of the European Union, the Data protection Act of the UK and the California Consumer Privacy Act of California in USA (CCPA), Draft Rules for US AI Regulation (Nantais, 2020; Walch, 2020). It can be seen from the above that AI regulation is an important matter in healthcare adoption and varies from country to country as well as in context.

4.3.9. Environmental

These are factors in the environment that influence or impact the environment of an organization and its decision or use of technology. Ben-zeev *et al*, (2014) cite economy as an environmental factor that may affect adoption; adoption may be higher in higher than lower income countries (Benzeev *et al*, 2014). Another sub-factor under environmental factors is industry pressure which is the need to compete with industry competitors who have adopted the technology and achieved results (Govindasmy, 2019). For instance, in the healthcare sector where adoption of disruptive technologies and technology in general is lagging (Iyanna *et al*, 2022), more healthcare organisations are therefore adopting AI and other disruptive technology because their competitors have adopted the technology and they want to do the same to satisfy customers or to enjoy the rewards of adoption (Govindasamy, 2019; Garcia-Moreno *et al*, 2016).

The following factors of AI have been identified from literature and research on technology adoption in general as well as from AI adoption: Data, Ethical, legal, Regulatory, Skills, Acceptance, Technological requirements, Organizational requirements, Environmental. These have been discussed with regards to AI adoption in healthcare. (See appendix 4 for table representing the AI factors identified from literature and their sources and findings specific to AI).

4.4. Elements of Organisational performance

The BSC management framework for performance measurement by Kaplan and Norton, 1992 (Kaplan and Norton, 1992), has formed the basis of healthcare performance measurement in several studies where the four perspectives- financial, customer, internal business, Innovation and Learning have been applied directly or adapted to cover the organisations strategic objectives (Catuogno *et al.,* 2017) in different areas of the healthcare sector such as in medical devices (Basu *et al.*, 2020), hospital operating room (Lin *et al.,* 2013), hospital pharmacy department (Enwere, Keating and Weber, 2014), private hospital (Shukri and Ramli*,* 2015), teaching hospital haematology department (Catuogno *et al.,* 2017), hospital (Rahimi *et al.,* 2016), hospital (Wu *et al.,* 2020) and several others. Some researchers have either modified or expanded the BSC perspectives when applied in healthcare settings (Martunis *et al.*, 2020; Dimitropoulos, 2017).

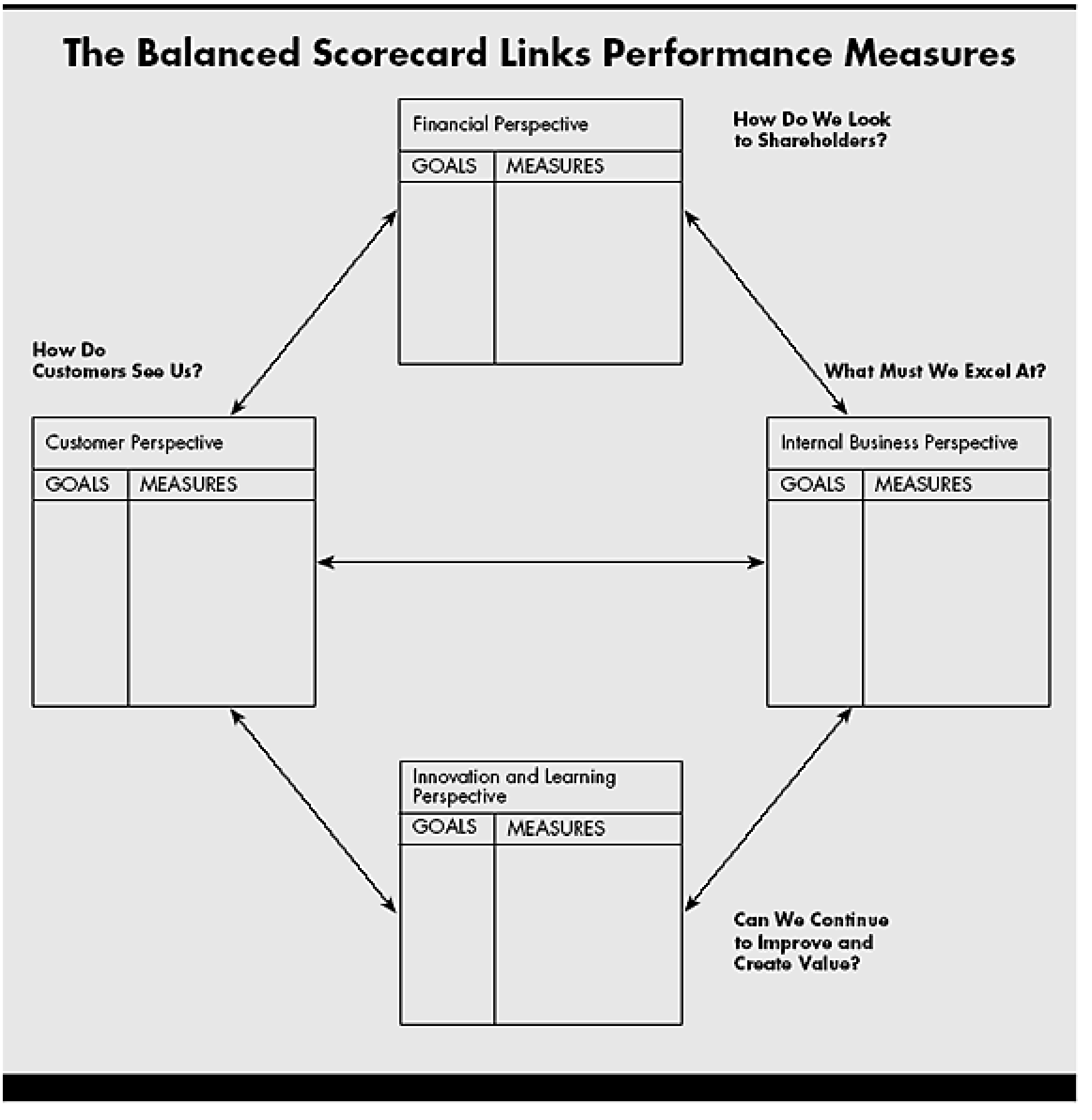


Figure 4.1: The Balanced Score Card

Source: Kaplan and Norton, 1992

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The Figure 4.1 illustrates the performance measures: Financial perspective, Customer perspective, Internal business perspective, and Innovation and Learning perspective. BSCs have been applied to improving several aspects of healthcare including financial performance, healthcare quality, healthcare safety, administration, operations, research, education, scholarship (Enwere, Keating and Weber, 2014; Bohm *et al.,* 2021). Several studies have reported positive impact of BSC on the performance of healthcare organisations on performance indicators such as healthcare workers satisfaction, patient satisfaction, and financial performance (McDonald, 2022; Tarigan and Bachtiar, 2019; Amer *et al.*, 2022). Therefore, the BSC can be applied to assessment of healthcare performance and hence its adoption and incorporation into the theoretical AI-OP Adoption framework.

Table 4.1: Elements of OP from studies

OP perspective	Study	Findings/ elements of OP factor related to healthcare
Financial perspective	Kaplan and Norton, 1996; Coskut and Senyigit, 2010; Enwere, Keating and Weber, 2014 Catuogno *et al*, 2017	Cost optimization, customer base, financial performance, financial health
Customer perspective	Kaplan and Norton, 1996; Coskut and Senyigit, 2010; Enwere, Keating and Weber, 2014; Catuogno *et al,* 2017	Safety, quality, Accessibility, loyalty, patient satisfaction, medication safety and quality, employee satisfaction, reputation, customer service, volume, and market share growth, clinical productivity, and efficiency
Internal business perspective	Kaplan and Norton, 1996; Coskut and Senyigit, 2010; Enwere, Keating and Weber, 2014; Catuogno *et al*, 2017	Operations, Quality of care, productivity, internal efficiency, internal operations, internal business, pharmacy operations, quality improvement, customer satisfaction, internal business process, service modernisation, quality performance, facility and equipment, quality, and process improvement
Innovation and learning perspective	Kaplan and Norton, 1996; Coskut and Senyigit, 2010; Enwere, Keating and Weber, 2014; Catuogno *et al,* 2017	Education, Research and Scholarship, Innovation, impact, employee learning and growth, workforce area, organisational learning, operations and management, organisational health, learning and growth, process improvement, human resources, external environmental assessment, social commitment, processes, internal growth and learning.

Source: The Researcher

The Table 4.1 above represents different perspectives of OP studied by different researchers and the elements or factors of OP in healthcare identified.

4.5. Development of AI-OP Adoption Framework

Consequent to the review of literature on the application of AI to OP earlier, in Chapter 2 (section 2.3 and 2.4), evaluation of AI frameworks Chapter 2 (section 2.7.), and literature evaluation using the Four quadrant framework in Chapter 2 (section 2.8) the Researcher identified shortcomings of the existing frameworks of AI in the healthcare sector. This resulted in the baseline for the development of a framework for the adoption of AI for OP in the healthcare sector. An effective framework to support the adoption of AI for OP in the healthcare sector is crucial for several reasons; A review of the healthcare sector reveals that several changes are occurring some of them are: ageing population with an increasing number of persons suffering long-term health conditions, increasing prevalence of communicable (in low and middle income countries) (Gouda *et al.*, 2019) and non-communicable diseases (NCDS) such as cardiovascular diseases, cancer, chronic respiratory diseases, diabetes etc. This has led to an increase in global mortality with a disproportionately larger impact on low- and middle-income economies where approximately 75% of these deaths occur (Gowshall and Taylor-Robinson, 2018). These and other issues have resulted in a high healthcare burden, a challenging situation for healthcare systems which are already challenged by the issue of low work force (Figueroa *et al.*, 2019).

The healthcare sector just like many other sectors has turned to emerging technologies (e.g., RFID, GPS, Nanotechnology, Big data, AI etc.) as a strategy to address these changes and to improve performance (McGrady *et al.,* 2010; Thimbleby, 2013; Esteva *et al.*, 2017). Many of these technologies are being applied to the healthcare sector in areas such as disease diagnosis and treatment recommendation, administration, patient engagement, and adherence etc. sometimes with better performance than humans (Davenport and Kalakota, 2019). According to Martec's Law, the integration of new technologies and approaches by organisations require specific strategies (Purcarea, 2019). Martec's law states that while changes in technology occur very rapidly changes in organisations do not. This implies that identifying technology in this case AI as a strategy and even the type of technological approach to be applied is not sufficient, strategic frameworks are required to enable the integration of such technologies with the operations, processes, and culture of the organisation (Brinker, 2016). Such frameworks must be robust, taking into consideration the complexities of healthcare settings to adequately support healthcare organisations to adopt AI. In view of this, the Researcher intends has developed a qualitatively researched strategic framework to support the adoption of AI by healthcare organisations as presented below (Figure 4.2). This framework has been designed from elements identified from AI and OP literature, Technology adoption literature and from strategic management literature, and contributions from experienced professionals and experts in Academia.

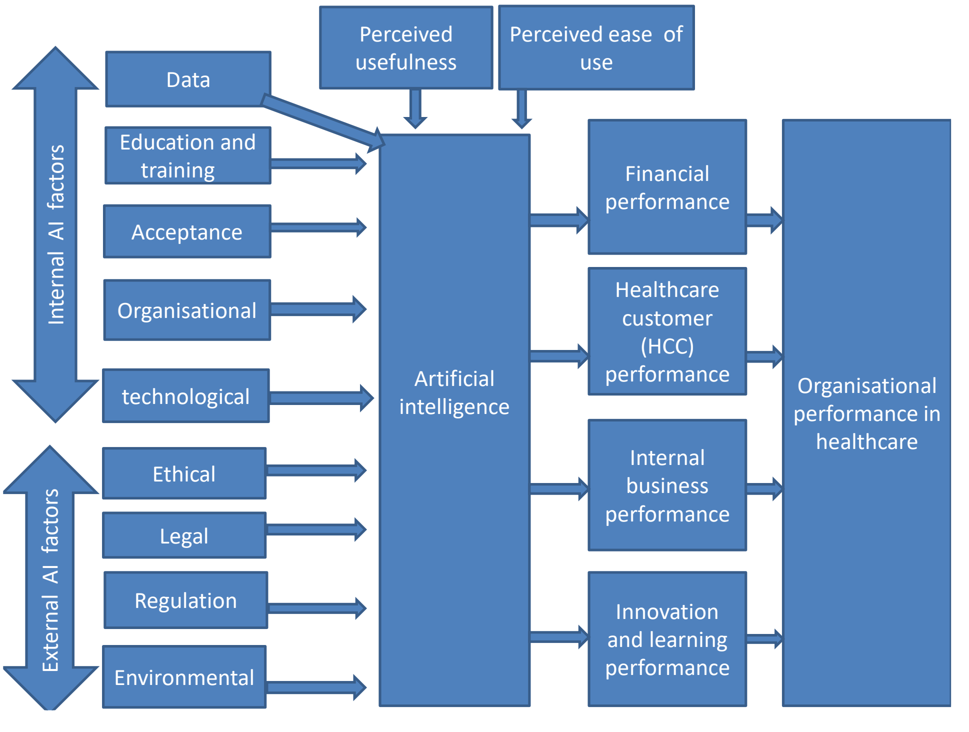

Figure 4.2: The Theoretical AI-OP Adoption Framework.

Source: The Researcher

4.6. Conclusion

This Chapter discussed the theoretical foundations of and the Technology acceptance theory and models which were instrumental in understanding the conceptual base of the Research. In addition, literature pertinent to the research was reviewed resulting in the identification of

Key factors for AI adoption and for organisational performance elements were identified from the literature. These factors have contributed to the development of the theoretical AI-OP adoption Framework which will be validated further in the Research.

PART II

5. CHAPTER FIVE: METHODOLOGY

5.1. Introduction

This Chapter describes the methodology in relation to the research questions and objectives as outlined in Chapter 1. To ensure that the Research addresses the specified objectives, it is necessary to choose an appropriate methodology to assess theoretical underpinnings, to collect and analyse data as well as to answer the research questions (Ahmed, Opoku and Aziz, 2016; Scholtz, *et al.*, 2020). The research process onion framework has been identified as a comprehensive framework that adequately covers the pertinent aspects of research methodology (Saunders *et al.*, 2019), it has therefore been chosen as an appropriate framework to address all the pertinent areas of the Research as illustrated below in Figure 5.1.

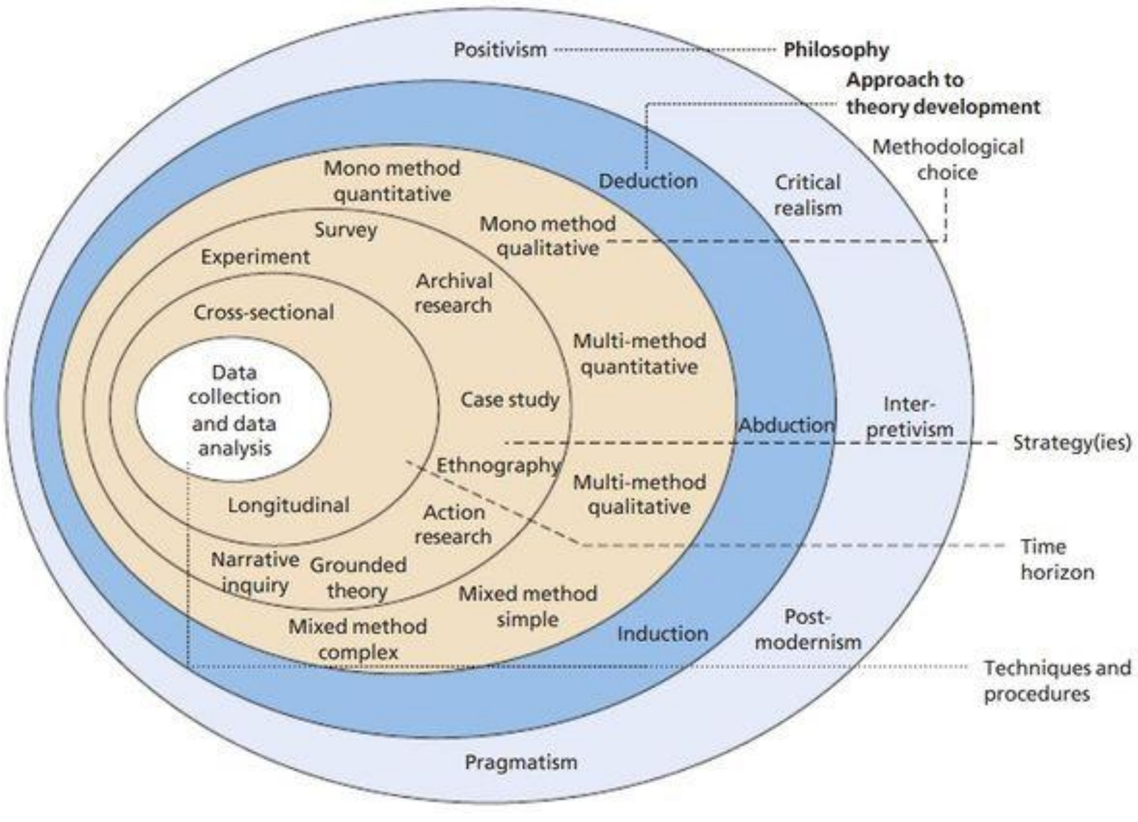

Figure 5.1: The Research Onion.

Source: Saunders *et al.,* (2019)

5.2. Research philosophy

Philosophical underpinning refers to the system of beliefs and assumptions on knowledge development (Saunders *et al.*, 2019). It has been identified as an important aspect of any research because it results in investigation based on a specific research paradigm (Brown and Duenas, 2019), where the research Paradigm refers to the set of common beliefs upon which the research is based that answer the axiological, ontological, epistemological, and methodological questions related to the research problem (Rao, 2019). Therefore, a study's first feature is to direct the research to a specific philosophy which reflects the important beliefs or assumptions, views, and expectations of the research (Saunders *et al.,* 2019). The Table below (5.1) explains further, the research philosophy terminologies.

Table 5.1: Research Philosophy Terminologies

Term	Meaning
Axiology	What does the researcher value, what is their motivation for the research? (The researcher may be motivated by funding, social justice, or inherent value of education etc.) How can ethical research be conducted within this area?
Ontology	This is the study of reality; the question of what truth is out there to know. The assumption is of one verifiable reality (realist) or multiple socially constructed realities (anti-realist or relativism).
Epistemology	This is the metaphysical study of the discovery of knowledge, the question of what composes knowledge and how it is acquired. (Positivist: Neutral knowledge through use of reliable/ valid measurements; post positivist: human knowledge is imperfect, only probable truths are possible; interpretivist: knowledge is subjective and formed at individual level; critical theory: knowledge is subjective but created between individuals and between groups)
Methodology	This refers to the strategy or overall plan of how knowledge can be acquired. (This mainly Quantitative or Qualitative).
Methods	This refers to the techniques procedures that can be used to acquire knowledge
Sources	Which data can be collected

Source: Brown and Duenas, 2019

According to Saunders *et al.,* (2019) a research study is characterised by four separate philosophical branches; the first is positivism, interpretivism, critical realism, post-modernism, and pragmatism (Saunders *et al.,* 2019).

Positivism describes reflects the natural scientist's standpoint. Ontology relies on objectivist assumptions of an objective world representable in a mirror-format (Brown and Duenas, 2019). Therefore, the positivist philosophy argues that credible research is based on observation and empirical data. Knowledge is achieved by observation and identifying event regularities that are based on causal relationships, laws, and functional relations (Melnikovas, 2018).

Interpretivism is an approach that is founded upon the subjectivist ontological assumptions that argues understanding of the social world through subjectivity (Brown and Duenas, 2019). Great emphasis is laid on understanding of the ways by which people experience the social world. The interpretivist research philosophy proposes that the researcher performs a specific and crucial function of observing the social world, and the research is dependent on the researcher's interests (Zukauskas *et al.*, 2018). Therefore, reality is socially constructed and dynamic, while knowledge and facts are viewed as relative and subjective. The strict contrast between positivist and interpretivist position is one that arises based on the distinction between the natural and social sciences put forward by their proponents and critics (Melnikovas, 2018).

Pragmatism is a research philosophy and is one that emphasizes facts. It proposes that research philosophy is determined by the research problem, and the practical results of research to inform future practice is considered of great importance (Zukauskas *et al.*, 2018). Pragmatism does not identify with any specific philosophical approach therefore researchers may select research methods, techniques, and procedures that are considered most appropriate to achieving the research aims and objectives (Saunders *et al.,* 2019).

Postmodernism is a research philosophy identical to interpretivism but extends further criticism of positivism and objectivism, assigning even more importance to the language function. It is not in concordance with modern objectivist, realist ontology of entities, but rather aligns towards investigation of dominant political ideas to establish truth, knowledge, and facts (Luhman and Cunliffe, 2013). It proposes that the prevailing ways of thinking therefore are not necessarily the best but appear to be so at a specific point in time and by specific groups of people (Saunders *et al.*, 2019).

Critical realism is a philosophy developed by Baskar in 1978 and supports a strong realist ontological assumption that proposes the existence of a world that is independent of human knowledge (intransitive dimension). Although this assumption identifies with the peculiarities of the social realm, it asserts that the social sciences are sciences in the same manner as the natural sciences (Bhaskar, 2008). Critical realism (CR) is a meta-theory that captures a variety of stances, ranging between positivism and interpretivism. It proposes scientific aspects of positivism that deal with regularities, regression-based models, law-like forms and strong interpretivism which refuses explanation in place of interpretation and focuses on hermeneutics and description at the expense of causation (Allana and Clark, 2018) Critical realism is argued to have the potential to provide a coherent and robust philosophical underpinning, thereby providing resolution to the inconsistencies observed in the theory and practice of positivism and interpretivism (Mingers *et al.,* 2013; Avenier and Thomas, 2015).

For this Research, the Researcher identifies with Interpretivism as their research philosophy because it is concerned with distinctiveness of a specific situation contributing to the fundamental investigation of contextual depth (Melnikovas, 2018). This is relevant to the in-depth investigation of the distinctive topic of AI and OP in healthcare. Furthermore, due to the focus of interpretivism on investigation in natural settings, understanding of the world from a subjective point of view and explanation from the reference point of the respondent rather than from the objective point of view of the observer (Chowdhury, 2014; Ponelis, 2015) the Researcher to investigate AI and OP in the natural healthcare setting to access the ideas and perceptions of those being interviewed in order to understand these concepts from the respondent's viewpoint.

5.3. Research Approach

Research in the field of business is mainly conducted using the inductive, deductive, and abductive approaches (Saunders *et al.*, 2019). Deductive research involves in-depth literature analysis, the development of hypothesis which is then tested by empirical observation to enable determination of validity. The research generally progresses from general to specific i.e. it starts with theories, from which hypotheses are developed, tested and theories developed, the Inductive approach on the other hand involves developing the research problem and proffering solutions to the problem through investigations, making observation and drawing of conclusion, ultimately resulting in the use of empirical methods for the development of new theory while the abductive approach is when data is collected for exploration of a phenomenon, themes are identified and patterns explained for the generation of new or modification of an existing theory which is tested through collection of additional data (Ibid). The inductive approach uses qualitative methods such as case studies, ethnography etc. and is most appropriate for answering research questions in organisational contexts of management that require answers to how, why, and organisational processes (Eriksson and Kovalainen, 2016). Data collection during the process of induction is usually through interviews which facilitate the collection of the information that is relevant for the generation of new theories (Bryman and Bell, 2015). The application, adoption, and implementation of AI to healthcare is an emerging research topic with no generally accepted theories to test, therefore this research uses induction to answer the research questions of how, why AI can be applied to the organisational performance of healthcare organisations by generation of data, analysis of data and reflection on the theoretical themes the data is and remaking observations, observing patterns and drawing conclusions. This contrast with the Deductive research approach which mainly involves testing of previously existent theory through the testing of hypothesis and Abductive approach which involves generation of new or modification of an existing theory which is tested through collection of additional data (Saunders *et al.,* 2019).

5.4. Research Methodology

Research methodology is the science of studying the process by which research is to be conducted composed of the methods, materials, scientific tools, and relevant techniques by which the Researcher answers, explains, describes, and predicts the concept under investigation (Rajasekar, Philominathan and Chinnathambi, 2016) which is crucial and critical to achievement of the research objectives.

It is pertinent to ensure that the research methodology chosen, appropriately addresses the nature, significance, purpose, quality, credibility of the study, and most importantly it should help the researcher answer the research questions and achieve the research objectives (Ahmed, Opoku and Aziz, 2016; Scholtz, *et al*.,2020). According to Saunders *et al*., (2019) methodological research involves the use of quantitative or qualitative research methods, where these methods may be applied individually as mono methods or by using mixed methods involving the simple or complex mix of quantitative and qualitative methods and multi methods incorporating different research styles (Saunders et al, 2019). Quantitative research is involved with the testing of theory, while qualitative methods involve the generation of new theory from data through the process of induction (Wright *et al.*, 2016). Quantitative method involves the investigation of concepts through a highly structured process involving the collection of numerical data and the subsequent application of the collected data through mathematical or statistical methods (Bryman and Bell, 2015). The Quantitative method is more appropriate for investigating cause and effect (Koffel, 2015). Conversely, Qualitative research involves the application of specific methodological approaches to the investigation and resolution of research problems (Bryman and Bell, 2015). Its approaches include phenomenology, ethnography, established theory, discussion, case study and narration-based analysis (Saunders *et al*., 2019).

This research applies qualitative research method which presents the researcher with the opportunity to analyse first-hand the explicit views of the research participants (Bryman and Bell, 2015). In this case the research participants are Key Informants (Most of whom are experts in the private and public healthcare sector) they include: healthcare technologists, Healthcare professionals and healthcare managers, who are involved in the application, adoption and implementation of AI technologies in the healthcare sector through the delivery of services. They are therefore the main players involved in the improvement of OP in the healthcare sector. Applying qualitative research methods in this research enables more in-depth analysis of the concept of AI and OP in the healthcare sector, thereby filling the knowledge gaps of applying AI to improving OP in the sector and resulting to the generation of theory to support healthcare organisations in adopting and implementing AI for better performance.

5.5. Research Strategy and Time Horizons

Research strategy refers to the different steps the researcher follows to answer the research questions. For this research, the strategy used is the case study which is one of the strategies associated with qualitative methods and exploratory research. With reference to time horizon, research may be cross sectional where data collection is done at a given time (Kesmodel, 2018), or longitudinal in which case the data is collected over a specific period allowing change to be monitored over time (Saunders *et al*., 2019). This research is classified as cross sectional as data is collected only at a specific point in time.

5.6. Research Design

Research design refers to the blueprint that directs and plans the research process from research questions through to the research outcomes. It involves integration of the various components of research such as data collection and data analysis to effectively resolve the research problem (Bryman and Bell, 2015). Research designs can be Descriptive, explanatory, or exploratory and is dependent on the type of research (Makri and Neely, 2021). When investigating a topic or research area where there has been limited or no prior research, the exploratory design can be used to ask questions to gain new insights for a new concept or phenomenon (Saunders *et al*., 2019). It is flexible, enables in-depth analysis through literature searches, expert interviews, focus groups etc. and generates detailed results that enable the development of new theories. It is the design of choice when using qualitative methods (Eisenhardt, Graebner, and Sonenshein, 2016) and is considered the most appropriate design for this Research. A descriptive research design is one that can be used to obtain an accurate overview of events, people, or situations (Kim, Sefcik and Bradway, 2016). It follows a highly structured format in its execution, usually investigates more than one variable and is often used where the research area has been previously investigated and a deeper understanding is sought. It can also be used for both qualitative and quantitative studies (Bryman and Bell, 2015). The explanatory research design is most appropriate when using quantitative methods, investigating the relationship between variables and to enhance knowledge in areas that have been previously researched (Hair, 2015). The research design used in this case is exploratory because the concept of AI application to OP in healthcare is relatively new, therefore qualitative methods facilitate a more in-depth understanding of the topic area (Makri and Neely, 2021; (Eisenhardt, Graebner, and Sonenshein, 2016).

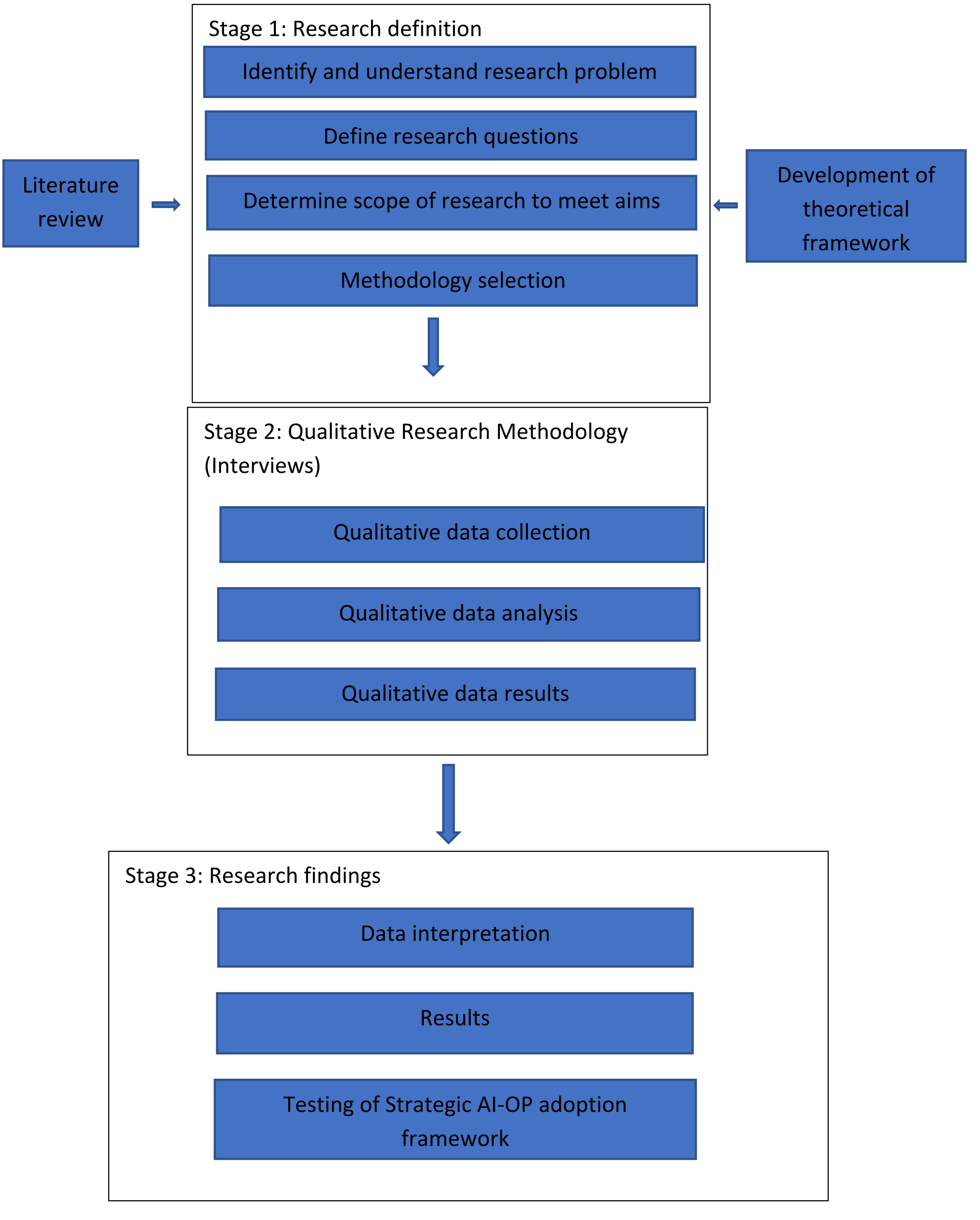

Figure 5.2: Exploratory Sequential Research Design.

Source: Cresswell and Plano-Clark, (2019) The Figure 5.2 above shows the plan for the research from identification of research problem to data collection and analyses and finally to data interpretation and results. The literature gap identified provides the theoretical basis for development of the theoretical AI-OP Adoption Framework. In stage 1 of the research design, the most appropriate research methodology is selected. In stage 2, appropriate designs are chosen for qualitative data collection and analysis. In stage 3, the qualitative data is interpreted and used to test the AI-OP adoption Framework for healthcare.

5.7. Research process

This subsection presents the research process for the study, which is composed of the desk research and the field research, resulting in the baseline for the AI- OP Framework.

5.7.1. Desk research

The purpose of the desk research was to establish a theoretical baseline for the development of the theoretical Al-OP Adoption Framework, as presented in Chapter 4 (Section 4.5.2), through in-depth review of literature and identification of the AI in healthcare literature gap in Chapter 3. The evaluation of AI in healthcare literature, composed of academic text publications, academic peer-reviewed journals, industry journals, provides a deeper understanding of AI practices in the healthcare sector, and enables the identification of the key strengths and weakness. The literature reviewed in Chapter 2 (Section 2.3, 2.4, 2.6) was further categorised (Section 2.7) using the Four-Quadrant Framework, classifying the literature into different research areas on the premise of purpose, into descriptive or prescriptive and outcomes into visionary or implementational (Section 2.7, Table 2.4). Key objectives of the desk research are stated in Chapter 1 (Section: 1.6). The theoretical AI-OP Adoption framework developed in Chapter 4 (Section 4.5.2) was further analysed, improvement and validated thereby addressing the existing literature gap and providing practical recommendations to academia and the healthcare sector.

5.7.2. Field research

The chosen approach to research methodology is to facilitate achievement of the main research contribution which is the Strategic AI-OP Adoption framework. Qualitative mono methods design has been identified by the Researcher as most appropriate for answering the research questions and enhancing the analytical power of argument and the strength of the study:

5.7.2.1. Source of primary research data:

- Qualitative research (QUAL): Semi-structured interviews with senior Healthcare managers, healthcare technologists and Healthcare professionals

5.7.2.2. Source of secondary research data:

- Literature review (academic peer reviewed journal articles and related healthcare sector publications).
- Existing academic and healthcare surveys and case studies conducted on healthcare organisations on AI and healthcare performance.

5.7.3. Sample composition

This section discusses sampling techniques that are suitable for mono research design and focuses on composition of the sample. The main idea behind qualitative research is to improve understanding of the research problem through purposeful selection of research participants. This contrasts with quantitative research which requires large populations (Bryman and Bell, 2015). Sampling techniques are mainly classified into probability and non-probability. In Probability sampling, each member of the population carries an equal chance of being selected whereas for non-probability sampling the chance of selection for each member of the population is not confirmed (Etikan; Musa, Alkassim, 2016). Types of probability sampling include: the simple random sampling, systematic random sampling and stratified random sampling, cluster random sampling and multistage random sampling (Bhardwaj, 2019). While Non-probability sampling are of mainly four types: purposive sampling, respondent-assisted sampling, and quota sampling (Allen, 2017). Purposive sampling has been chosen for this research because although it is not intended to support representativeness it focuses on specific phenomena or processes. Purposive sampling is therefore sampling that intentionally selects participants on the bases of their ability to explicate specific themes, concepts, or phenomena (Robinson, 2014). This type of sampling involves the selection of information-rich sources for comprehensive study. In purposive sampling, it is assumed that the research participants have wealth of experience of the research topic such that they serve as rich sources of information when they share their views (Palinkas *et al.*, 2015). In order, to answer the research questions as well as achieve the research aims and objectives thereby enhancing rigour of the study and reliability of the data and results, a clear rationale and criteria for sample collection is required (Campbell *et al.,* 2020). The purposive sampling method sampling method involves the selection of samples based on specific criteria such as availability and disposition to participation, ability to cover a range of points, access to geographical location and ease of access, as it is impossible to include every member of a population due to the infinite nature of populations (Robinson, 2014; Palinkas *et al.*, 2015). The main criticism of purposive sampling is that researchers who apply this sampling method may not sufficiently disclose the selection criteria used, and this results in reduced transparency of the research, reduced applicability of this information in analysis to enhance the understanding of complex social processes. However, where there is transparency about selection criteria, purposive sampling enhances understanding of complex processes and can elucidate and increase more perspectives particularly those considered as outliers in representative samples (Robinson, 2014).

Different types of purposive sampling strategies have been mentioned in literature such as extreme or deviant case, intensity, maximum variation, homogenous, typical case, critical case, snowball, criterion, theoretical, confirming and disconfirming, stratified purposeful, opportunistic, purposeful random, combination sampling among others (Benoot *et al,* 2016; Palinkas *et al.*, 2015). For this research, Critical case sampling strategy has been identified as most appropriate as it allows logical generalization and maximum application of information based on the logic that if true in one case it is most likely true in the other cases, this can support stakeholders in organisations to make decisions on innovation (e.g., AI) (Suri, 2011; Benoot *et al.,* 2016). It also has the advantage of being useful in resource limited settings so that resources are not spent on non-critical cases (Etikan; Musa; Alkassim, 2016).

5.7.4. Sample size and data saturation

Sample size needs to be determined in qualitative studies as well as in quantitative studies but by different means. For qualitative studies, sample adequacy has to do with the appropriateness of the sample composition and size. The sample size is important when evaluating the quality and trustworthiness of qualitative research. According to Vaseliou *et al.*, (2018), qualitative sample sizes should be large enough to enable the unveiling of new and deeply textured understanding of the phenomenon being studied but be small enough to enable in-depth case-focused analysis (Vaseliou *et al.*, 2018). In qualitative research there is no set requirement for number of samples; sample size is contextual and largely dependent on the scientific paradigm under which the research is being conducted (Boddy, 2016). The most accepted concept for sample size is "saturation, which is closely linked to a specific methodology, even though the concept is inappropriately applied (Malterud *et al.,* 2016). In order, to ensure sufficient level of research validity and ensure that the study qualifies as a standard piece of research in social science, the Researcher targeted data saturation. Data saturation has been defined as the point at which additional data does not result in newly emerging themes (Given, 2015). The Researcher has put into consideration a limitation to sample size which is the population of Healthcare Managers, Healthcare technologists and Healthcare professionals that are available for interviews and time available for gathering data. Based on this, the initial sample size was set between 15 to forty interview participants was considered likely to provide ample qualitative data to achieve the aims and objectives of the research and to answer the research questions. A minimum of 16 healthcare organisations were selected for the interview process, to allow for diversity of the qualitative data collected. As AI is a distinctive as well as novel phenomenon across the healthcare sector, key factors for its adoption and implementation, were considered. Based on suggestions in literature of sample sizes of 6 to 7 interviews for homogenous samples and a higher end of 12 interviews for non-homogenous samples required to reach saturation (when no new or relevant data occurs), a sample of 19 respondents was deemed as optimum to allow well-grounded deductions of the population and to effectively answer the research questions (Galvin, 2015; Dejonckheere and Vaughn, 2018; Guest, Namey, and Chen, 2020). These KIs interviewed were mostly experts or seniors in their areas of specialty, with some holding decision-making positions in private or public healthcare organisations in Nigeria and UK. Appointment of experts was by purposive sampling chosen based on the following eligibility criteria:

i. A practicing Healthcare professional, Healthcare manager or Healthcare technologist.

ii. Experience of AI application, adoption, or implementation in healthcare.

iii. Possession of relevant competence in the intersection of Healthcare and AI.

iv. Experience of Healthcare AI in Nigeria or the United Kingdom.

Five of the KIs were in healthcare practitioner roles, six of them in healthcare management roles and eight of them in healthcare technologist roles. Six of them worked in public healthcare settings while worked in private healthcare settings. In relation to experience, thirteen of the KIs had experience of AI application, adoption in Nigeria while 6 of them had experience in the UK. All the KIs had experience and competence of AI in healthcare, as well as competence in the intersection of Healthcare and AI. The respondents were selected based on these eligibility criteria which made them qualified to provide relevant and valuable information.

5.8. Mono method Data collection

This section explains the data collection techniques used in this research, mono method which involves the collection of qualitative datasets. Mono-methods involve the use of a single data collection strategy in research. Mono-methods are not intrinsically inferior to research that apply mixed methods and has been selected because it is most suitable putting into consideration the research objectives, level of existing knowledge on the research and available time and resources (Vizcarguenaga-Aguirre and López-Robles, 2020). Qualitative mono method data collection supports researchers to study phenomena in their natural settings and from the perspective of respondents and based on the meaning they adduce to the social reality coupled with active involvement of the researcher who is the data collection and interpretation instrument (Ojebode *et al*, 2018). Based on the research objectives and research questions for this research, qualitative mono methods are more suitable to investigate the newly developing topic of AI and OP in healthcare. Therefore, the use of qualitative mono method for this research enables a deeper understanding of a complex concept in a complex system such as that of AI in healthcare and from the perspective of experts in the healthcare sector.

5.8.1. Qualitative versus quantitative research

Qualitative research can be defined as a naturalistic, emergent, inductive, interpretive approach to studying people, cases, phenomena, social situations in natural settings to elucidate in descriptive terms meanings people attach to world experiences (Yilmaz, 2013). Qualitative research design takes its roots from anthropology and sociology. Several terms have been used to describe the qualitative mode of inquiry, such as cultural, constructivist, naturalistic, phenomenological, postmodernism, post-positivism attitude, and post-structuralist. Qualitative approaches are characterised by investigation of concepts or phenomena in natural environment and inclusive of challenges (Mehrad and Tahriri, 2019).

Qualitative and quantitative research methods are oftentimes contrasted as representations of two different world views (Hammarberg *et al.,* 2016). In the quantitative viewpoint qualitative research is perceived as unscientific due to its focus on words which are considered to have less precision than numbers, lack of emphasis on variables, insubstantial due to small samples which are considered as non-objective, biased based on the focus on the researchers' experiences and non-representative of the broader population (Aspers and Corte, 2019). In contrast, in the qualitative viewpoint, quantitative research is perceived as lacking consideration for individual experiences in the cause of generalising, inadequate understanding of aggregate data, failure to acknowledge researcher bias and expectation in the research. Although qualitative research methods are both standard methods for answering research questions, they differ in certain characteristics (Hammarberg *et al.,* 2016). Qualitative research methods have been chosen over quantitative in this research based on its characteristics presented in Table 5.2. Which support the interpretivist paradigm and enables answering of the Research questions.

Table 5.2: Characteristics of Qualitative and Quantitative Research

Quantitative	Qualitative
Assumptions	Assumptions
Reality is single, tangible, and integrated.	Realities are multiple, constructed, and holistic. Reality is socially constructed.
Social facts are an objective reality.	
Researcher and researched are independent, a dualism.	Researcher and researched are interactive, inseparable.
Expertise of method	Expertise of subject matter
Emphasis is on variables which are also identifiable and relationships measurable	Less emphasis on variables which are often complex, intermixed, and present a measurement challenge.
Objective and value-free investigation.	Subjective and value-based investigation.
Theory and data are distinct.	Theory and data are interrelated.
Purposes	Purposes
Generalisability (Statements are generalised, i.e. based on scientific rules, time, and context free)	Contextualisation (Statements are idiographic i.e. focused on individual cases or events, based on time and context)
Predictive	Interpretative
Causal analysis	Analysis is based on actors' understanding and perspectives
Approach	Approach
Research design is fixed	Research design is dynamic
Commences with hypotheses and theories	Concludes with hypotheses or grounded theory
Statistical manipulation required	Statistical testing not compulsory
Instruments are formal and structured	Researcher is the instrument
Experimentative and interventional	Naturalistic or non-intervention
Deductive reasoning (from general to specific)	Inductive reasoning
Component analysis	Searches for patterns
Seeks consensus, the norm	Seeks pluralism, complexity
Data is transformed numerical indices	Minimal use of numerical indices

Source: Adapted from Yilmaz, (2013)

Qualitative research has several advantages as well as disadvantages as follows:

Advantages: First, it is idiographic i.e., focuses on individual perceptions, experiences, actions, and therefore in-depth study of phenomena; secondly it can be applied to understanding human behaviour in different settings; thirdly data collection uses direct methods such as direct observation, interviews etc. it is therefore subjective and detailed and lastly structure is flexible and can therefore be designed to support adequate analysis of complex issues. Disadvantages: Firstly, qualitative research may ignore contextual sensitivities and emphasise meanings and experiences e.g., phenomenology. Secondly, it may neglect social and cultural construction of variables investigated. Thirdly, it may be viewed as lacking in reliability and consistency as no scientific means of verification. Fourth disadvantage is that of complex data analysis and interpretation. Fifth is the problem of lack of generalisability to the whole population due to small sample size and lastly it requires a significant amount of time (Eysisi, 2016; Rahman, 2016)

This research is Qualitative dominant because it supports in-depth analysis of the concepts of AI and OP in healthcare and through data from open-ended questions. Analysis of this rich data supports the development of the AI-OP in Healthcare Adoption Framework. In the current Research, the collection of qualitative data is by semi-structured interviews. The above advantages and disadvantages of Qualitative research have supported the Researcher to identify and maximize the advantages and mitigate the disadvantages. In this section the definitions, characteristics, advantages, and disadvantages of qualitative research methods have been expounded and justify the Researchers choice of Qualitative methods research.

5.8.2. Research interviews

This section discusses interviews used in this qualitative research, justification for interview type, design of the interview process, and selection of the respondents.

5.8.3. Semi- structured interviews

Interviews can be distinguished by the degree to which they are structured (i.e., a questionnaire), open (e.g., free conversation or autobiographical interviews) or semi-structured (Punch, 2013). Semi-structured interviews are commonly used in qualitative research and are the most frequent qualitative data source in health services research (Dejonckheere and Vaughn, 2019). They are characterized by open-ended questions as well as the use of an interview guide which outlines the questions and sometimes subquestions that reflect the issue under investigation (Stuckey, 2013). Semi-structured interviews are one of the most used types of interviews in qualitative research and the healthcare context (Kallio *et al,* 2016). For this research, semi-structured interviews were used as they support the collection of in-depth information from professionals who have expertise, personal experiences and perceptions of Healthcare AI (Dejonckheere and Vaughn, 2019). In addition, the pre-developed interview guide that helps keep interview within topic area; respondents can elaborate through open-ended questions; the Researcher enjoys flexibility to ask additional questions if a new line of thought develops and therefore producing more robust data as well as its support for comparative analysis (Alsaawi, 2014; Busetto *et al*, 2020). Investigating the impact of AI on OP in the healthcare sector is a new area of research as there are no studies on AI and OP in the context of healthcare and based on data from Nigeria and the UK. The Researcher developed the interview guide by thoroughly reviewing existing research on the topic of Artificial intelligence and organisational performance in healthcare which led to development of a list of potential topics and interview questions which were then cross checked with the main research questions to check whether they were clear, precise, appropriate in terms of focusing on the issues relevant to the topic and what has been established by existing research, answering the research questions and generating the data required (Morris, 2015; Busetto *et al*, 2020; Wheeler, 2021). The Researcher also reviewed the way others had addressed their research questions; it was observed from the literature review that there was a lack of focus on how AI impacts OP in the healthcare sector.

The questions were then arranged into a loose but logical structure then afterwards pilot testing was done (Morris, 2015). Four pilot tests were conducted with two professionals and two researchers within the Researchers professional networks. The Researcher used the pilot tests to assess the language, clarity, and active listening of the interview questions and made some adjustments to improve on these areas (McGrath *et al*, 2018; Busetto *et al.,* 2020). Due to the impact of the Covid-19 pandemic the Researcher conducted face to face interviews over the internet. The Researcher ensured that there was adequate engagement with the respondents by picking up on non-verbal cues that indicated enthusiasm, hesitation, confusion, hereafter appropriate adjustments were made (Bird, 2016). Due to the scant nature of research on the impact of AI on OP in healthcare, there was limited research from which interview questions could be adopted. However certain research informed the Researcher on research questions in the research area such as the study of Chen *et al.,* (2020) which focused on respondent's job, organisational role, and professional experience; factors for AI introduction and adoption; benefits and impacts of adoption and challenges of AI adoption (Chen *et al.,* 2020).

5.8.4. Design of Research interviews

This section presents the process of developing the interview questions around key AI Healthcare research areas identified from reviewing the literature.

An important feature of Semi-structured interviews is that they support the collection of new, exploratory data specific to a research topic through the interview questions. Based on this it is pertinent that the interview questions be developed appropriately. Therefore, the Researcher followed Clark *et al.*, (2021) 9 steps for formulating interview questions based on the research area, research questions and interview topics as illustrated in the Figure 5.3 below.

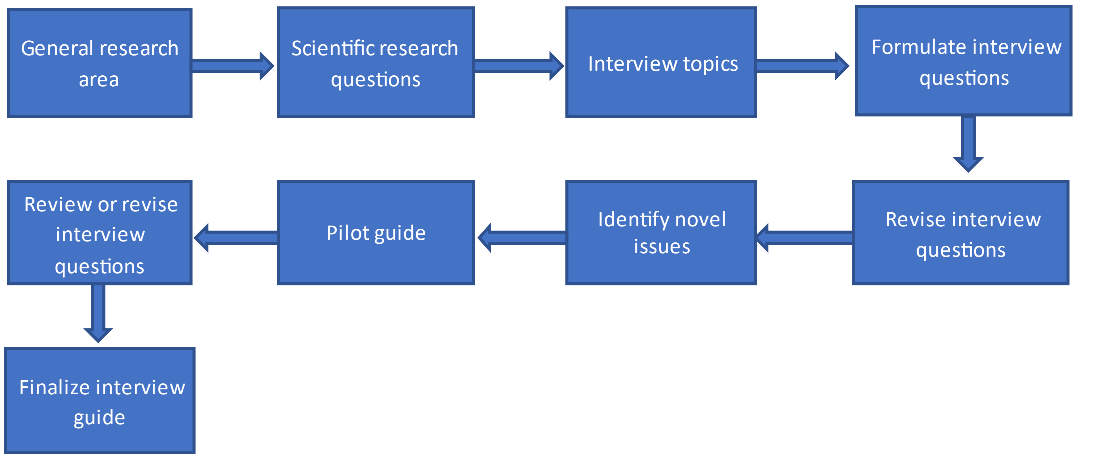

Figure 5.3: Formulation of interview questions.

Source: Clark *et al.,* (2021)

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Key research areas identified from reviewing the literature are outlined below.

- Definition of AI
- Subfields of AI

- Important factors for AI adoption in healthcare
- Impact of AI on Healthcare safety and quality performance
- Impact of AI on Healthcare operations performance
- Impact of AI on Healthcare education, research, and scholarship performance
- Impact of AI on Healthcare financial performance
- Benefits and challenges of AI adoption in healthcare
- Frameworks for improving Healthcare Organizational performance with AI
- Strategic and management recommendations for AI adoption in healthcare
- Strategic and management recommendations for using AI to achieve OP in healthcare.

From the key areas of research identified and based on the interview formulation process adopted from Clark *et al.,* 2021, Fourteen questions were developed based on the following six areas:

1. Organisational information
2. Respondent information
3. General AI
4. Impact of AI on OP in healthcare
5. Challenges in healthcare AI adoption
6. Factors in healthcare AI adoption

5.8.5. Selection of Research respondents

The Researcher used non-random purposive sampling method to identify a sample of Nineteen individuals from both the UK and Nigeria healthcare sector. These professionals were within the Researchers own professional and academic network who met the research criteria of being professionals and having years of healthcare AI expertise and familiar with the research topic.

5.9. Data Collection and Data Analysis

5.9.1. Data Collection

The data collection for this research, involved conduction of qualitative semi-structure interviews with a sample of 19 key informants (KIs) in healthcare that are currently involved in applying, adopting, or implementing AI and are identified as critical cases because they reflect AI in healthcare. These KIs are made up of healthcare managers, Healthcare technologists and Healthcare professionals. The Researcher's view is that data from these critical cases in addition to findings from the body of literature make a case for a comprehensive AI-OP framework that can be reliably applied by healthcare organisations.

5.9.2. Analysis of Qualitative data

To analyse qualitative data, the data must first be collected through an instrument in this case through interviews. This is outlined below in steps 1 to 11. Analysis of data is discussed after the interview process.

5.9.2.1 Interview process and Analysis of data

To ensure that semi-structured interviews are conducted effectively they must be properly designed. Dejonckheere and Vaughn, (2019) propose the following 11 steps which have been applied in the healthcare context (Dejonckheere and Vaughn, (2019).

Table 5.4: Eleven step Interview process

ITEM	STEP
1.	**Determination of study purpose and scope** The purpose of the interview was clarified after which the key information required was determined. In this case, information required is on AI in healthcare.
2.	**Identification of participants** This step involved deciding those who will best provide answers to the research questions. The ideal respondents were those available, willing to be interviewed and possess lived experiences and knowledge on the topic of interest. In this case the participants were key informants, healthcare managers, healthcare professionals or healthcare technologists.
3	**Consideration of ethical issues** It is necessary to consider ethical issues for qualitative interviews before the actual interview. In this research respect, sensitivity, and tact were applied to the interviewers and research process. All sensitive and personal information relating directly to the respondent were protected by taking precautions and adequately informing respondents about the study purpose and format.
4	**Planning logistical aspects** Adequate preparation is required to make the interview process successful. For this research logistics, planning, contacting of potential respondents, obtaining informed consent, time of interview, location of interview, and recording of interview were resolved, and made convenient for the researcher and respondent.
5	**Development of interview guide** The interview guide was adopted from the literature and previous research. The topic was continually adapted and improved from the start of the data collection process as the interviewer gained more knowledge on the research topic. The interview guide focused on the topics of interest specific to healthcare AI as mentioned above. The interview guide was pilot tested to ensure appropriateness of questions, conversational tone, and adequacy of time. After this, necessary adjustments were made to the questions.
6	**Establishment of trust and rapport** To develop trust, the Researcher explained in plain language, the reasons for conducting the research, contextual and cultural factors related to the research. The Researcher approached the interview professionally, treated the Respondents as experts and was open to their perspectives.
7	**Memoing and reflection** Post interview, it is essential the interviewer reflects on both the interview process and its content as it may be daunting to take notes or reflect during the interview. After each interview, the Researcher wrote down their thoughts, ideas, and reflections and what they learnt. This helped to improve the quality of the next interview. To establish rapport, the Researcher was open to the respondent's point of view.
8	**Analysing the data** The data analysis strategy should be developed during the research planning stages as analysis occurs simultaneously with data collection. The process of data analysis begins with note taking, modification of data collection procedures, writing of reflective memos throughout the process of data collection. Generally, the data analysis process for this research involved transcribing the data, generation of initial codes, generation of themes and reporting. The process is detailed in the data analysis section.
9	**Demonstration of research trustworthiness** This refers to demonstration of the validity and reliability of the research and is explained in more detail under quality of the research (Section 5.10.1).
10	**Conduction of the Interview** Introductions were made at the beginning of the interview and the purpose of the study explained. The respondent's permission was requested to record the interview and the equipment tested to ensure proper working. The respondent was then guided through all the interview questions.
11	**Presentation of findings** Finally, the results from the interview are reported following specified reporting procedures.

Source: Dejonckheere and Vaughn, (2019).

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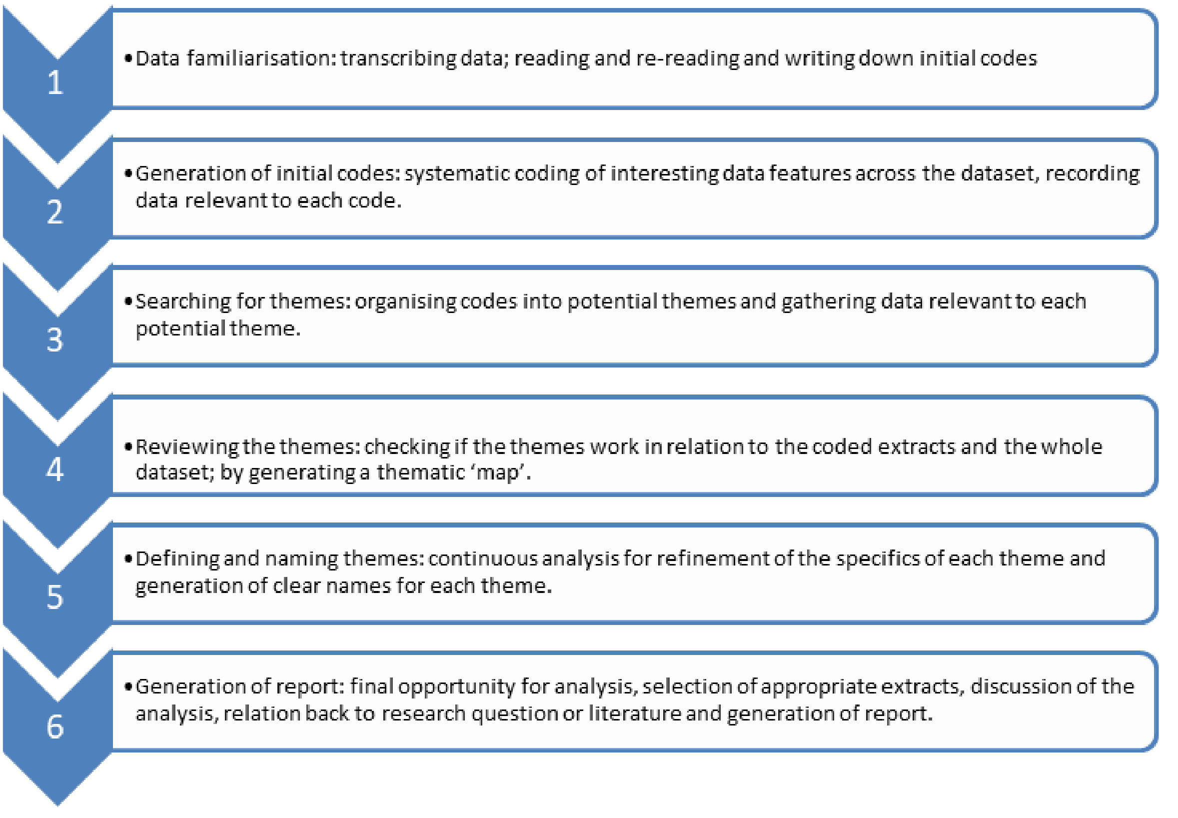
5.9.2. Analysis of Qualitative data

According to Bennet *et al.,* (2018), there are 3 main approaches to qualitative data analysis namely: Analysis based on content, analysis based on language and analysis based on visual data (Bennet *et al.*, 2018). Thematic analysis (TA) is a method of identifying, analysing, and reporting themes in data. It is frequently used in qualitative data analysis and may focus on the content of respondent's statements and involves identifying, analysing, describing, and reporting patterns known as themes within data. TA could be inductive, where codes are derived from the data in an open coding process, or deductive, where predetermined categories are applied. In the deductive process, non-fitting codes are classified outside the framework, supporting the development of new findings (Ibid). Thematic analysis was considered most suitable for this research because of several reasons; its wide application in social research and the fact that identification of important observations is not based on quantifiable measures such as the proportion of their appearance in the data, but on whether the theme linked something of importance in the data to the research question and on prevalence of theme in relation to space within the data items and across the entire data set (Clarke and Braun, 2013). Its theoretical flexibility which enables engagement with multi-disciplinary theories and perspectives of AI and OP thereby supporting generation of more in-depth and relevant analysis for the chosen field which resulted in the theoretical framework and answering of the research questions. TA enabled the Researcher to engage with analytical practices in line with other qualitative analysis approaches such as sorting through data to identify similar phrases or relationships, this process applied to analysis of the data for this research. Lastly, TA enabled analysis of different types of data and data set sizes, for this research TA was applied to analysing data from different healthcare organisations and different professionals in the AI, OP, and healthcare intersection (Lester *et al.*, 2020). Braun and Clarke 6 steps for thematic analysis as illustrated in Table 5.4 below, were applied to the research.

Table 5.4: Six-step thematic analysis procedure



Source: Braun and Clarke, (2013).

5.10. Quality of the Research

It is necessary to establish credibility in qualitative research just like in quantitative. The concepts of validity and reliability were originally developed from quantitative research tradition and are also applicable to qualitative research. New concepts such as precision, credibility, transferability, dependability, reflexivity have been developed to establish the quality of qualitative studies (Sullivan and Sargeant, 2011).

5.10.1. Validity

Validity in qualitative research refers to the appropriateness of the tools, processes, and data in terms of validity of desired outcomes, appropriateness of methodology to answering research questions, appropriateness of research design to the methodology, appropriateness of sampling and data analysis, and finally the results and conclusions are valid for the sample and context (Leung, 2015). In congruence with the interpretive epistemological paradigm, the Researcher ensured validity by ensuring that the interpretative process was conducted systematically and rigorously by ensuring communicative validity and interpretative awareness. Communicative validity by ensuring that what the Researcher understood was consistent with what the respondents meant. Interpretative awareness by ensuring that the interpretation of the respondent's perceptions, experiences of AI application, adoption, and implementation was not just reflective of the Researcher's beliefs, values, and biases. This was done by treating all statements as equally important and asking follow-up questions (phenomenological epoché) (Bonache and Festing, 2020).

5.10.2. Reliability

Reliability refers to the soundness of the research, particularly in relation to the appropriateness of research methods and the way they are applied in the qualitative study (Rose and Johnson, 2020). Approaches to reliability include demonstrating clarity of analytical process, including responses to support research findings, engagement with other researchers and the ways in which those methods were applied and implemented in a qualitative research study. Reliability ensures that other researchers understand the research and can undertake many of the research methods described (Noble and Smith, 2015; DeJonckheere and Vaughn, 2019; Rose and Johnson, 2020). The Researcher demonstrated reliability by justifying the research methods used, ensuring clear reporting of the data analysis process, showing that the results accurately and fairly represent the data. By presenting thick and verbatim descriptions of respondent's responses, preventing researcher bias and accounting for bias where inherent such as in sampling.

5.10.3. Ethics

The Researcher applied for ethical clearance from the University of the West of Scotland prior to commencing the study. Clearance was aimed at mitigating potential risks that the Researcher or the participants may be exposed to, and to ensure compliance of the Researcher with the general principles and standards of ethical research. The Researcher was required to provide two forms (in English); a consent for collecting written consent of data collection and the information sheet to provide participants with information about the study such as study purpose and standards of anonymity and confidentiality to be applied. These forms were distributed to the participants and received back prior to the data collection. It was also required that the data be safely stored on the Researcher's personal computer and accessible only to the Researcher and the Director of studies.

5.11. Conclusion

The Chapter has theoretically and analytically articulated the study research methodology, presenting the study as qualitative in nature, of interpretivist philosophical stance and adopting an inductive research approach. On exploration of potential data collection and analysis methods, the Researcher considered qualitative mono methods as most suitable for the research. Mono methods research was chosen as the preferred design for the study due to its support for extension of research scope. The Researcher used semi-structured interviews as instrument to collect qualitative data. The Chapter also explains the process of qualitative data analysis, discusses the issue of validity, reliability, and ethics in supporting the potential value of the study when applied to practice. Overall, the achievement of a sufficient level of research quality is crucial to the Researcher's aim of making an original contribution to academia and Organisational performance in the healthcare sector.

6. CHAPTER SIX: RESULTS

6.1. Introduction

This Chapter provides an overview of the Research findings, themes, and the process through which they have been developed. The sections within the Chapter support elucidation and validation of the research process through reflection on the experiences that occurred during the field phase of the research (Mortari, 2015).

Data were collected through the process of semi-structured interviews with Respondents who are referred to as **Key Informants** in this Research. The interviews resulted in the generation of relevant and practical themes. The findings and themes were developed through the analysis of interview responses, notes taken during the field research and existent data from academic and industry publications. The interviews served as the primary method of data collection, and this terminated when data saturation was achieved. The point of Data saturation was considered to have been achieved when interviews did not generate any new or relevant data within relation to the research questions. A total number of six themes were identified and established within the data collected. The themes provided answers to the last three research questions as follows: How does Artificial Intelligence (AI) impact Organisational Performance (OP) in healthcare? What are the challenges of AI adoption in healthcare? What are the factors for the adoption of AI for OP in healthcare? Each of the themes answered the research questions by providing an understanding of the impact of AI on four perspectives of organisational performance in healthcare, the challenges of AI adoption on healthcare and important factors for AI adoption in healthcare. The four themes clearly indicated that AI has mainly potential impacts on the four perspectives of organisational performance in healthcare investigated and can play a significant role in improving organisational performance in healthcare. The fifth theme identifies the challenges and issues that come into play during AI adoption and implementation in healthcare, and the sixth theme identifies factors of importance for AI adoption in healthcare.

Themes developed from the collected data and research findings are explained in greater detail within their prospective sub-sections and supported by interview data, notes from field work, academic and industry literature. Theme 1 was identified as **Potential improved financial performance.** This theme was identified based on participant's perception and understanding, that when AI is adopted in healthcare, it impacts financial performance elements which will potentially improve the financial performance. Theme 2 was identified as **Potential improved healthcare customer performance**; established based on participant's perception and understanding that when AI is adopted in healthcare, it impacts healthcare customer performance elements which will potentially improve the healthcare customer perspective of performance. Theme 3 was identified as **Potential improved internal business performance** based on participant's perception and understanding that AI adoption in healthcare impacts the improvement of internal business elements which will lead to potential improved internal business performance. Theme 4 was identified as **Potential improved Innovation and Learning performance** identified based on the participant's perception and understanding that adoption of AI in healthcare impacts elements of Innovation and Learning which result in potential improved Innovation and Learning performance. These four themes are all connected on the premise of potential improvement of organisational performance. Theme 5 established as **Challenges and issues in healthcare AI adoption** was identified based on the participant's understanding and perception of challenges encountered in the process of AI adoption. Theme 6 was identified as **Key factor for healthcare AI adoption** was identified based on participant's perception and understanding of important factors for healthcare AI adoption.

Each developed theme was supported with the interview data, notes from field work, academic and industry publication. The data were then analysed to enable identification of repetitive and key words or phrases. Key words and phrases were then grouped into clusters which were analysed and subsequently developed into themes. The themes supported the process of answering the research questions, achieving the research aims and objectives.

6.2. Interviews with Key Informants

The interview questions were developed from academic literature on Artificial intelligence, Organisational performance and the healthcare context, the general business context as well as other relevant contexts. The Researcher also conducted situational scanning of AI and OP adoption in healthcare by reviewing the literature (McGrath *et al.,* 2018). This included existing academic research of the impact of AI on OP in healthcare conducted in the Nigerian healthcare sector and in other healthcare settings, relevant industry research and publications. Furthermore, the Researcher by using probes engaged with KIs many of whom are experts or seniors in their areas of specialties to enable a better understanding of their knowledge, perceptions and lived experiences and for more insightful data. Also, Interviews were conducted using a semi-formal approach to enable the development of good rapport and free flow of conversation (Dejonckheere and Vaughn, 2019).

KIs willingly provided responses to questions directed at them based on their areas of specialty and experience and when unsure they asked for clarification to which the Researcher provided feedback in a neutral manner as much as possible (For example when asked questions about financial performance which is a perspective of OP, respondents who are not Business or management oriented first hesitated, but with probes and clarification from the Researcher they were able to respond to the questions). KIs confidently expressed their opinions towards sensitive issues and in most cases gave reasons for answers to interview questions, enabling the provision of more valuable information (Self, 2021).

The role of trust is considered crucial to the success of research with human participants (Guillemin *et al.,* 2018). In the respondent's context, trust can be built through inculcating anonymity and confidentiality in the research process (Oltmann, 2016). In this instance, the Researcher tried as much as possible to minimize the collection of information that may identify the respondent and where this was not possible, it was ensured that the identifying information was not linkable to the subjects' responses. The Researcher also took necessary steps to ensure confidentiality as ethically required. A statement of anonymity and confidentiality of respondent's information was provided in writing before commencement of data collection and analysis. After conducting the first interview, to ensure active listening by the respondents, the

Researcher made some adjustments to the interview questions around simplification of questions and clarity of language (McGrath *et al.,* 2018). For instance, respondents seemed to understand the questions better based on perception because they may not have been involved in investigating the impacts of AI, even when they have the experience of AI adoption, so perception was used as a probe. All the respondents contacted demonstrated a high level of interest in participating e.g., while most promptly attended some made adjustment to schedules and those who could not complete the interview agreed to having a second interview rearranged. Respondents showed interest in the Research by responding positively to request for future contact relating to the Research. All respondents were interested in getting a copy of the completed work while some were interested in the Researcher presenting their findings to their organisation on completion of the study. This high level of interest shown demonstrates the respondent's willingness to participate in the research which is an important requirement for semi-structured interviews (Dejonckheere and Vaughn, 2019). Interviews were conducted over a time frame of 45-60 minutes. While the interviews proceeded the Researcher took notes to enable probing based on some relevant points raised by the respondents. Nineteen interviews were conducted between June and August 2021, all of them remotely (As most of the respondents could only participate remotely due to the Covid-19 pandemic restrictions). All respondents gave consent for the interviews to be recorded.

6.2.1. Demographics of Key Informants

The sample for data analysis was composed of interviews of 19 Key informants who fell into at least one of the following specialisations: Healthcare professionals which included Doctors, Surgeons, Nurses, Radiologists, and other clinicians etc., Healthcare managers such as Managers, consultants, and Healthcare technologists such as Data scientists, AI engineers etc.

These KIs were mostly seniors in their areas of specialty, with some holding decision-making positions in private or public healthcare organisations in Nigeria and the UK. Appointment was by purposive sampling (Chapter 5, Section 5.6) based on the following eligibility criteria:

I. A practicing Healthcare practitioner, Healthcare manager or Healthcare technologist,

II. Experience of AI application, adoption, or implementation in healthcare

III. Possession of relevant competence in the intersection of Healthcare and AI

IV. Experience of Healthcare AI in Nigeria or the United Kingdom

At the time of conducting interviews, five of the KIs were in healthcare practitioner roles, six of them in healthcare management roles and eight of them in healthcare technologist roles. Six of them worked in public healthcare settings while 13 worked in private healthcare settings. In relation to experience, 7 of the KIs had experience of AI application in Nigeria while 12 of them had experience in the UK. There were 4 female and 15 male respondents, the high proportion of males is thought to be due to the area of study, which is an intersection of healthcare and technology, with technology being a male dominated field. All the KIs had experience and competence of AI in healthcare, as well as competence in Healthcare AI technology intersection. The respondents were selected based on the previously stated eligibility criteria which made them qualified to provide relevant and valuable information. The table 6.1 below provides an informative summary of the respondents; their Professional background; Position/ role; Current area of specialisation or expertise; Level of experience; Type of healthcare organisation/ setting; Location; Areas of experience.

Table 6.1: Informative summary of Key Informants

Code	Professional background	Position/ role	Current area of specialisation or expertise	Level of experience	Type of healthcare organisation/ setting.	Location	Areas of experience	Type of AI
KI 1	Data science	Clinical Neuroscientist	Application of AI in healthcare and preventative medicine	Expert	Professional services setting	UK	Application of ML technologies	Natural language
KI 2	Data science	Data scientist	Application of image analysis and computer vision, Clinical	Senior	Paediatric hospital setting	UK	Analytics programming	Neural networks
KI 3	Engineering	AI Consultant/ manager	Application of Automation to healthcare	Senior	Public Health, Pharmaceutical, Logistics.	UK	AI Consulting	Robotics
KI 4	Business and Management	Manager/ Strategist	Application of AI to Preventive healthcare	Senior	Clinical informatics company	UK	Performance evaluation,	Machine learning
KI 5	AI engineering	AI researcher and Engineer	Application of AI to Preventive healthcare	Senior	Research and development organisation	UK	Diagnosis of infections and	Neural networks
KI 6	Management	Care home manager	Application of AI, Digital technology, support and	Senior	Care home setting	UK	Health and social care management	Machine learning
KI 7	Management	Technology strategist/ manager	Multinational technology corporation	Senior	Health and social care setting	UK	Business intelligence	Robotics
KI 8	Computer science	Technologist	Application of Emerging business solutions	Senior	Pan African-focused healthcare organisation	Nigeria	Software based solutions	AI based Telemedic
KI 9	Medicine	Physician	Digital health and Telemedicine	Expert	Telemedicine and digital health services	Nigeria	Telemedicine	Image processing
KI 10	Data science	Data scientist	Application of digital technologies and AI to	Middle	Paediatric hospital setting	UK	Advanced ML support	NLP
KI 11	Medicine	Healthcare management	Application of AI to evidence-based practice	Senior	Technology services company	UK	Medical consultant	Expert systems
KI 12	Business and management	Healthcare management	AI, data science best practice and strategy	Senior	Technology services company	UK	Decision making and data	Computer vision
KI 13	Medicine	Consultant urological surgeon	Application of AI to surgery	Senior	Hospital	UK	Surgeries	
KI 14	Engineering	AI engineer/ Researcher	AI Healthcare research	Senior	Collaboration with health institutions	Nigeria, Africa	Automation and data analysis	Machine learning
KI 15	Engineering	AI engineer	Application of AI to diagnostic radiology	Senior	Healthcare solutions company	Nigeria	Model training	Neural networks
KI 16	Medicine	Medical doctor	Application of AI to healthcare		Hospital	Nigeria	Patient treatment	Deep lear
KI 17	Medicine	Surgeon	Application of AI to orthopaedic surgery	Senior	Hospital	UK	Default diagnostics	Robotics
K 18	Medicine	Chief Medical Officer	Application of Smart technology and digital health	Senior	Health technology company	Nigeria, Africa	Robotics	Machine learning
KI 18	Medicine	Medical doctor	Application of AI to healthcare	Senior	Healthcare start-up Company	Nigeria	Decision making support	Voice and Machine
KI 19	Engineering	Software Engineer	Application of AI to ERP in healthcare	Senior	Healthcare start-up Company	Nigeria	Diagnostic Healthcare ERP	ML

Source: The Researcher

6.2.2. Analysis of Interviews

According to Braun and Clarke, there are 6 steps in the Thematic Analysis process (Braun and Clarke, 2013) as illustrated in Chapter 5, Section 5.7.2. Following the outlined 6 steps, themes were identified from the interviews with key informants and are presented in this Chapter. The interview process started with general questions to the respondents about the healthcare organisation or setting where they have experienced AI, their role, the impact of AI on their role and the subfield of AI that they have applied or adopted. Next the Researcher proceeded to ask the respondents questions on the impact of AI on four different perspectives of performance, challenges of adopting AI and important factors for AI adoption based on their knowledge, perceptions and lived experiences. Interviews were held with a total of 19 respondents and all respondent names were changed to protect their confidentiality. The following themes were identified Potential improved financial performance, Potential improved healthcare financial performance, Potential improved healthcare customer performance, Potential improved learning and innovation performance, Challenges of AI adoption in healthcare, and Important factors for AI adoption in healthcare. The themes and subthemes developed are presented in the next section.

The findings presented provide a rigorous investigation of the impact of AI on organisational performance in healthcare based on the knowledge, perceptions, and experiences of Key informants in the AI, management, and healthcare intersection. The impact of AI on OP in healthcare has been explained from a strategic point of view using an adapted strategic healthcare performance framework incorporating healthcare performance elements. The Figure 6.1 below is a summary of the main recurrent themes from the thematic analysis, a summary of the key findings is provided at the end of each sub-section.

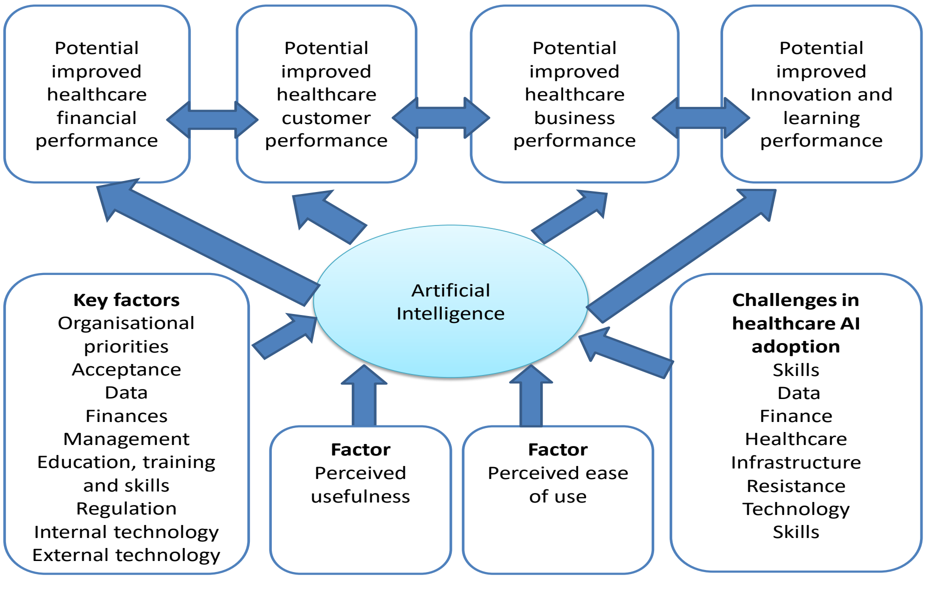


Figure 6.1: Summary of the Themes from the thematic analysis

Source: The Researcher

To ensure that respondents had a proper understanding of AI and that their experience of AI application or adoption was relevant to the Research, they were questioned on their definition of AI. Their different definitions are illustrated in the Figure 6.2 below. Most of the definitions centre on intelligence in line with definitions in the literature.

Figure 6.2: Terms used by Key Informants to define AI

Source: The Researcher

Figure 6.3 is an illustrative representation of the geographical location of the Key informants which covered Nigeria and the UK with a percentage representation of 32% and 68% respectively.

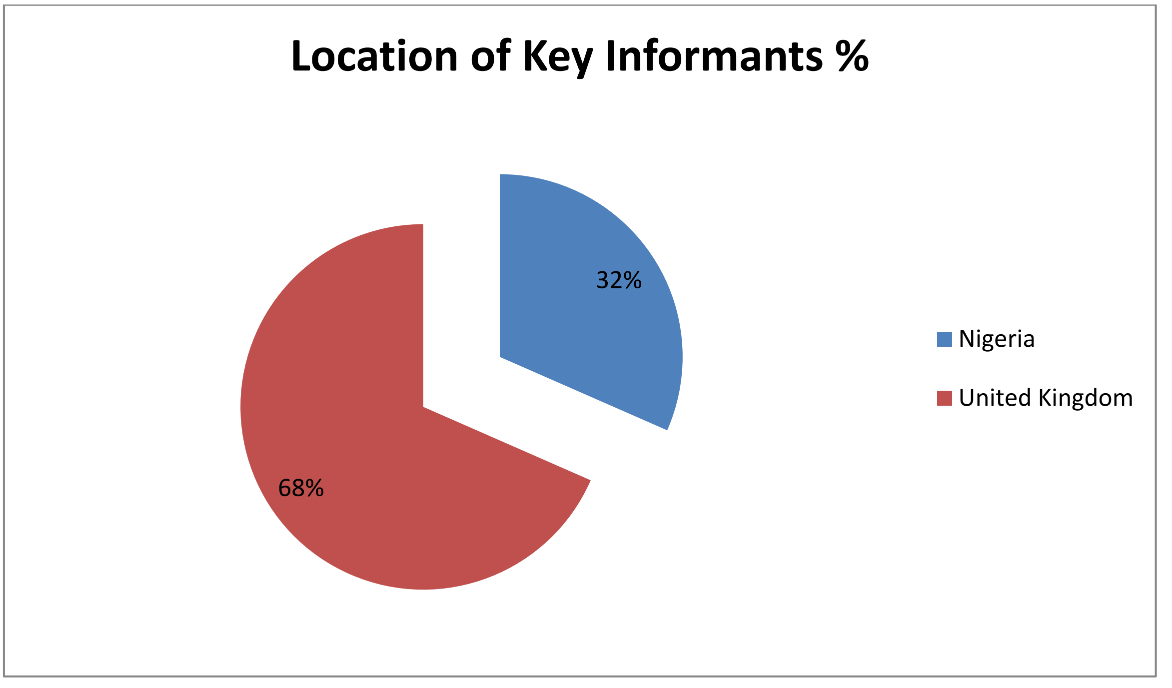


Figure 6.3: Geographical area of operation of respondents

Source: The Researcher

6.3. Potential Improved Healthcare Financial Performance

Potential improved healthcare financial performance for this study is demonstrated by the capacity of AI to potentially improve financial performance in healthcare. When asked about how AI impacts the financial performance of healthcare organisations, all respondents tended to believe that AI exerts positive impacts on healthcare financial performance. They however appeared to have varying perceptions of the nature and time frame of impact of AI on healthcare financial performance. Four Subthemes were identified as illustrated in the figure below.

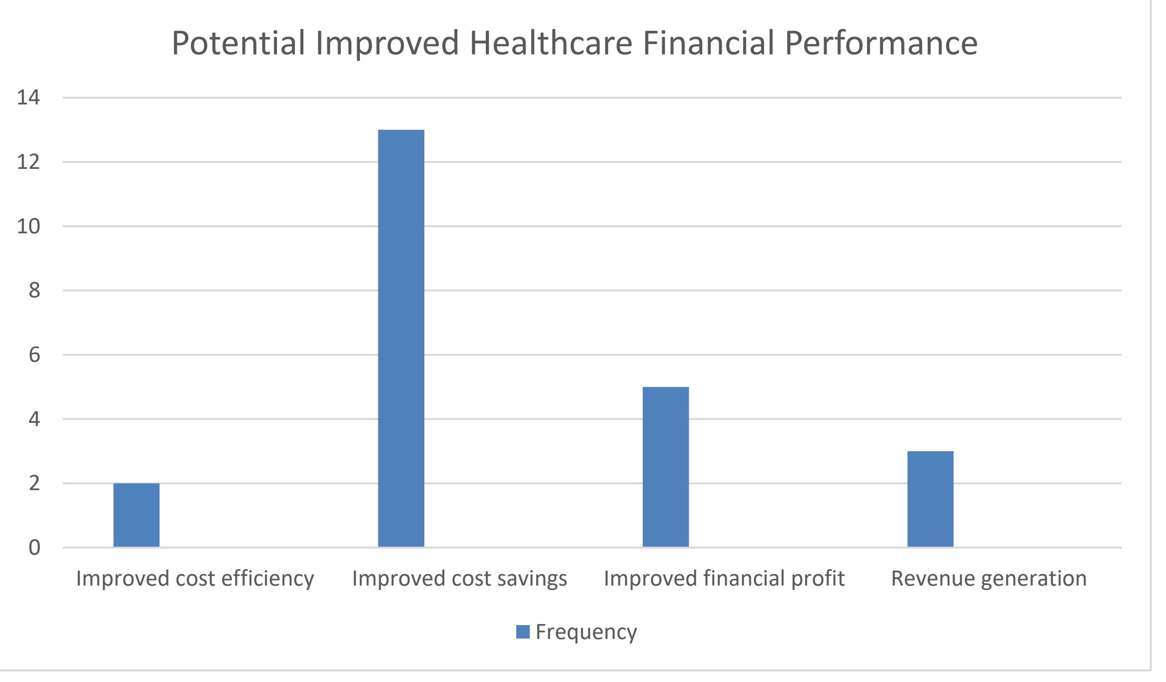


Figure 6.4: Potential Improved Healthcare financial performance

Source: The Researcher

The Figure 6.4 above shows the frequencies of the different subtheme components of PIHCFP. While the subtheme cost savings had the highest frequency, followed by the subtheme financial profit, with the last two subthemes cost efficiency and revenue generation having the same frequency. From the above, it can be inferred that the strongest impact of AI on healthcare financial performance is improved cost savings.

6.3.1. Improved cost efficiency

Cost efficiency was identified as a subtheme of Potential improved healthcare financial performance. Two of the 19 respondents pointed out, that AI improves healthcare performance through Cost efficiency. Respondents perceived that AI enables the use of the same amount or lesser number of resources to achieve greater outputs. Some of the responses included:

‘’ […] *So, AI is about how to help doctors do what they need to do quicker and efficiently so we can see more patients. So how can AI help with that? Could AI be used to then run through those lists? Pull out who needs to be discussed and reduce that list by say, 30% 40%? How many hours of manpower that reduces, its cost efficiency and from a cost point of view, for example, a patient waiting for hip surgery comes to A&E they get seen by a doctor, they get medication, there's a cost for that for the service for them presenting. And it gets the point where they turn up so many times it's cheaper to do the operation, than have them wait and then have more and then strictly treat the complications of that waiting. So, AI has a role. But again, I keep saying it needs to be evaluated, but there's a lot of potential.” (KI 13, UK).*

‘’ [….] In terms of cutting down on labour costs, there ought to be, but it depends on how long sighted the person you are speaking to is. So, if you're thinking about the time in years, as opposed to weeks and months, so if you have that kind of forecast of years, then we can see how there will be cost efficiency (KI 17, UK).

The focus by respondents on Cost efficiency demonstrates that in healthcare, AI can result in reduction of human resource requirement which will lead to a decrease in associated cost for acquiring human resource and ultimately resulting in cost efficiency. Accordingly, this cost efficiency is potential in the sense that it is attainable in the future and may not be immediately observed. Therefore, AI potentially improves the cost efficiency element of healthcare financial performance through decrease in human resource requirement and decrease in healthcare costs.

6.3.2. Improved cost savings

Cost savings was another identified subtheme of Potential improved healthcare financial performance. This subtheme theme had the highest frequency within the theme; with 13 out of 19 respondents supporting it. When asked about how AI impacts healthcare financial performance, most of the respondents perceived that AI improves healthcare financial performance and that this impact is exerted through Cost savings.

> *‘’ [.….] I think there are positives to be made, because you would identify patients at the right time for the right treatments for the right interventions. And so, you would save money because you wouldn't be doing costly things like MRIs when they maybe aren't needed, or you will be triaging patients at the right time (KI 1, UK)*

> *‘’So, we know that the group of care homes involved in using the AI had a reduction of 999 calls by 23%. This is obviously a big impact on the health system both from the ambulance service and from the hospital perspective time saving rather than financial saving. And obviously that means then that the GPS don't roll the travel time. Does that translate to cost saving? And if they can see more patients, for sure that is a cost saving, but certainly it's I guess it gives potential (KI 6, UK)’’.*

> *‘’ [.….] Because a hospital can reduce the number of radiologists they employ if they adopt AI thereby reducing expenses and saving costs “[.….] (KI 15, Nigeria).*

One respondent however, argued that AI may result in additional costs due to misdiagnosis which is unlikely to happen if a healthcare practitioner was involved in the diagnosis.

> *‘’ [.….] On the other hand, there may also be additional costs due to misdiagnosis if AI is allowed to make all the diagnosis. It may diagnose everything for instance in medicine there is a grey area where there are people who have a little differentiation from the normal even though they are normal. These persons will normally be cleared by a doctor since such situations occur in practice but when they are diagnosed there is increased cost” [.….] (KI 16, Nigeria).*

Based on the recurring focus on cost savings above, respondents generally perceived that AI enables cost savings by decreasing costs mainly through reduced costs which translates to cost savings. These perceptions demonstrate that although there is general agreement by the respondents that AI enables cost savings, there is the possibility of additional costs arising due to misdiagnosis by AI.

6.3.3. Improved financial profit.

Financial profit was the third subtheme of the theme Potential improved healthcare financial performance. This subtheme had the next highest frequency of occurrence within the theme with 7 out of 19 responds identifying it as an impact of AI on healthcare financial performance.

> *‘’ [.....] But on the other hand, these systems are costly to run, they're costly to maintain that they're costly to, to build up a workforce that is empowered and enabled to run these systems. But I think all in all, the net financial costs where the net financial benefit would be positive. Now, even though it might be a little bit of a challenge initially, on the long run it may be financially beneficial (KI 1, UK).*

> *‘’ [.....] So, for us as an organisation, there's no financial benefit because the same tasks do need to take place. The financial benefit though is to the health system ‘’ [.....] (KI 6, UK).*

Some of the respondents noted that AI leads to financial benefit through improved efficiency:

> *‘’They can also attract more patients and increase their bottom line due to faster and more accurate diagnosis’’ (KI 16, Nigeria).*

> *‘’So, first of all, let me say that AI will definitely bring financial gain. And you can easily see where it will bring financial gain. So anytime you make things easier for people, or you generate new ways of doing things more efficiently. It tends to lead to financial gains. Yeah, so yeah, I am 100% sure that there is (KI 18, Nigeria).*

Another respondent noted that in cost savings in addition to improved efficiency would result in financial benefit and improved financial performance.

> *‘’So, in terms of finances, or financials, I would say with time, right? If we really look at and analyse what the data while we're doing things in a conventional way, to where we are doing things in a more precise way using [...] AI solutions, you will be saving costs, and if you add the lump sum together, you know that it's quite a lot of cost that you're saving there. So, I believe that there will be a significant improvement in or effect on return on investment’’ (KI 8, Nigeria).*

It is clear from the responses that respondents consider that AI has a potential impact on healthcare financial performance through improved financial profit such as net positive finances, increased profits, and improved Return on Investment (ROI). Also, the impact of cost savings appears to be a potential rather than immediate owing to the reportedly slow speed of AI adoption in healthcare.

6.3.4. Revenue generation

Revenue generation was the fourth subtheme of the theme Potential improved healthcare financial performance. When asked about how AI impacts healthcare financial performance, 3 out of 19 responses considered Revenue generation as an impact of AI on healthcare financial performance.

> *'' [....] You can then use AI as a research tool, that research tool then generates money for the trust, because you're doing research in AI, so and there's a good international increase in the hospital international reputation, as you are seen to be leading the way in AI and because AI is in early development, it's just a matter of time [....]''(KI 13, UK).*

> *'' [.....] But imagine if you use AI to build a new tool and people buy the app? You can easily see there is revenue and a whole lot of financial gain. Yeah. But we working in the health sector are more interested in impacts [....] '' (K1 18, Nigeria).*

The focus on revenue generation demonstrates that respondents consider AI to have a potential impact on healthcare financial performance through provision of sources for generating revenue, such as through potential investment in research, data services and healthcare applications.

Based on the recurrent focus of respondents on the above theme and subthemes, the results of this Research answer the research question of how AI impacts OP in healthcare, by showing that AI potentially impacts healthcare financial performance. By improving cost efficiency, cost savings, financial benefit and by providing additional sources of revenue generation, the impact are more likely to be potential rather than immediate. Though the result of this research shows that the impact exerted by AI is potential improved performance, the result of improved financial performance is consistent with impacts reported by other studies that have applied or adopted AI in healthcare settings reviewed in Chapter 2 such as reduced costs (Gonel, 2020), cost savings (Incze *et al.,* 2021) improved financial benefit (Shi *et al*., 2015). This result is also in agreement with other research on the impact of AI on OP such as the study of Lee *et al.,* (2018) which reported cost savings as an impact of AI on Healthcare financial performance.

6.4. Potential Improved Healthcare Customer (HCC) Performance

Potential improved healthcare customer performance is demonstrated by the capacity of AI to potentially improve customer performance in healthcare (HCC which refers to the end receivers of healthcare and this term is synonymous to patients and service users for the purpose of this research). When asked about how AI impacts healthcare customer performance, 17 out of 19 respondents recognised the potential impact of AI on improving HCC performance. The following Subthemes identified within this theme explain the respondent's perceptions on how AI impacts HCC performance: Improved healthcare quality, Improved access to healthcare, Improved HCC engagement, Improved health outcomes and Improved patient safety.

6.4.1. Improved HCC Satisfaction

Improved HCC satisfaction was the first subtheme of the theme Potential improved HCC performance. Respondents considered AI as exerting an impact on HCC performance through Improved HCC satisfaction.

One of the respondents noted that AI can improve HCC satisfaction as well as quality of care:

> *'' [.....] So, it's something that can enhance patient satisfaction, and improve the quality of care they're getting, because people get to be diagnosed earlier'' (KI 5, UK).*

A few of the respondents reported that improved HCC experience occurs before improved HCC satisfaction

> *'' [.....] Improved access to healthcare will really improve patient experience and ultimately customer satisfaction [.....]''(KI 16, Nigeria).*

> *'' [.....] There are a lot of things that brings patient satisfaction. And number one, it depends on diagnosis. It is very difficult to be satisfied if you're diagnosed with terminal cancer, right? But if the patient has had a good experience [....] and it has been aided by AI, then of course, in some ways the patient will be pleased [....] (KI 14, UK).*

One respondent argued that HCC satisfaction is unlikely because of distrust in AI

> *"In terms of patient satisfaction, there are not many studies about patients on AI. The problem is, is deep distrust with data, and AI, if people the public think that robots are*

huge, or computers are managing their care, there will be a big uproar, so let's be quite careful about it … (KI 13, UK).

Another respondent suggested that HCCs may not get to the point of satisfaction due to lack of awareness of AI:

'' [….] I think most patients are blissfully unaware all they see is [….] like a virtual check in. And this is the way it goes on as long as they get delivery, the delivery of care [….] (KI 14, UK).

One respondent suggested that AI may result in HCC dissatisfaction in problematic situations.

'' [….] Some patients don't really think about how it happens until something goes wrong that's when there'll be a critical system. That's when really, they contact HR and customer services [….] (KI 14, UK).

The focus on Improved HCC satisfaction shows that respondents consider AI to have a potential impact on HCC performance through HCC satisfaction.

6.4.2. Improved Healthcare quality

Improved Healthcare quality was the second subtheme of the theme Potential improved HCC performance. Respondents considered AI as exerting an impact on HCC performance through Improved Healthcare quality. Some of the respondents who responded to the question recognized AI as impacting HCC performance through Improved healthcare quality: More so, their accounts suggest that AI first improves efficiency in processes before healthcare quality.

''[…..] All healthcare organisations compromise on care given due to resource constraints. AI adoption allows smart tools to free up time for humans to perform more value added care and now even allows first-pass triage for some conditions to be done en-masse […..]'' (KI 3, UK).

''[…..] And through that there may be improved quality of care because of the improved efficiency […..]'' (KI 11, UK).

''[…..] And I think it provides the opportunity for organisations to release capacity back into time spent caring. I think, again, if I think about the sort of chat-bot type capability, it's all about making sure that, you know, health and social care, and indeed, you know, healthcare response teams are able really to work on more complex cases [….] (KI 7, UK).

The focus on Improved Healthcare quality shows that respondents consider AI to have a potential impact on HCC performance through healthcare quality because there is increased efficiency of processes, increased efficiency of time, and increased efficiency of human resources will allows healthcare professionals focus on more care component while AI can cover tasks that do not require the human touch.

6.4.3. Improved access to healthcare

Improved access to healthcare was the third subtheme of the theme Potential improved HCC performance. Respondents considered AI as exerting an impact on HCC performance through Improved access to healthcare. All respondents who responded to the question recognized AI as impacting HCC performance through improved access to healthcare.

One of the respondents felt that there is improved access to healthcare through reduced waiting times:

> *''Reduced patient waiting times to perform the examination [….]'' (KI 9, Nigeria)*

Another of the respondents felt that there is improved access to healthcare through reduced waiting times and improved access to specialist services:

> *''[….] On the customer side [….] accessibility, they don't have to pay heavily to see a specialist, for instance, in Nigeria, you know, and they don't have to go through the long waiting process […] AI encourages more women to be open to having frequent examinations to detect and prevent breast cancer from an early stage'' (KI 5, UK).*

Others felt that improved access to healthcare was through improved access to specialist services:

> *''Conversational AI and Chabot's are providing a wealth of approved and authorised information pertaining to kind of an individual's care or treatment. And I've seen that a lot within the [….] adolescence and improved mental health [….]'' (KI 12, UK).*

> *''[….] I think there is a great impact on patient's access to care [….] Patients particularly in certain fields e.g., the field of psychology, may not be comfortable speaking to another human being about their issues'' (KI 16, Nigeria).*

Other respondents mentioned the potential impact of AI on healthcare services in remote and resource constrained settings like Nigeria.The consistent focus on Improved access to healthcare shows that respondents consider AI to have a potential impact on HCC performance through improved access to healthcare.

6.4.4. Improved HCC engagement

Improved HCC engagement was the fourth subtheme of the theme Potential improved HCC performance. Respondents highlighted AI as exerting an impact on HCC performance through Improved HCC engagement. All responses on HCC engagement originated from UK respondents.

Some respondents recognized AI as enabling engagement between persons working in the healthcare system and healthcare customers, thereby improving the human component of care.

> *''Interesting, […] we have this more augmented intelligence, where clinicians and I don't just mean doctors, I mean, phlebotomist, I mean, porters, I mean, anybody in the healthcare system, are able to use these technologies to enable their workflows or help them with their jobs, that actually they can get back to being more human with their customers, with patients […]'' (KI 1, UK).*

> *'' [….] Then around patient engagement, so, you know, AI is being used within digital therapeutics, wearable's and remote devices and capturing data unique to you about, [……] to provide a personalised level of care, you know, is almost this marriage of, you know, the physician, you manage your own care, and, you know, an independent actor, which is collecting that data […]'' (KI 12, UK).*

Some respondents noted the importance of communication and engagement in ensuring that HCCs understand how decisions about their health is made using AI as this will facilitate their understanding of the impacts of AI.

> *'' [….] And I think that something as uniquely important and personal as your health, you need to feel that empowered as well. And it's not something that's just done to you and done behind closed doors '' [….] (KI 1, UK).*

One respondent argued that HCC engagement leads to knowledge and empowerment of HCCs:

> *'' […] What i mean by losing the public is that what we must not do is roll out technologies without making sure that the public have a say and are empowered and understand how their data is being used. And actually, they can see the impact of what rolling out these technologies can do. And I think that something as uniquely important and personal as your health, you need to feel that empowered as well. And it's not something that's just done to you and done behind closed doors (KI 1, UK).*

The focus on Improved HCC engagement shows that respondents from the UK consider AI to have a potential impact on HCC performance through HCC engagement.

6.4.5. Improved health outcomes

Improved Health outcomes was the fifth identified subtheme of the theme Potential improved HCC performance. Respondents considered AI as exerting an impact on HCC performance through Improved health outcomes.

Most of the respondents recognized AI as impacting HCC through improved health outcomes.

> *‘’ […] And that can halve the deaths from acute kidney injury. And as I said, with that, in hospital acquired pneumonia, you would be saving 70,000 lives a year in the UK [….]’’ (KI 4, UK).*

> *‘’ [….] So even in the long term, the health outcomes are improved, because when maybe a lump that is just coming up when it has not even gotten super cancerous when they expose themselves to these monthly updates, they are able to quickly detect cancer and commence treatment [….]’’ (KI 5, UK).*

> *‘’ [….] Improved patient care and outcomes [….]” (KI 9, Nigeria).*

> *‘’ […] So, you spot the cancer earlier, so you have a better outcome (KI 11, UK).*

> *‘’ [….] more efficient diagnosis and better health outcomes [….]” (KI 18, Nigeria).*

6.4.6. Improved Healthcare customer (HCC) safety

Improved HCC Patient safety was the sixth subtheme of the theme Potential improved HCC performance. Respondents reported AI as exerting an impact on HCC performance through Improved HCC safety.

All respondents recognized AI as impacting Healthcare customer performance through HCC safety

> *‘’[….] So, overtime, yes, it improves the patient, safety, right patient as they are able to initiate calls, and the nurses are able to attend to such calls promptly […]” (KI 8, Nigeria).*

> *‘’One of the areas of application to patient safety is in the monitoring of hospital infections [….] AI can be used to raise alert to these cases […]” (KI 10, UK).*

One respondent noted that impact on HCC performance may not be visible early in AI adoption.

> *“[…] In terms of patients, or, you know, safety for individuals, I think, I think it gets more concerning when we're in the early intervention type mode, you know your tools going to miss something, are there safeguarding concerns that might be missed? [….]” (KI 7, UK).*

The repeated focus on Improved HCC safety shows that respondents perceive AI as having a potential impact on HCC performance through HCC safety.

Consequent to the recurrent focus of respondents on the above subthemes, the above result answers the research question of how AI impacts OP in healthcare, by showing that AI potentially impacts HCC performance. By improved HCC safety, Improved access to healthcare, Improved healthcare quality, Improved health outcomes, Improved HCC engagement and Improved HCC satisfaction. Although the observed impact on HCC performance is potential, the result agrees with several studies cited in the literature review in Chapter 2 which show that AI improves health outcomes of healthcare customers such as (Amiri *et al.,* 2013; Karuvan *et al.*, 2020); improved HCC engagement (Moyle *et al.*, 2018); improved healthcare (Sara *et al.,* 2020); improved access to healthcare (Oyelere *et al.,* 2017; Viscaino *et al.,* 2020). This result is also in agreement with other research on the impact of AI on OP such as the study of Bohr and Memarzadeh, (2020) which reported reduced workload as an impact of AI on HCC performance.

6.5. Potential Improved Internal Business Performance

Potential improved internal business performance is demonstrated by the capacity of AI to potentially improve internal business performance in healthcare. When asked about how AI impacts the internal business performance of healthcare organisations, all 19 respondents tended to believe that AI exerts potential positive impacts on internal business performance. They however appeared to have varying perceptions of how AI impacts on internal business performance. The following 6 Subthemes identified within this theme explain the respondent's perceptions on how AI impacts Healthcare internal business performance: Decreased disease burden, Decreased workforce crisis, Decreased workload, Decreased wastage of resources, Improved efficiency, Improved productivity.

6.5.1. Decreased disease burden

Decreased disease burden was the first subtheme of the theme Potential improved internal business performance. Respondents considered AI as exerting an impact on internal business performance through decreased disease burden.

A few respondents recognized the impact of AI on decreasing disease burden.

> *‘’[….] Then secondly from a holistic point of view it will also decrease the burden that comes with women who have now been diagnosed with breast cancer such as reduced human resources and treatment costs [….] take for instance if 90% of women in a particular sample population use this system. We know that they are not going to get to say stage three or stage four cancer so far, they are doing this regular check-up, it prevents it’’ (KI 5, UK).*

> *‘’ [….] There will also be reduced cost of treatment due to faster diagnosis and treatment of the disease at earlier stages than in chronic situations which require longer treatment or maybe management [….] This will be in the long term due to the complexity of the medical environment, where adoption may not be rapid at first (KI 16, Nigeria) ‘’.*

Therefore, the respondents believe that AI impacts healthcare Internal business performance through decrease in disease burden.

6.5.2. Decreased workforce crisis

Decreased workforce crisis was the second subtheme of the theme Potential improved internal business performance. Respondents considered AI as exerting an impact on internal business performance through decreased workforce crisis.

Some respondents recognized the impact of AI on decreasing workforce crisis in healthcare:

> *‘’ [….] The workforce has a lot of operational types which could be improved, and stresses could be reduced. And I think that's really important given what was just seen, understandably, after the pandemic and exodus of clinicians from the health care system’’ (KI 1, UK).*

> *‘’ [….] We are talking less tired health workers. So, through AI we can have doctors that are much fresher who are more in tune to handle patients. A lot of doctors you see in hospitals especially in Africa are coming back to work with a lot of hours of call, they are tired [….]’’ (KI 16, Nigeria).*

The focus on decreased workforce crisis shows that respondents consider AI to have a potential impact on internal business performance.

6.5.3. Decreased workload

Decreased workload was the third subtheme of the theme Potential improved internal business performance. Respondents considered AI as exerting an impact on internal business performance through decreased workload.

Some of the respondents reported that AI impacts business performance by decreasing the workload of healthcare professionals:

> *‘’ [….] I think also, there is something around actually helping the workforce. I think, you know if we just think about ophthalmologists, there aren't enough in the country. So what if you had a second reader that could run overnight and triage your jobs for the next day to say, look, I think these are these scans are showing a problem. But you don't need to look all these other scans because they’re fine. These are the ones that you need to focus on, because you're the human expert’’ (KI 1, UK).*
>
> *‘’ [….] AI will help reduce the workload of professionals in healthcare by narrowing down options so there is less burden on the radiologist [….]” (KI 15, Nigeria).*

The focus on decreased workload shows that respondents consider AI to have a potential impact on internal business performance.

6.5.4. Decreased wastage of resources

Decreased wastage was the fourth subtheme of the theme Potential improved internal business performance. Respondents considered AI as exerting an impact on internal business performance through decreased wastage of resources. Some of the respondents reported that AI impacts business performance by decreasing wastage of resources:

> *‘’ […] What the presumed/ potential impact will be basically less wastage, less human time doing menial tasks, and a lot of things that like. So, AI can potentially help reduce those menial tasks and there a lot of menial tasks in medicine that computers can do to save free up human time [….]’’ (KI 13, UK).*
>
> *‘’ […] I'm not a business admin expert, but what i know for certain is it could lead to less waste of resources especially in terms of work hours in terms of more efficient management of work which could lead to increased productivity of the workforce [….] (KI 16, Nigeria).*

6.5.5. Improved efficiency

Improved efficiency is the fifth subtheme of the theme Potential improved internal business performance. Respondents generally considered AI as exerting an impact on internal business performance through improved efficiency.

All the respondents that responded to this question reported that AI impacts PIIBP through improved efficiency.

‘’[….] Yeah, so certainly around efficiency, because instead of having a Nurse who can do the obs., so fits in with the way she can do that, and then with everything else, you know. You've got senior who's doing it, and that obviously means that you can do it quicker, you can do it more regular’’ (KI 6, UK).

‘’ [….] So, the benefit you've got with using technology and those AI algorithms is that you're going to save clinician’s time. And I think it becomes even more important when you've got, for example, the COVID situation where you've got like a backlog of like, operations or you know, services, you've got a demand on staff. The time saved is then put towards reducing backlogs […..]’’ (KI 10, UK).

‘’AI speeds up the time to obtain medical examination and reporting, improves diagnostic accuracy, therefore improving internal efficiency [….]’’ (KI 9, Nigeria).

Some fields if not more productive, have become more efficient. AI technologies have improved healthcare communication; so, there are systems definitely that are in place where AI is helping hospitals communicate with each other in a smart way, having physicians communicate with each other, having a patient communicate with physicians, and certainly making it possible for things to be done outside of the hospital sector (KI 17, UK).

6.5.6. Increased productivity

Improved productivity is the sixth subtheme. Respondents considered AI as exerting an impact on internal business performance through improved productivity.

‘’ [….] But especially, you know, especially for the kind of RPA, and those sort of bot technologies. I think there's a big productivity gain to be had for organisations there. In terms of, you know, making swifter decisions, particularly for clinicians using it for imaging etc., you know, absolutely certain. (KI 7, UK).

‘’ [….] So, I think it's mainly efficiency first, and then the other things like productivity of the clinicians as well. They can do more within the specified time frame or even less time [….]’’ (KI 11, UK).

‘’ [….] So yes, impacting productivity, because AI automates some of the mundane workflows of clinicians, it improves the productivity of clinicians and also they can be able to attend to know more patients in a day (KI 14, Nigeria).

‘’ [….] A lot of manual processes are cut out when AI is used by radiologists therefore improved business processes, increased productivity (KI 15, Nigeria).

‘’ [….] So I think you have to see us, particularly during that kind of period of COVID where a lot of remote based consultations, remote assessments, remote diagnosis that has definitely improved productivity in some fields” (KI 17, UK).

The focus on Improved productivity shows that respondents consider AI to have a potential impact on internal business performance. Based on the recurrent focus of respondents on the above subthemes, the above result clearly answers the research question of how AI impacts

OP in healthcare, by showing that AI potentially impacts internal business performance. This is consistent with results from the literature review in Chapter 2 which highlighted the following impacts of AI on internal business performance; reduction of workload (Ye, 2015); improved efficiency (Ozden *et al.*, 2015; Litjens *et al.*, 2016; Desautels *et al.*, 2017). The research agrees with other empirical research such as the research of Li *et al.,* (2019) and that of Ko *et al.,* (2020) which reported improved efficiency as an impact of AI on OP.

6.6. Potential Improved Innovation and Learning Performance

Potential improved Innovation and Learning performance is demonstrated by the capacity of AI to potentially improve Innovation and Learning performance in healthcare. The following Subthemes identified within this theme explain the respondent's perceptions on how AI impacts Innovation and Learning performance: Improved learning, Improved Innovation, Improved processes, Improved research, and development. All respondents perceived AI as exerting potential impacts on Innovation and Learning performance. They however appeared to have different perceptions of how this impact is exerted.

6.6.1. Improved learning

Improved learning is the first subtheme of the theme PIILP. Respondents considered AI as exerting an impact on internal business performance through improved leaning.

> *''[….] By providing the right answer at the right time that is most up to date, rather than going to webinars or attending a course every six months, or every year in which you may already be like seven months behind. Evidence based, clinicians are provided quantum care learning, with the latest guidance [….]" (KI 11, UK).*

> *''[….] I don't think that there is any area that AI cannot improve. We developed an application that nurses use to learn how to resuscitate new-borns. Well, one of this has been deployed in National hospital and Lagos teaching hospital [….] we worked with University of Washington [….]'' (KI 18, Nigeria).*

One respondent however argued that learning is not well disseminated even though opportunities abound:

> *''[….] There are big opportunities to learn and do more with it [….] I don't think that the learning has necessarily been spread as widely as we might all hope. And I think that, you know, the NHS, like other organisations struggles to share its good news [….]'' (KI 7, UK).*

The focus on Improved learning demonstrates that respondents consider AI to have a potential impact on Innovation and Learning performance.

6.6.2. Improved innovation

Improved innovation is the second subtheme of the theme PIILP. Respondents considered AI as exerting an impact on Innovation and Learning performance through improved innovation.

> *‘’So, I think these systems are very good in those areas of bridging innovation and pushing innovation to say actually. I think we see that far more in the pharmaceutical industry than we do in healthcare [….] ‘’ (KI 1, UK).*
>
> *‘’ [….] Smarter, more effective ways to teach junior doctors to do sutures, you know, because that's what they spend nearly 40% of their time doing, you know? So, yeah, I mean, that's one area where I think actually AI and augmented reality, virtual reality, etc., has an absolutely very important part to play [….]’’ (KI 12, UK).*
>
> *‘’AI has been applied innovatively to other areas of healthcare research like the Ubenwa app that is being used to diagnose birth asphyxia in babies at birth [….] ‘’ KI 16, Nigeria).*

The focus on Improved innovation shows that respondents consider AI to have a potential impact on Innovation and Learning performance.

6.6.3. Improved processes

Improved processes are the third subtheme of the theme PIILP. Respondents considered AI as exerting an impact on Innovation and Learning performance through improved processes.

Generally, respondents agreed that AI helps to improve processes in healthcare:

> *‘’[….] But, you know, you've created 1000 images that are x rays of a very rare condition, and suddenly someone has to sit and go through them [….] And the AI is kind of helping them do that. I think there's a there's a potentially huge impact. I think imaging is undoubtedly the most advanced area where AI has touched healthcare [….]” (KI 4, UK).*
>
> *‘’[….] Enhances accuracy of medical examinations and enhances accuracy of reporting [….]’’ (KI 9, Nigeria).*

The focus on Improved processes shows that respondents consider AI to have a potential impact on Innovation and Learning performance.

6.6.4. Improved Research and development

Improved Research and development is the fourth subtheme of the theme PIILP. Respondents considered AI as exerting an impact on Innovation and Learning performance through improved research and development.

> *‘’[….] The whole world is investigating different proteins and different types of molecules to try and get a vaccine. And then how do you know, how do you monitor spread in a hospital? And whatever it is, right? So, I think that when you have big questions like that, you need to give clinicians and more widely public policymakers tools to take that kind of floodlight and make it a torch. And that's what AI can do [….]” (KI 1, UK).*

> *‘’[….] And so, I would say the benefits are there though not fully tapped, but the benefits around research and development with AI are there [….] So, if we have a framework [….] have a proper data warehouse, or data lake, then we can begin to do clinical research [….]’’ (KI 8, Nigeria).*

> *‘’I am currently working in research, and I know for sure that investments in AI research have actually helped in healthcare, because it has made possible the testing out of new ideas, new technologies, and certainly innovation [….]” (KI 14, Nigeria).*

The focus on Improved research and development shows that respondents consider AI to have a potential impact on Innovation and Learning performance.

Based on the recurrent focus of respondents on the subthemes above, it is clear that most of the respondents believe that AI potentially improves Innovation and Learning performance in healthcare through improved learning, improved innovation, improved processes, improved research and development.

6.7. Challenges in Healthcare AI Adoption

Seven typologies of challenges were identified from the analysis of the interviews with the Key informants (Healthcare managers, Healthcare professionals, Healthcare technologists). These are: Skills-related challenges, Data-related challenges, Finance-related challenges, Healthcare specific challenges, Infrastructure-related challenges, Resistance-related challenges, Technology-related challenges, Skills-related challenges.

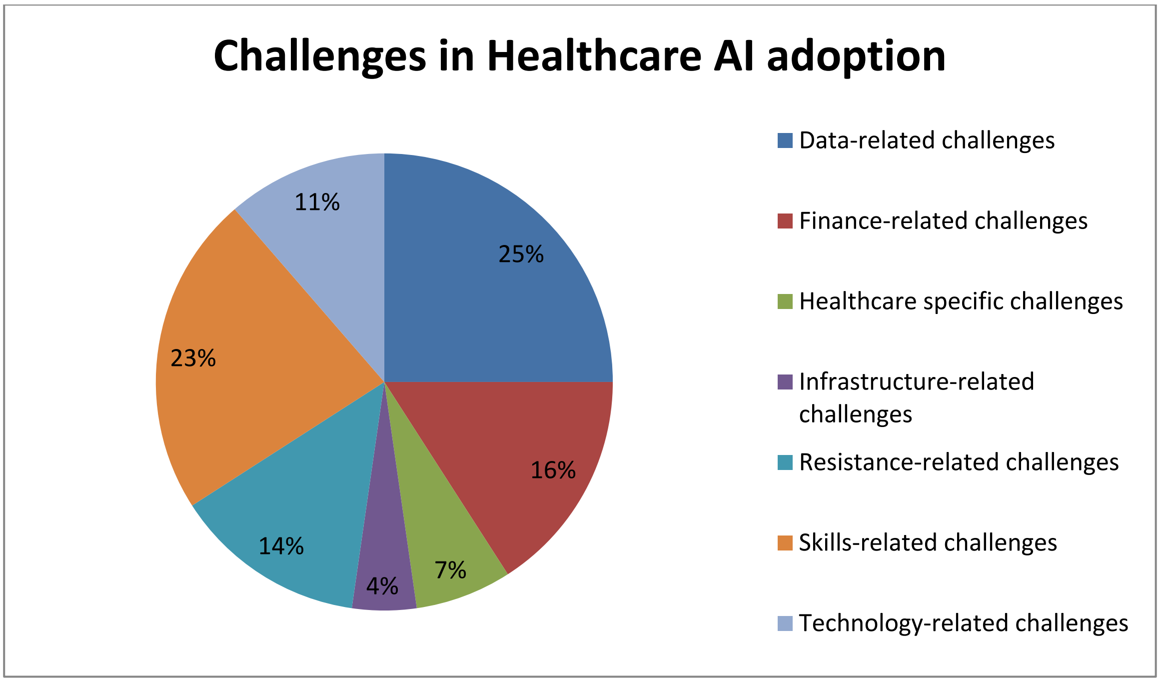


Figure 6.5: Typology of Challenges in Healthcare AI adoption (Percentage frequency)

Source: The Researcher

The diagram in Figure 6.5 above illustrates the percentage frequencies of the typology of challenges identified from interviews with the three groups of KIs. Finance-related challenges had the highest frequency while Infrastructure and Trust both have the equal and the lowest occurring frequencies.

6.7.1. Skills-related challenges

One of the most frequently mentioned challenges were skills-related challenges. When asked about the challenges in healthcare AI adoption, 23% of responses identified skills related challenges as important in the adoption of AI in healthcare. Most of the responses regarding skills-related challenges were similar: a general lack of AI-related skills, with few comments that varied based on location.

Challenges mentioned by respondents include:

> *''Yeah, I think the major challenge is a question; do we have the right human technical manpower that will continually update the AI models [….] I think that's the only barrier that I see. And I don't really see it as barrier because I feel like the UK government always sponsors such initiatives so it shouldn't be a barrier really […]'' (KI 5, UK).*

''So, I've mentioned already kind of skills and training. That's a big one. And I think that the lack of skill and understanding within the sector means that it's not well placed to challenge commercial organisations on what they're doing, and how the thing works. And they need the level of skill in order to provide the level of challenge. And that I think it is important [….]" (KI 7, UK).

''[….] And I think the, the other challenge is the general lack of AI awareness, knowledge and understanding [….]'' (KI 6, UK).

A few comments showed variance regarding location of respondents for example:

''The issue of lack of clinical experts who are knowledgeable or skilled in AI, so for instance, to build an AI solution, you actually need AI experts, you need also need clinical experts to bring in their inputs and sometimes they are very few, in cases of under-resourced communities like Nigeria, experts are very rare, and so how do you get people to contribute to the AI engineers to build the solutions that's a barrier [….]'' (KI 14, Nigeria).

''Another problem is lack of trained experts as well as lack of access to training and education in the country. Interested persons have to travel overseas to learn or take online courses [….]'' (KI 15, Nigeria).

Based on the recurrence of the challenges above, it is clear that most of the respondents agree that skills-related challenges affect healthcare AI adoption.

6.7.2. Data-related challenges

Data-related challenges were one of the most frequently mentioned challenges with about 25% of responses identifying them. The responses however differed regarding location of respondent. Respondents from Nigeria were mainly concerned about primary data infrastructure such as the lack of standard digital healthcare data collection and management systems.

Some comments from the respondents illustrate this:

''One of the major areas where we are also not doing well within this space is the use of data. Yes, while we have several data available to use, but most of these data are not mined [….]" (KI 8, Nigeria).

''Most of our healthcare systems are not designed to capture data [….]'' (KI 14, Nigeria).

''The data collection system in Nigeria is not standardized. I mean, it is mainly from individual hospitals, but we need like generalised data, and we need a lot of data for AI which is not available. And also concerning data the next issue is, most Nigerian hospitals still use handwritten records [….]"(KI 16, Nigeria).

‘’ [….] And, in fact, one of the sad parts of the healthcare industry in Nigeria is take for example, the Manual data say that existed over the years [….] we can see that we have like, maybe 40 50 60 years of healthcare data that is just going to go into oblivion like practically almost useless [….] (KI 19, Nigeria).

On the other hand, respondents from the UK generally mentioned secondary data infrastructure challenges, data culture and data/ algorithmic bias.

Yeah, the main challenge is data flows across an organisation [….] having lots of spreadsheets and having siloed, non-interpretable, non-API type systems means you can't get the data out and you can't even start to make sense of you can't do basic reporting. And we saw that in the COVID pandemic you know, it's very difficult for hospitals to even tell you how many people had died from COVID that day, that's how bad it is. And yet I can track my pizza [….]”(KI 1, UK).

‘’One of the most important things is clean data, good quality data. We've got big challenges there. Yes [….]’’ (KI 7, UK).

‘’I think one of the biggest challenges is, it's kind of like implementing a more data, kind of like ideology [….]’’ (KI 10, UK).

‘’So, for example, in skin cancer, we found that when they were training the AI technologies, they'll train it on Caucasians. So you got a black skin, the computer doesn't necessarily know skin and it is in that so you know, there's health disparities that it may open because if the coding is done by Caucasian, they may not bear in mind that ethnic minority [….]’’(KI 13, UK).

Considering the recurrence of the data challenges above, it is clear that most of the respondents agree that data-related challenges affect healthcare AI adoption.

6.7.3. Finance-related challenges

Finance-related challenges were the most frequently mentioned challenges with about 16% of responses identifying them. The responses however differed regarding location of respondent and the type of healthcare sector.

Majority of the UK respondents did not report cost as a barrier, more so in the public healthcare sector due to the possibility of government funding.

“In the public sector, I don't think for the UK funding should be a barrier, [….] there is funding available for all these things [….] “(KI 5, UK).

A few respondents however, reported finance as a challenge in the private healthcare sector:

“It is when private entities are adopting it that it becomes more expensive, because of course, robots are expensive [….]” (KI 5, UK).

One respondent argued that cost could be a solvable barrier in the UK context:

“Cost, a barrier [….] obviously a big thing but I think people are coming around to these funds like the one that government's doing, where the money helps bridge that [….] (KI 13, UK).

Another respondent highlighted the need for cost-effectiveness:

“With so much noise in the space at the moment, it can be difficult to choose a cost-effective and trustworthy implementation partner […..]’’(KI 3, UK).

In all cases, respondents from Nigeria highlighted finance-related challenge for AI adoption in the Nigerian context, comments include:

“[….] And I would also say cost to be honest, right? Cost is also one of the major roadblocks towards adoption of AI solutions, because no, they're not cheap, right? [….] But again, you also understand that the healthcare environment in Nigeria is really acutely underfunded. So there's a part where most of the hospital owners are paying from pocket as there is virtually no access or immediate access to funding [….]’’ (KI 8, Nigeria).

“[….] And also, the issue of high costs of implementing AI and the lack of healthcare funding in the country’’ (KI 15, Nigeria).

“The first thing is the cost in Nigeria [….] because some of these tools are quite expensive. We are not even talking of like the basic cost of running a team [….]’’(KI 18, Nigeria).

“[…] Cost is going to be a barrier so like I said we are still struggling with the basics. And part of that struggle is resources, funding. Businesses are not that buoyant to implement some of these things, even when they want to [….]’’ (KI 19, Nigeria).

6.7.4. Healthcare-related challenges

Healthcare-related challenges represented about 7% of responses to challenges. A few respondents highlighted issues specific to the UK healthcare sector.

Two respondents mentioned the slow rate of healthcare AI adoption:

‘’[….] NHS is like the tugboat to turn left, it takes so long, everything slow. Multiple managers, there's multiple, for example, our project just to get off the ground, I put out I had about 30 meetings now to meet with multiple different players, basically, just to get the thing off the ground, you want to be of it, you got to meet a governance, you've got to meet legal people, you've got to meet the clinical people. And it's just, there's so many

stakeholders, and sometimes it's so inefficient, it doesn't foster the AI kind of learning, basically. So that's one frustration. [....]"(KI 13, UK).

''[....] So, I think the adoption is going to be hampered by speed [....] So, it's very difficult to get all the elephants dancing in a healthcare setting so only where it is a unique solution to a unique problem. Like we can get a vaccine quickly for the pandemic, because, you know, otherwise, if we wait the normal length of time, there's a problem. So, we'll break the rules, we'll go quickly [....]'' (KI 4, UK).

One respondent was concerned about the conservative nature of healthcare:

''[....] I think risk tolerance and risk preparedness is another, so you know, perhaps being a bit too conservative in some instances [....]'' (KI 7, UK).

6.7.5. Infrastructure-related challenges

Infrastructure-related challenges were one of the least frequently mentioned challenges with about 4% of responses identifying them. The responses in this case, were limited to the Nigerian healthcare context.

Although respondents agreed on infrastructure related challenges, one respondent argued that this is not likely the case in the private healthcare sector:

''[....] Number one; infrastructure is a big issue in Nigeria, take for example lack of power. AI cannot be successfully implemented without that [....]" (KI 15, Nigeria).

''[....] I think infrastructure could be a challenge, [....] but most private hospital owners have long moved away from that. [....] I mean hospital owners that we have in Nigeria, they're really pulling their weight, to put all the infrastructure in place for themselves, they put the mains, they put the backup power supply they put the water, everything in place [....]''(KI 9, Nigeria).

6.7.6. Resistance-related challenges

Resistance-related challenges were the most frequently mentioned challenges with about 14% of responses mentioning them. The responses were consistent regarding respondent's location.

''If the clinicians don't want it, you've got a chance to sell your AI into a hospital system, but it will never get used. So, IBM Watson is a great example. We've got this fantastic thing. What is it? Well, you don't care. Do you know i don't care bring it. It's fantastic. It's got IBM written on it. Getting clinicians to adopt it is very, very challenging [....]'' (KI 4, UK).

And, I think one of the biggest challenges, which you know is resistance from physicians and medical professionals, who feel like AI is threatening their livelihoods or their *legitimacy, right, and their judgement [….] we found in like, like a random controlled trial type of environment, is that the physicians would then kind of backtrack on their diagnosis, because they didn't want it to be, you know, similar to the algorithm [….]''(KI 12, UK).*

''A third issue is that of resistance to adoption from older generation of healthcare professionals who have preference for the old way of doing things […..]''(KI 15, Nigeria).

''So, the first thing is people in general don't embrace change that much. Particularly if a system seems to be working, there's always the resistance to change it, particularly people in some fields of surgery because it takes decades and decades to learn your craft and to master it. So, the question is, why should you all of a sudden start to do things differently, if they're not been tried and tested [….]'' (KI 17, UK).

6.7.7. Technology-related challenges

Technology-related challenges were one of the least frequently mentioned challenges with about 11% of responses mentioning them. The responses appeared to vary regarding location of respondent and technology requirement.

One respondent from the UK mentioned the lack of secondary technology requirements:

''There is no off-the-shelf AI tool for many applications [….]'' (KI 3, UK).

Conversely a respondent from Nigeria reported the need for primary technology requirements:

''For the Nigerian healthcare sector, the challenges are the basic ones. The basic challenge is we are still trying to adopt computers into the healthcare industry. On a general scale we are still talking about getting all the hospitals to use automated system [….]'' (KI 19, Nigeria).

One respondent highlighted the lack of explainability and interpretability of AI:

'' [….] One of the things i keep seeing in this field is that although AI is a new technology which is very beneficial in healthcare, it is very difficult to explain or interpret. Right, it's just works. And that isn't going to work with the clinicians, how does it work? So that is one of the challenges, which I think is technical, because it's something that needs to be fixed by AI experts [….]"(KI 14, Nigeria).

Based on the recurrent focus of respondents on the subthemes above, it is clear that most of the respondents perceived that there are different types of challenges affecting healthcare AI adoption which need to be resolved to facilitate adoption.

6.8. Key Factors in Healthcare AI Adoption

Eight key factors for Healthcare AI adoption were identified from the analysis of the interviews with the Key informants (Healthcare managers, Healthcare professionals and Healthcare technologists). These are: Acceptance, Data, Finances, Management, Organisational priorities, Regulation and guidance, Skills, and Technology factors. The Figure 6.6 below shows the Key factors for AI adoption in healthcare as identified by respondents.

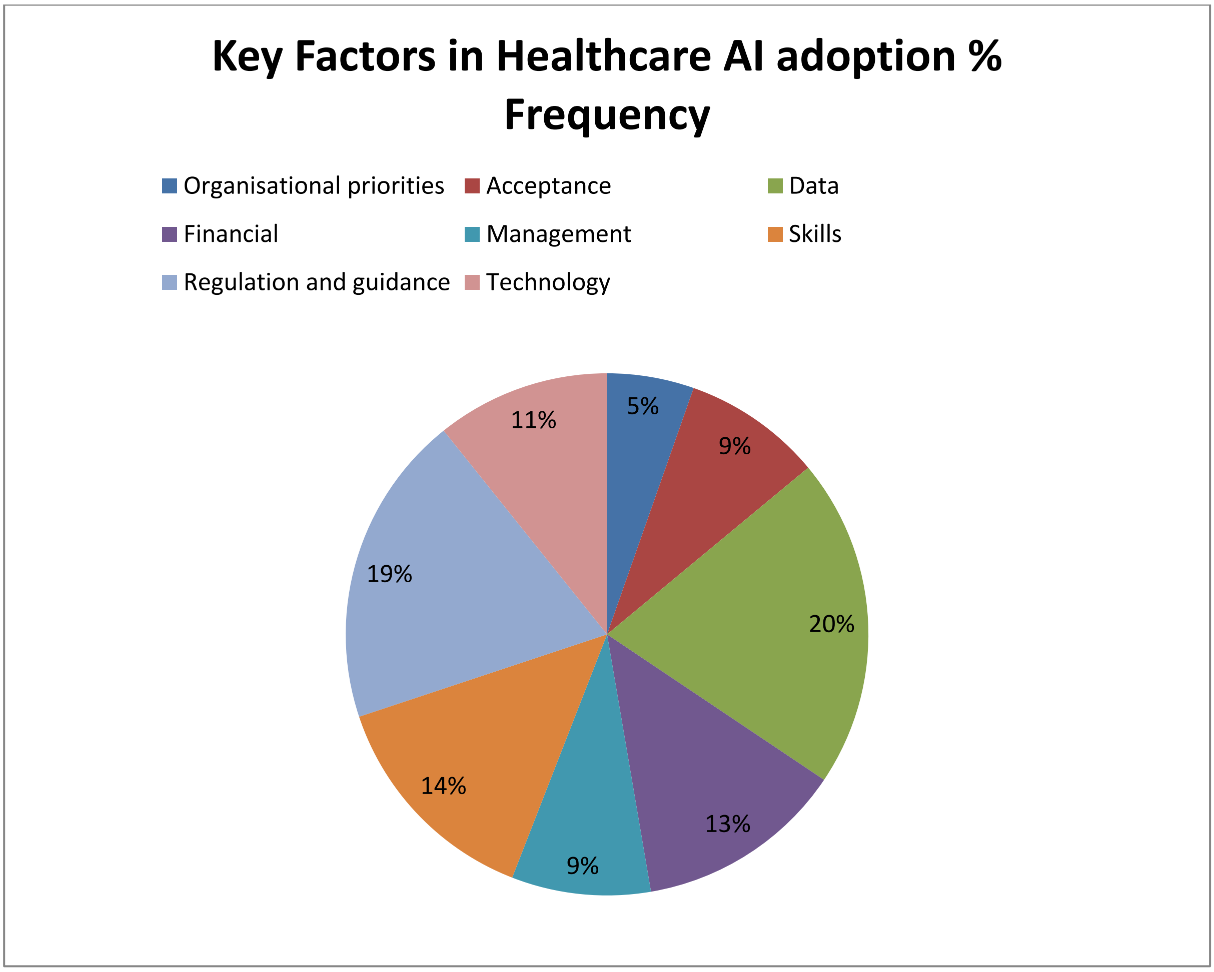


Figure 6.6: Key Factors in Healthcare AI adoption

Source: The Researcher

6.8.1. Organisational priorities

Some respondents (5% responses) recognized the importance of aligning AI with organisational goals, objectives, priorities, requirements. This factor was consistent across locations:

Generally, respondents agreed that it is important for healthcare organisations adopting AI to first identify their organisational, objectives, needs, problems:

> *'' [....] But then you need to identify given your business problems [....]" (KI 1, UK).*
>
> *''[....] So I think this, actually depends on which organisation is trying to adopt AI? What are their needs, what solution are they adopting? Right? [....]'' (KI 14, Nigeria).*
>
> *''[....] But I think there is also value in being able to put together a proper business case that justifies your objectives such as cost savings or patient outcome improvement [...] it's about being specific about what you are trying to implement, and the cost of implementation, but also the savings that will come about or increase in productivity [....]''(KI 17, UK].*

Some respondents furthermore argued that it was important to align AI with organisational challenges to ensure that AI is providing a solution:

> *''[....] Yeah, so I think there are two things here. So one is, does the AI product actually solve the challenge, there is a priority for that. Every hospital trust will have slightly different priorities and challenges [....]'' (KI 11, UK).*
>
> *''[....] Yeah, and then the last thing is, you know, the application itself, whether it's really solving a problem that [....]'' [KI 18, Nigeria].*

6.8.2. Acceptance factor

Some respondents (9% of responses) highlighted Acceptance as an important consideration across both locations:

> *'' [....] So, I think just, you know, if you are going to go there, then that you need a very long though out process with your workforce, so that they are part of and they are driving and owning that journey. It is really down to them [....]'' (KI 1, UK).*
>
> *'' [....] So, everybody has to agree, right? And then you have to get your buy-in, and then deploy the system, it's very important that you get the buy in of the end users otherwise you're putting the beautiful system out, there would be useless, right? [....] " (KI 8, Nigeria).*
>
> *'' [....] Work with your clinicians who are using the tool and you work it out and get their buy in, it will probably just go a bit smoother [....] '' (KI 10, UK).*

‘’ [….] Can they really, are they going to accept this, what will they need to accept this? [….]” (KI 18, Nigeria).

6.8.3. Financial factors

About 14% of responses highlighted funding as an important factor, this was consistent across locations:

‘’ [….] But also, you need to make sure that those things are available and that's hugely costly, right. If you think about epic, or Cerner, or putting in a massive transformation like that into hospital, you're in the multi millions, before you even start to see a return. And that's the real problem [….]’’(KI 1, UK).

‘’ [….] Then, of course, the third one is funding. It is really important to maintain it, sometimes …. needs internet to run, to have that to continue, adequate to sustain it. So, this is where you think about the sustainability of an idea [….]’’ (KI 18, Nigeria).

6.8.4. Data factors

Respondents (20%) reported data as an important factor, this was consistent across locations:

‘’ [….] You need data to train systems or to deploy. And to build these kinds of systems, if you don't have that engineering in place, and you don't have a longitudinal view of data of a patient, i.e., an electronic health record, then you cannot start this journey [….] the most important part of that equation is taking a step back and saying, is my data curated in a way that I can move forward? And if the answer is no, that's where you should stop, and you should focus on getting the data, right [….] You have to start from the data and getting the data flows, right. And for me, that's about having an electronic health record for a patient that's at least a year old, because you need normally a training set, you know [….]’’ (KI 1, UK).

‘’ [….] Data is one the most important factor as it is required to train models. Also specific to data is the need to get data the right type of data for the population you are working with. For instance, data trained on Caucasians may not be as effective if such models are deployed in African populations [….]” (KI 15, Nigeria).

‘’ [….] The kind of data you input depends on the kind of problem you're trying to solve. So, it's not just data. So, you have to have a question in mind. So, it could be graphics, certain simple things that saying, you know, your heights, your blood pressure, your blood glucose, your temperature. So literally from basic patient demographics one can put that in down to more complex things [….]” (KI 17, UK).

6.8.5. Technological factors

Generally, responses (11%) recognised the importance of technological factors, and this was consistent across locations, some of the responses showed that technology could be internal or external:

Some respondents cited external technologies:

> *" [….] You have to get it right, before you even think about these more advanced technologies. I think probably, then it's thinking about what cloud providers to use. So, if you're going to have a ready-made system, these systems take time to train [….] Are there already accelerators out there, like Microsoft is offering or Google or AWS that gets you 80% of the answer and then you need to train the system a little bit more [….]''(KI 1, UK).*

> *" [….] Yeah, so there are technological requirements when deploying or implementing an AI model. In the case of our AI, it has already been deployed and implemented on our server. But usually, an organisation may need to put the model on a local system like a computer because of the sensitive nature of healthcare data [….]'' (KI 15, Nigeria).*

A couple of respondents referred to Internal technologies:

> *" [….] Okay, at the barest minimum, usually what we do is the backbone of the entire application or entire solution must be very okay. And what do I mean by backbone? I'm referring to as simple as the network infrastructure, right? Because you're talking about AI, there must be the internet working right or network infrastructure in the different department in the barest minimum [….]''(KI 9, Nigeria).*

> *" [….] The very first will be the technological requirements such as the computers, systems CPUs, desks [….]'' (KI 16, Nigeria).*

A few respondents mentioned the need for integration:

> *"[….] So, I think that's another consideration is integration with the hospital systems [….]" (KI 1, UK).*

> *"[....] And we want to now integrate that into our normal processes. Within……., there are a couple of ways potentially to do it, integrating into our EPR system. So, in fact, the integration could be done directly into the system whereby the readout would come out as a field in epic. So in the front end, and in that way, it can be made very straightforward to be used as part of the clinical record and stuff [….]" (KI 2, UK).*

Some respondents reported patient safety as one of the most important technology factors since they relate directly to HCCs:

> *"[….] Safety considerations are very important; AI has a lot to offer anyone who needs care, but it must be implemented in a way that the net risk to an individual patient is*

reduced, not just when compared to a patient who would not have received care otherwise [….]" (KI 3, UK).

"[….] So yeah, a lot of things to be considered, but it has to be the patient safety, which has to come first [….]'' (KI 11, UK).

One respondent highlighted patient safety issues such as efficiency of AI and issues of safeguarding that may arise due to AI use especially in the early stages of AI adoption.

"[….] One has to be really clear that whatever you're implementing for healthcare, patient safety cannot be compromised. And it's that period of learning for the physicians that are using this can be detrimental to the patient. I feel that's sometimes that is where the balance lies [….] In terms of patient, or, you know, safety for individuals, I think, I think it gets more concerning when we're in the early intervention type mode, you know your tools going to miss something, are there safeguarding concerns that might be missed?'' (KI 7, UK).

6.8.6. Skills factor

Responses (14%) reflected skills as an important consideration:

" [….] Training and education for clinicians is very important. I'm a big believer, it is important to enable clinicians and other sector specialists to do the donkey work of AI without needing to be data scientists themselves necessarily so making it simpler [….]'' (KI 4, UK).

" [….] You have to train the staff for them to understand what it is and how to use it [….]'' (KI 6, UK).

" [….] As for education and training of clinician, no doctor is the same, some are very tech savvy and very effective with AI, some don't actually know what we're talking about. So, you got to bring everyone to the same level playing field to get user acceptance, because it's going to be the doctors who are going to be using these systems [….]'' (KI 13, UK).

" [….] Healthcare professionals should take AI courses. Also, AI should be incorporated into the curriculum, although there are AI technologies that can be used by healthcare professionals without the need for extensive training and knowledge [….]'' (KI 14, Nigeria).

" [….] There will have to be training of medical doctors on some of the basics of what is possible what how they can use this technology. This is not currently in the system though private doctors can have up to date courses to bring them up [….]'' (KI 16, Nigeria).

" [….] So, for robotic surgery, you have to be certified. Yeah, you have to be certified to use it, you have to be trained to use it [….]" (KI 17, UK).

"[….] In today's world, there are lots of Coursera materials that can be used to educate people in healthcare [….]'' (KI 18, Nigeria).

As we get that in place, the question now becomes, do we have the skill set? Do we have the expertise, do we have the people to manage these things and use these things. Because it's not just about throwing tools out there. AI does not work on its own. That's, the interesting thing about AI that nobody talks about. We forget that AI is not AI on its own. [....]" (KI 19, Nigeria).

A few respondents highlighted the need for healthcare professionals to have technical AI skills:

> *" [….] So, what I think is that there is a big educational piece missing, though, which is how, how do clinicians use or understand the outputs of these systems? And how do they work hand in glove with data scientists or with technologists because I think we wouldn't ask them to be an MRI engineer. They just have to understand what comes out of the MRI and go, actually, that high piece of signal looks like it could be cancerous [….]'' (KI 1, UK).*

> *" [….] And, for AI, I think it actually needs more education. Because even for one of the most common AI applications such as in radiology where we try to like examine x rays. I think it's actually very ideal for even clinicians to actually understand about data science and AI. And it's going to help them to actually know what's going on behind the hood, if not, necessarily to the technical level of AI expert engineers but at least certain areas, because ideally, most AI engineers also don't have some ground level of what goes on in the healthcare space for them to build a solution around it [….] (KI 14, Nigeria).*

Some respondents noted that older healthcare professionals required more AI training than younger ones:

> *"[….] So I think the thing around getting the nurses to adopt it was a real challenge. In general, we tend to employ older nurses who tend to be towards the end of their careers when they've had enough of the NHS, and they want to have an easier life. And therefore, at the moment, we're dealing with a generation of nurses that were trained and developed to do everything on paper, all which is super I've no issue with it. People think it will be the carers who are the ones that need the support with technology, their transitions, a breeze, compared with the nurses who don't use it in their personal life so much [….]'' (KI 6, UK).*

> *"[….] I know that you could see that you didn't even need to show young people they already knew how to do some of these things. It is almost like they are digital natives right, when you give them these things they just adjust. And the young people, you know, and middle-aged people are very excited about it [….] whereas the older HCP when they are taught, struggle to adjust, the intuitiveness is harder. The uptake is more with the younger people [….]" (KI 18, Nigeria).*

6.8.7. Regulation factor

All respondents considered the issue of regulation in all forms including, ethics and laws to be of key importance in the adoption of AI, however regulation and guidance appeared to vary with location and healthcare setting:

Respondents acknowledged the existence of AI regulation and guidance in the UK healthcare sector, and the need for more clarity regarding this:

> *"[….] I think it needs to be an ecosystem approach first of all [….] But, you know, I don't think AI should ever make any decisions about us. I think it's just like, stethoscopes and MRI systems don't they report, and then the human being, who is regulated? And they're very kind of clear regulations around them, as a professional person, actually make that diagnosis. So I think, I think that's a very important point around what should be done, I think there are very positive steps being made in this area. And we're seeing again, you know, organisations like NHS x, kind of think about having an AI lab, and what should people be thinking about, we've seen the FDA come out with guidance and regulations on digital health and AI, we've also seen nice guidelines. So I think, and the Turing Institute have brought out 20 questions or framework that you should ask as a clinician, very, very good, it's kind of if I would say the Bible to, to make sure that that you're looking at as a clinician, but you know, this is this is a large ecosystem of partners that that all need to kind of be around the digital table, and kind of really think about what needs to be considered? [….]''(KI 1, UK).*

> *"[….] So, talking about the legal, ethical and regulatory factor, there is a digital toolkit (Data security and protection toolkit) that you have to first complete since you are dealing with people's personal data. There is need to do a DPIA (Data protection Impact Assessment) as well to help identify and minimize the data protection risks of the project. Potentially, I mean, it depends on size of organisation risk, etc. But, certainly, they should be looking at doing that. We do want to err on the side of caution. GDPR, you need to make sure you're aligned with that obviously. We have a contract with the NHS, so we ensure that we're complying with the NHS requirements. Also, social care, we've got contracts for social care. So we needed to ensure that we will comply with those and then obviously and with the requirements under the CQC Reporting. So I think one of the first things is for them to complete the DSP to the digital toolkit, okay [….]'' (KI 6, UK).*

> *"[….] Also legal, ethical and regulatory factor are important, and I think the sector would make bigger progress, if it got more firm guidance from the department of health and social care, on application of AI, either in a healthcare setting or in a social care setting [….]'' (KI 7, UK).*

> *"[….] Another area to be considered is regulation. I think most of NHS hospitals have research and ethics boards that get involved in anything that actually affects patient care. And I guess, once again, it depends on how technology plans to interface with patients. If it's more from a research point of view, then they have to go through those loopholes. If it's more from a productivity side of things litigation I think will be looked into in future [….]''(KI 17, UK).*

Some respondents cited regulatory provisions within the Nigerian context they highlighted the need for clearer AI regulation in Nigeria:

> *"[….] Regulatory factors front and centre [….]" (KI 9, Nigeria)*
>
> *"[….] And then the legal, so I think the legal aspect actually does come behind anything being brought into healthcare, because the healthcare sector is heavily regulated. They have a lot of regulations which is very good. So i think, moving to this data, data centric software's and AI driven software there has not been enough regulation regarding data privacy, data governance, data ethics, as regards AI solution, but I think all other ethical factor are actually considered in healthcare but not being considered enough and they are very crucial when adopting AI solutions [….]'' (KI 14, Nigeria).*
>
> *"[….] Legal ethical or regulatory frameworks are important when implementing AI. I think experts should stay safe by following the Nigerian laws like to play safe by using guidelines as healthcare data is sensitive. It is recommended that in Nigeria there should be policies or guidelines, you know, to help that process for AI experts or developers to work with when adopting AI as there are no such policies or guidelines [….]'' (KI 15, Nigeria).*
>
> *"[….] They are important anywhere. In Nigeria there is an e-health policy that is been developed. And I am not sure the full policy has been signed into law, it is still being developed and fine-tuned and all that. But in terms of implementation, we're still looking up to that. But there is definitely some policies and guidance relating to the area [….]''(KI 19, Nigeria).*

6.8.8. Management factor

Some respondents recognised the importance of management, its functions, and the need for this to be delegated to a specific unit or department:

> *"[….] One of the questions I think is probably where does this live in the organisation? [….] And whose mandate, is it? So, if you just think about how a hospital is run, you've got your CEO, you often actually don't have a CTO or chief data officer, you know, actually, what is the digital strategy for the hospital [….] (KI 1, UK).*
>
> *"[….] A good approach will be to have a department within which AI is managed by specific people such as experts who identify use cases and manage the process of adoption rather than just having it in the workflow. In Nigeria however in a lot of adoptions members of the team who are interested and open minded can manage the adoption process [….]'' (KI 15, Nigeria).*
>
> *"[….] And in terms of management of change, of course, we have people whose job in hospitals is transformation; implementers, change leads that's what they do. They manage change, they manage transformation. I think it's always better for those people to have some sorts of clinical orientation, and not just the managerial orientation, because that makes a better working relationship [….]'' (KI 17, UK).*

One respondent argued the location of AI management within a specific unit or department:

"[….] Anything that creates fiefdoms I don't think will support adoption, AI should be embraced and adopted across an organisation because it drives performance and better clinical outcomes. And it shouldn't be tasked to a department or a unit. People, I guess you should create organised systems where there's a level of data and literacy and understanding around what AI is, and its utility and its applicability in each setting [….]" (KI 12, UK).

Based on responses above, it is clear that respondents identify the following factors as key for healthcare AI adoption: Acceptance, Data, Finances, Management, Organisational, Regulation and guidance, Skills and Technology factors.

6.8.9. Perceived usefulness and perceived ease of use

Most of the respondents, over 50% agreed that they are more likely to adopt AI if they perceived it as useful and easy to use. They felt that if it helps their practice, the learning curve is short, and if the safety of the AI for the HCC is not compromised, then they would be willing to adopt.

Respondents felt that perceived ease of use and perceived usefulness predict adoption of as will be more likely adopted if it reduces the learning curve and workload of healthcare professionals:

"[….] So based on my experience with some clinicians, and one of the things I get to realise is that they need the evidence that it works. And also, the evidence it is easy to use and they don't have to go through another learning curve. And as long as that happens, I mean, I think they stand to benefit, because they focus, more on patients and more technical stuff'' (KI 14, Nigeria).

"[….] They will also find it easier to accept the technology if they see it as useful and easy to use. This is because HCPs may be unwilling to add to the high workload that they already have if AI is viewed as complicated (KI 15, Nigeria).

One respondent was concerned about compromising safety for ease of use:

"*[….] Perceived usefulness and perceived ease of can be considered. Like, if Apple ran a hospital and made computers and software systems, everyone would be happy because Apple products are easy to use. They're not clunky, you don't have to log in here and do their intuitive. So, absolutely it will be easier for clinicians to accept. But then the balance is if it's easy to use, how secure is that basically. So, you have to have that balance. And obviously, we've got personally identifiable information. So it's always about usability versus security is a challenge " (KI 13, UK).*

6.9. Conclusion

This Chapter has put forward the results of thematic analysis of Key informant interviews. These have been characterised and illustrated using descriptive statistics based on counts, frequencies, and percentages (See appendix 1 for tables from thematic analysis of qualitative data). It is clear from the responses that respondents consider that AI has potential impact on all four perspectives of healthcare performance: financial, customer, internal business, Innovation and Learning performance. This potential impact is exerted through the subthemes that have been reported for each theme. Based on the recurrent focus of respondents on the subthemes above, most of the respondents perceived several challenges affecting healthcare AI adoption which need to be resolved to facilitate adoption.

7. CHAPTER 7: DISCUSSION

7.1. Introduction

This Chapter validates the links between this Research, academic research, and practice in the context of the healthcare sector. The aim of this Research is to investigate the impact of Artificial Intelligence (AI) on Organisational Performance (OP) in the Healthcare sector with evidence from Nigeria and the UK and to develop a framework for the adoption of AI for OP in the Healthcare sector supported by implementation guidance. The Nigerian and the UK health sectors were selected to mirror resource-constrained ad resource-sufficient healthcare settings respectively. This Research combines evidence from academic literature, healthcare sector literature and evidence from this Research and its findings. Key themes and the corresponding subthemes within the healthcare performance field are discussed in line with pertinent literature. Hereafter, the key factors for healthcare AI adoption and challenges in healthcare AI adoption are discussed in line with relevant research. Next the revised framework and its testing are discussed, practical guidelines for effective implementation of the framework are provided, followed by strengths and weaknesses of the framework. And lastly the Chapter is concluded.

Technology acceptance theory has been cited by several researchers as important in understanding the acceptance, adoption, and use of technology in healthcare as well as in other fields (Brock and Khan, 2017; Dwivedi *et al.,* 2017; Hong, Thong, and Tam, 2017; Lim, Lim and Phang, 2019). Several researchers in healthcare have also highlighted the significance of these theories in understanding the factors that affect adoption and use of technology in healthcare (Gucin and Berk, 2015; Beldad and Hergner, 2017; Nguyen *et al*, 2020). The TAM has been used to explain the acceptance and use of technology in healthcare on the premise of two factors; perceived ease of use and perceived usefulness identified as important predictors (Li *et al.*, 2019). Therefore, tying upon the existing Technology acceptance theory and the Technology acceptance model, (David, 1989; Davis, Bagozzi and Warshaw, 1989), the themes identified in this Research can be understood as a reflection of healthcare professional's perception of AI in healthcare (Macdonald, Perrin and Kingsley, 2017).

as easy to use and useful. While PEU is the degree of effortlessness an individual expects to have when using a specific technology, PU is the degree to which an individual believes that his or her job will be enhanced by using a specific technology (Diop *et al.,* 2019).

Healthcare organisations will take the first step in technology adoption; however, the success of technology adoption is critically reliant upon adoption by the end users which are the healthcare professionals (Hostgaard *et al.*, 2017; Ruiz-Morilla *et al.*, 2017). It is therefore necessary to understand healthcare professional's perception of technology application in healthcare (Macdonald, Perrin and Kingsley, 2017). Healthcare professionals in this Research have therefore identified based on their perceptions; the impacts of AI application and adoption and in healthcare, the challenges encountered in adoption as well as the factors considered as important. These findings are expected to support the adoption of AI by healthcare organisations and end users.

Six themes arose from the interviews with Key informants (KIs) which have been presented in the results section in Chapter 6 and summarised below. The results of this research demonstrate that:

1. AI potentially improves healthcare financial performance through improved cost efficiency, improved cost savings, improved financial profit and revenue generation.
2. AI potentially improves HCC performance through Improved healthcare customer (HCC) satisfaction, Improved healthcare quality, Improved access to healthcare, Improved HCC engagement, Improved health outcomes, Improved patient safety.
3. AI potentially improves Internal business performance in healthcare through Decreased disease burden, Decreased workforce crisis, Decreased workload, Decreased wastage of resources, Improved efficiency, Improved productivity.
4. AI potentially improves Innovation and Learning performance in healthcare through Improved learning, Improved Innovation, Improved processes, Improved research, and development.
5. There are key factors required for AI in healthcare adoption these are Acceptance, Data, Finances, Management, Organisational priorities, Regulation, Skills, and Technology factors.
6. There are challenges in healthcare AI adoption these are Data-related challenges, Finance-related challenges, Healthcare specific challenges, Infrastructure-related

challenges, Resistance-related challenges, Technology-related challenges, Skills-related challenges.

7.2. Potential improved healthcare financial performance (PIHFP)

PIHFP refers to the capacity of AI to potentially improve healthcare financial performance. Based on the results of this study, AI potentially improves financial performance in healthcare through, cost efficiency, cost savings, financial profit, and revenue generation.

7.2.1. Improved cost efficiency

Cost efficiency from the healthcare perspective, has to do with producing higher healthcare outputs for a given set of inputs or at a given cost (Devaraj *et al.,* 2013; Jiang and Wu, 2020). Based on respondents' responses it appears that AI reduces human resource requirement which will lead to a decrease in associated cost for acquiring human resources and ultimately resulting in cost efficiency. According to healthcare literature, cost efficiency supports the improvement of care and at the same time reduces costs which is one of the 'quadruple aims' for healthcare (Phipps, 2019). This implies that AI can potentially improve cost efficiency by using the same quantity of allocated resources or less to achieve more results, this impact of AI is potential in the sense that it is attainable in the future and may not be immediately measurable.

7.2.2. Improved cost savings

Based on evidence from responses It appears that AI results in improved cost savings by decreasing costs from medical tests, treatments and procedures, hospital consumables, ambulance service, human resources costs, reduced treatment costs and other associated healthcare costs. Improved cost savings has also been identified in the literature as an impact of AI on financial performance in healthcare (Ashfaq *et al.*, 2019; Lee *et al.,* 2021). It can therefore be implied that AI improves healthcare financial performance, and this impact is exerted through Cost savings. However, the impact of cost savings appears to be potential rather than immediate owing to the reportedly slow speed of AI adoption in healthcare. It appears that cost savings is a predictor of financial profits as it is reported to occur before financial profits in many cases.

7.2.3. Improved financial profit.

Evidence from the research shows that AI can result in financial positives through net positive finances, increased profits, and improved Return on Investment (ROI). Financial profit is thought to occur mainly due to savings from decreased human resources costs, improved efficiency, and therefore decreased healthcare consumables and other associated costs. AI has been applied to healthcare revenue management cycle to improve the efficiency of the revenue management process with a positive impact on cost savings translating to financial profits (Pounds, 2021). It can therefore be implied that AI has a potential impact on healthcare financial performance through improved financial profit.

7.2.4. Revenue generation

According to evidence from respondents AI can result in revenue generation by providing additional sources of revenue for healthcare organisations through potential research opportunities, data marketing services and development of healthcare apps to meet the needs of HCCs. Revenue generation has been cited in literature as an impact of AI on healthcare financial performance; a study by Ilan, (2021) on the reduction of costs using AI-based digital pills reported that savings from applying the digital pill may result in increased sales revenue for healthcare organisations (Ilan, 2021). It can therefore be implied that AI has a potential impact on healthcare financial performance through revenue generation. The results for this theme and reports from literature imply that AI potentially improves healthcare financial performance.

In line with the results of this Research, Lee *et al.,* (2018) applied ML algorithms to estimation of the cost savings of preventive dental services delivered to children enrolled on Medicaid based on use of topical fluoride and dental sealants in six South-eastern American states. AI successfully estimated lower expenditure for children who received topical fluoride and dental sealants before caries development than for all other children, with significant difference in cost (Lee *et al.,* 2018). The study demonstrates how AI can be applied to healthcare cost-savings and improved healthcare financial performance. Another study by Golas *et al.,* (2018) applied a 30-day readmission risk prediction model using deep unified networks (DUNs) to patients of heart failure discharged from a hospital admission. To help identify those patients that could benefit the most from disease management programs in to decrease hospital admissions as well as healthcare cost. AI resulted in the highest cost savings for the hospital. Their study demonstrates that AI can potentially impact cost savings and therefore healthcare financial performance (Golas *et al.,* 2018). The results of these studies support the results of this research that AI has a potential impact on healthcare financial performance.

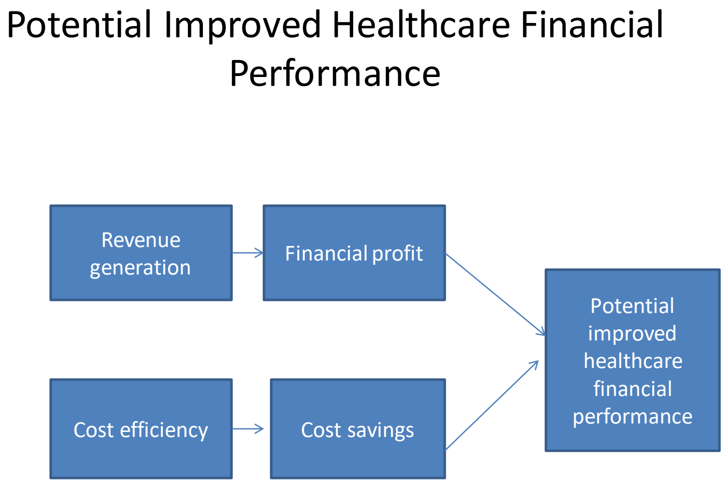


Figure 7.1: Potential Improved healthcare financial performance (PIHFP)

Source: The Researcher

The Figure 7.1 above illustrates the link between the four themes of Potential improved healthcare financial performance. Revenue generation is linked to financial profit, with revenue generation acting as a predictor and they both impact PIHFP, while cost efficiency is linked to cost savings, also acting as a predictor with both impacting PIHFP.

7.3. Potential Improved Healthcare Customer (HCC) performance (PIHCCP)

PIHCCP is demonstrated by the capacity of AI to potentially improve customer performance in healthcare customers (HCC) who are the end receivers of healthcare, and this term is synonymous to patients and service users for the purpose of this research).

7.3.1. Improved HCC satisfaction

Responses from the interviews show that AI has potential to improve HCC satisfaction. HCC may be satisfied based on the healthcare experience they pass through. If they have a good experience such as quality of care or a good health outcome, their level of satisfaction may increase. Improved quality of care is reported to precede HCC satisfaction and appears to also be a predictor of HCC satisfaction. While HCC experience may precede HCC satisfaction and therefore act as a predictor of HCC satisfaction, HCC experience may also precede HCC dissatisfaction in problematic situations. AI has been cited in literature as having an impact on improved HCC satisfaction (Lam *et al.,* 2021), and this implies that AI can potentially improve HCC satisfaction.

7.3.2. Improved healthcare quality

According to responses from the interviews, AI can improve healthcare quality. AI enables healthcare professionals to deliver higher quality and more value-added care to HCCs by focusing on more complex healthcare issues through the application of AI to certain processes e.g., En-masse first pass triage, administrative healthcare issues and other less complex issues. When there is improved healthcare quality the healthcare outcomes can be expected to improve, this is illustrated in figure 7.2 below. AI has been cited as improving the quality of care and improving efficiency in the healthcare sector (Lee and Yoon, 2021). Based on this and the results from qualitative research it can be implied that AI potentially improves healthcare quality through efficiency of healthcare processes.

7.3.3. Improved access to healthcare

Based on evidence from the interview responses, AI can potentially impact on HCC performance through improved access to healthcare by reducing waiting times, and improving access to specialists in such as psychologists, psychiatrists, cardio-thoracic surgeons, and

Nephrologists. Improved access to healthcare can predict improvement in health outcomes because earlier diagnosis, treatment translates to higher chances of recovery and therefore improved health outcomes this is illustrated in figure 7.2. AI has been applied to improving access to healthcare more in remote and resource constrained settings (like Nigeria); Qin *et al.*, (2019) conducted a retrospective inspection of three Deep learning DL systems (CAD4TB, Lunit INSIGHT, and qXR) for the detection of tuberculosis-related abnormalities on chest radiographs from outpatients in Nepal and Cameroon (resource-constrained settings). AI successfully interpreted the chest radiographies and triaged people for pulmonary tuberculosis in a resource constrained setting. This research demonstrates that AI can be applied to reduce disease burden in resource constrained settings thereby improving access to healthcare for healthcare customers in human resources constrained settings (Qin *et al.*, 2019).

7.3.4. Improved HCC engagement

The interview responses showed that Al has potential impact on HCC engagement. AI improves healthcare engagement between healthcare professionals and healthcare customers by releasing time for healthcare professionals to focus more on HCCs, thereby improving the human component of care. Healthcare engagement may enable improved communication with HCCs, such as knowledge of information about the use of technology to their health and how they can be involved in decision making in their health, leading to their empowerment. HCC engagement was not identified as a subtheme of HCC performance in the Nigerian healthcare sector, and this may imply a need for improved engagement in this sector. There is need for patient engagement, communication, education, and involvement in decision making in the Nigerian healthcare sector has been highlighted in the literature (Lawal *et al.,* 2021). HCC engagement may predict HCC satisfaction because when HCCs are more engaged, they will be more informed, more involved in decision making, more empowered and therefore more satisfied, this is illustrated in figure 7.2 below. AI is thought to improve HCC engagement through easier access to care, risk reduction and the sharing of personal information which in turn boosts healthcare customer confidence (Kumar *et al.,* 2021). It can therefore be implied therefore that AI potentially improves HCC engagement.

Some respondents noted the importance of communication and engagement in ensuring that HCCs understand how decisions about their health is made using AI as this will facilitate their understanding of the impacts of AI.

7.3.5. Improved Health outcomes

Responses showed that AI can improve health outcomes for HCCs. AI can potentially decrease morbidity and mortality through earlier, faster, and more accurate diagnosis of acute diseases e.g., in acute kidney disease, hospital acquired pneumonia, and acute infections such as cancer. In line with the results of this research, Phakhounthong *et al.,* (2018) successfully applied machine learning algorithms to quantify the risk of dengue fever severity from the administrative datasets of a large tertiary care hospital in Thailand (Phakhounthong *et al.,* 2018). This demonstrates that AI can potentially improve health outcomes and therefore HCC performance.

7.3.6. Improved Healthcare Customer (HCC) safety

The safety of HCCs involves prevention, and mitigation of adverse events resulting from the process of delivering healthcare (Vincent, 2012). Responses showed that AI can improve HCC safety. Improved HCC safety can be achieved through avoidance of harm to HCC and using AI to reduce medication errors, to make faster and accurate diagnosis, to monitor infection, and to monitor patient's health for progress or decline. The safety of healthcare customers has been cited as an important element of OP in the healthcare sector (Welp, Meier, and Manser, 2015).

The results of this theme demonstrate that AI has potential impact on HCC performance through improved HCC safety. This is in line with the results of the research by Uzir *et al.,* (2020) which applied an Artificial Intelligence system named AIoT-based Domestic Care Service Matching System (AIDCS), to an existing electronic health (eHealth) system to enhance elderly-oriented domestic care services. The study reported observation of key performance indicators after AIDCS implementation improved customer satisfaction and the quality of the service delivery (Uzir *et al.*, 2020).

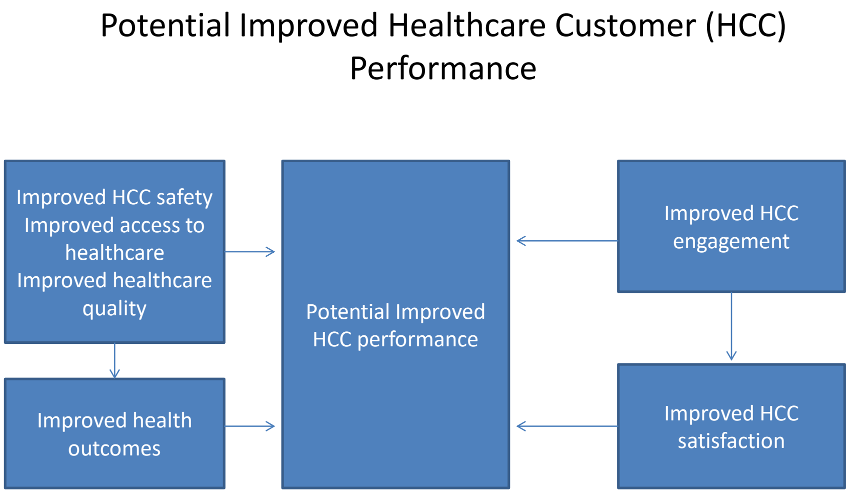


Figure 7.2: Potential Improved HCC performance (PIHCCP)

Source: The Researcher

The Figure 7.2 above illustrates the link between the six themes of Potential improved HCC performance. Improved HCC safety, Improved access to healthcare, Improved healthcare quality are all linked to improved health outcomes, with all four impacting PIHCCP. Improved HCC engagement is linked to improved HCC satisfaction and they both impact PIHCCP.

7.4. Potential Improved Healthcare Internal Business Performance (PIHIBP)

PIHIBP is the capacity of AI to potentially improve Healthcare internal business performance. AI impacts the internal business performance through Decreased disease burden, Decreased workforce crisis, Decreased workload, Decreased wastage of resources, Improved efficiency, Improved productivity

7.4.1. Decreased disease burden.

Responses from the interviews show that AI can decrease the burden of disease through earlier and accurate diagnosis of disease, thereby preventing the disease from progressing to later stages that will require more resources to be managed. Prevention of disease can lead to decreased healthcare costs and improved health outcomes at both the individual and population health levels. This result resonates with literature; the potential impact of AI on decreasing disease burden and preventive healthcare has been reported (Jiang *et al.*, 2017; Sunarti *et al.*, 2021). Liang *et al.,* (2019), applied an automated natural language processing system with deep learning techniques for the extraction of clinically relevant information from EHRs. The model showed a high level of accuracy, comparable to paediatricians in the diagnosis of common childhood diseases in a resource -constrained setting. The research demonstrates that AI can support physicians in accurately diagnosis, reduction of healthcare costs and decreasing disease burden in areas with inadequate healthcare infrastructure e.g., healthcare resource -constrained settings (Liang *et al.,* 2019).

7.4.2. Decreased workforce crisis.

Based on the interview responses, AI potentially decreases healthcare workforce crisis. AI can reduce the workforce crisis by supporting with healthcare processes such as administrative tasks, manual tasks, decision support, disease diagnosis, and thereby reducing the workload and stress on healthcare professionals, making them available to focus on other tasks that require human input. AI is thought to be able to provide significant support all through the healthcare process from diagnosis to treatment making the work of healthcare professionals easier. The healthcare workforce shortage continues to be a global problem and more so in resource-constrained settings such as in Nigeria and Africa where there is a short fall of approximately one million health workers (Oguntimilehin and Ademola, 2014). This has negative effects on quality of care such as increased length of hospital stay, increased patient morbidity, poor professional knowledge, lower quality of services and on health outcomes for patients in the areas of; mismanagement of patients due to missing, incomplete, inaccurate, or illegible documentation (Shihundla, Lebese and Maputle, 2016) increased adverse effects, mortality, and medical errors (Perez-Francisco *et al.,* 2020). AI can supplement the overburdened health workforce by supporting with certain processes thereby decreasing the workload of healthcare professionals and decreasing workforce crisis. This view is also supported by literature AI can be applied to administrative tasks, image analysis, medical automation and patient monitoring thereby decreasing workload and the healthcare workforce crisis (Meskó, Hetényi and Győrffy, 2018; Bohr and Memarzadeh, 2020). This demonstrates that AI can potentially decrease the healthcare workforce crisis and improve internal business performance.

7.4.3. Decreased workload

Based on the interview responses, AI impacts internal business performance by decreasing workload, reducing the time and energy spent by healthcare professionals in the process of diagnosis. AI can point healthcare professionals in the right direction thereby reducing the workload and the time spent. In certain healthcare fields e.g., Ophthalmology AI can be used as a second reader when reading diagnostic scans before the ophthalmologist interprets them, thereby decreasing workload. AI can be used in processes like triage, administrative tasks to reduce the workload on healthcare professionals. This view is also supported by literature AI; can be applied to administrative tasks, image analysis, medical automation and patient monitoring thereby decreasing workload and the healthcare workforce crisis (Meskó, Hetényi and Győrffy, 2018; Bohr and Memarzadeh, 2020).

7.4.4. Decreased wastage of resources

Interview responses showed that AI can decrease wastage of resources by reducing the time spent by healthcare professionals on administrative tasks, mundane workflows, thereby freeing up time for them to focus on more complex healthcare issues. Therefore, there is decreased wastage of the resources of human resource, and time. This view is supported by the literature; AI reduces the process and time in diagnosis through medical ultrasound imaging; usually the qualified clinician uses manual methods to collect and visualize images, then evaluates them to detect, identify and monitor the disease. Contrastingly, AI technologies such as Machine learning (ML) and Deep learning (DL) automatically identify patterns based on complexity and quantitatively assess them for imaging data thereby assisting the physician to achieve results of higher accuracy and reproducibility (Shen *et al.,* 2021). This demonstrates that AI can impact healthcare internal business performance by decreasing wastage of human resources.

7.4.5. Improved efficiency

AI impacts internal business performance by improved efficiency in different ways such as time efficiency, process, or operational efficiency. Some tasks can be assigned to less qualified professionals, whereby the time saved can be used by more qualified professionals to focus on more complex or pressing issues e.g., during the peak periods of Covid-19 pandemic. Improved process and operational efficiency through more precise, faster, and accurate healthcare processes such as improved diagnostic procedures, surgical procedures, smarter communication resulting in remote consultations. AI technologies have the capacity to improve diagnostic accuracy, reduce medical errors and ultimately improve treatment outcomes in certain fields of healthcare such as in medical imaging and diagnostics. AI was applied to timing prediction for weaning mechanical ventilation in ICU. AI successfully reduced the average time of ventilator use by about 22 hours while maintaining medical quality (Liu *et al.*, 2021), this research demonstrates that AI can improve healthcare efficiency.

7.4.6. Improved productivity

From the analysis of interview data, it can be implied that AI can potentially improve productivity. AI potentially impacts internal business performance through improved productivity. Healthcare professionals have some of their manual processes removed e.g., radiologists do not need to manually examine scans, there is automation of some of the mundane workflows of healthcare professionals, remote consultations and overall faster decision making in healthcare driven by efficiency. Where Improved efficiency precedes improved productivity and is acting as its predictor. AI has been cited as improving healthcare productivity. The literature has highlighted the use of AI to decrease the time spent on certain repetitive processes thereby making the faster and more efficient and enabling clinicians to focus more on patients and their needs. In nursing for instance, AI is reported to result in about 30 to 50% increase in productivity (McKinsey Global institute, 2017), this demonstrates that AI can potentially impact healthcare internal business performance through productivity.

Consistent with the results of this research and this theme, Hirasawa *et al., (*2018) applied AI-based computer-aided diagnosis (CAD) systems to detecting and characterizing digestive region polyps, cancers, and inflammation, with reports of higher accuracy (Hirasawa *et al.,* 2018). This demonstrates that AI can decrease the workload of endoscopists and improve diagnostic accuracy, and therefore efficiency and healthcare internal business performance. Similarly, Yamamoto *et al.*, (2020) in their study successfully applied DL (deep learning) to diagnosis of osteoporosis with high accuracy. The results of these studies support those of this research by demonstrating that AI impacts healthcare internal business performance. A real-world example of the application, adoption, and implementation of AI to improve efficiency in healthcare and therefore internal business performance is the Moorfield's eye hospital

London's application of AI to accurate referral decision making for over 50 eye diseases with accuracy matching human experts and greater speed (NHS, 2020).

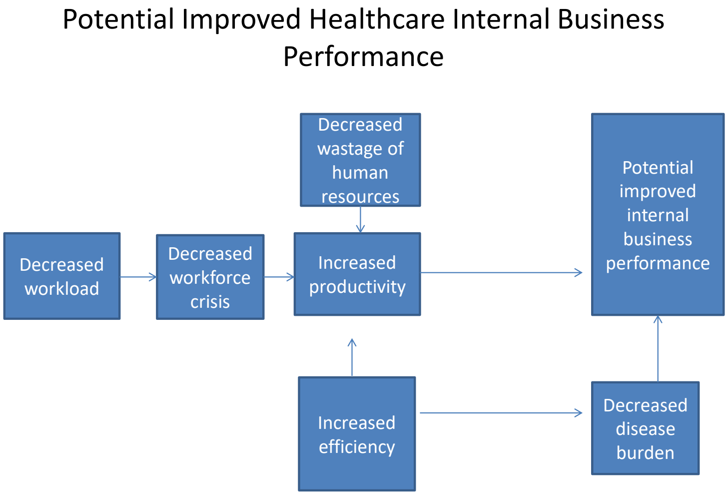


Figure 7.3: Potential Improved healthcare internal business performance (PIHCBP)

Source: The Researcher

The Figure 7.3 above illustrates the link between the six themes of PIHCBP. It appears that decreased workload is linked to decreased workforce crisis, increased productivity, decreased disease burden and ultimately potential improved business performance.

7.5. Potential Improved Innovation and Learning Performance

7.5.1. Improved learning

Responses from interviews show that AI appears to improve learning in healthcare. Healthcare professionals undergo AI specific training when adopting AI which improves their own learning and personal development and that of the organisation as the training is applied to their practice. The advent of AI has encouraged evidence-based self-learning in healthcare professionals and new ways of examinations and assessments. This appears to reduce the learning curve for healthcare professionals such as doctors by exposing them to AI tools and preparing them for the current disruption of AI in healthcare. Therefore, AI potentially improves healthcare learning and Innovation and Learning performance. This result is also consistent with reports in the literature (Paranjape *et al*, 2019; Sousa *et al.*, 2021). The results of the qualitative research however reveal that in the public health service (NHS), Learning may not be as well disseminated due to lack of information sharing on AI adoption.

7.5.2. Improved Innovation

Responses from interviews reflect that AI impacts healthcare learning and performance through improved innovation. AI has resulted in innovation in healthcare fields such as pharmaceuticals e.g., detection of fake drugs, innovative applications in medicine such as disease diagnosis and may help drive innovative medical teaching e.g., through virtual reality. The potential impact of AI on healthcare innovation has attracted interest from researchers, physicians, technologists, and other stakeholders (Lee and Yoon, 2021). A study by Miyashita and Brady, (2019) reported that AI in the form of Wi-Fi-enabled armbands remotely monitoring in real time, vital signs such as respiratory rate, oxygen level, pulse, blood pressure and body temperature Southeast England residents, significantly reduced readmission rates and visits to emergency and expensive home visits (Miyashita and Brady, 2019). The result implies that AI potentially improves innovation and Innovation and Learning performance.

7.5.3. Improved Processes

The interview responses show that AI appears to improve healthcare processes. This is thought to be by improving the accuracy of diagnostic processes, decision making, medical reporting and other healthcare processes. AI therefore potentially improves processes in healthcare and Innovation and Learning performance. Improvement of healthcare processes by AI have been cited in the literature such as in the application of machine learning and signal processing to identification of tuberculosis from digital chest radiographs (Lopes and Valiati, 2017).

7.5.4. Improved Research and Development

Evidence from the Research respondents show that AI appears to improve research and development in areas such as vaccine development during the wake of Covid-19 pandemic, infection monitoring and control etc. and the testing of new ideas and technologies in healthcare. For the case of Nigeria, there abound opportunities for AI to impact research and development through clinical research, but this opportunity appears not to be actualised due to lack of data and appropriate data infrastructure. Data from clinical examinations is being used by start-ups and other AI companies to support accurate diagnosis and proper treatment of healthcare customers, thereby improving research and development in healthcare. The application of AI to healthcare research and development is resonated in the literature; AI technologies learn and diagnose from medical research and patient's treatment records to support healthcare professionals in decision making for diagnosis and treatment of disease (Lee and Yoon, 2021). A study by Esteva *et al.,* (2017) reported that AI can diagnose skin cancer more accurately than a professional dermatologist (Esteva *et al,* 2017).

Consistent with the findings of this research that AI potentially impacts healthcare Innovation and Learning performance. Ambagtsheer *et al.,* (2020) applied AI to algorithms in accurate identification of frailty among Australian residents aged above the age of 75 years. They compared this to an electronic Frailty Index (eFI) developed from administrative data on residential aged care. AI accurately identified frailty in the residents with accuracy of approximately 75 % (Ambagteesher *et al.,* 2020). This research demonstrates that AI can be potentially applied towards identifying frailty which is a new area under study in healthcare. Similarly, another study by Jiang *et al*, (2018) investigated disease outbreak prediction and surveillance using remote sensing data and ML algorithms to successfully predict the global transmission patterns of Zika virus (Jiang *et al.,* 2018). These studies imply innovative application of AI to improve the Innovation and Learning perspective of healthcare performance.

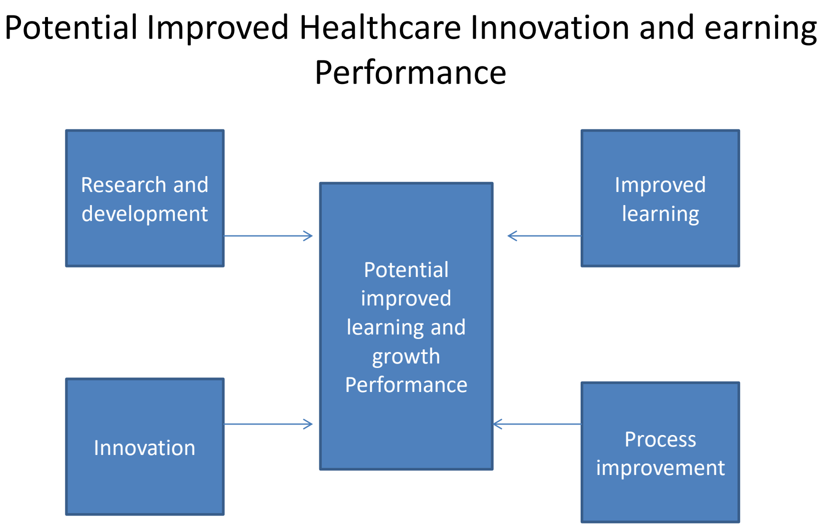


Figure 7.4: Potential Improved healthcare Innovation and learning performance (PIHILP)

Source: The Researcher

The Figure 7.4 above illustrates the link between the four themes of Potential improved healthcare Innovation and Learning performance. All four themes are directly linked to PIHILP.

7.6. Challenges in Healthcare AI Adoption

The following eight challenges were identified for AI adoption in healthcare: Data-related challenges, Finance-related challenges, Healthcare specific challenges, Infrastructure-related challenges, Resistance-related challenges, Technology-related challenges, Skills-related challenges. The Figure 7.5 below illustrates the types of challenges respondents identified as affecting healthcare AI adoption.

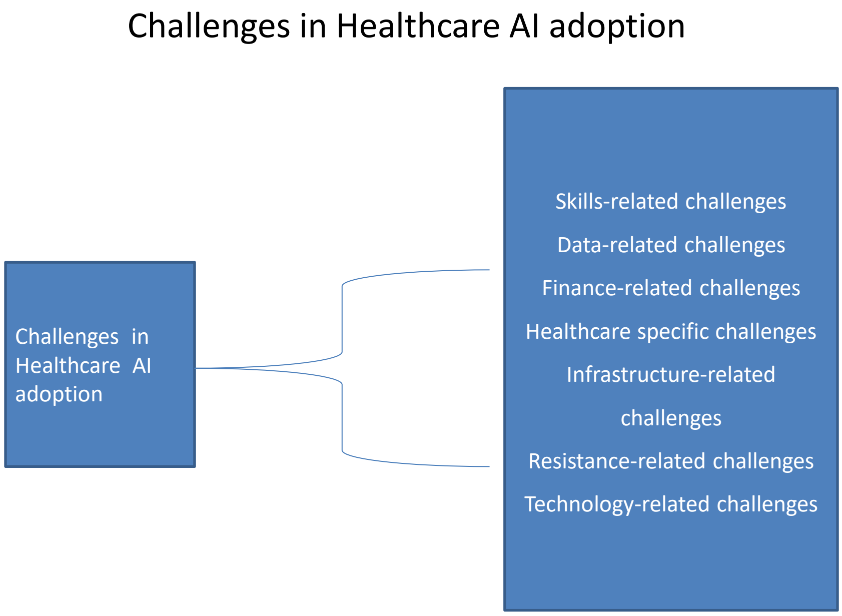


Figure 7.5: The Typology of Challenges of healthcare AI adoption

Source: The Researcher

7.6.1. Data-related challenges

The data challenges appeared to vary based on location, with respondents from Nigeria highlighting more primary-related data infrastructure challenges such as: Lack of processed, curated or mined data, lack of digital data, with most healthcare data available in the form of hand written paper records, lack of data collection and management systems for collection, storing and management of data, lack of a centralised data collection system, issues of data sharing where HCCs are not willing to share their data for research purposes due to concerns with the data management system or sometimes due to being conservative about their healthcare issues; therefore negatively affecting research and development in healthcare. Other researchers have mentioned data and related challenges in Nigeria (Owoyemi *et al.*, 2020) and other resource-constrained settings; organisational structure, lack of resources and infrastructure, low level of literacy, lack of understanding of the need of research (Steinmetz and Tijdens, 2015; Potnis; 2020).

Some UK respondents mentioned the implications of in-actionable data such as; non-real time data, data not collected for the right purpose, data that cannot be interpreted, reported or applied e.g. data from spread-sheets, siloed, non-interpretable data from non API (application programming interphase) which may have negative effects such as not having actionable data to work with in regular and even critical situations e.g. in the Covid-19 pandemic. Other UK respondents mentioned data issues such as data manipulation, algorithmic bias due to intrinsic, heuristic biases when training data which may result in health inequalities especially when there is lack of representativeness in the selection of coders. For instance, Caucasians may not bear in mind differences in features such as skin colour. For instance, a team of 10 women building an algorithm for IVF treatment may consider features different from a team of 5 men and 5 women. In line with this result, Gijsberts *et al.,* (2015) study on race/ethnic differences study on the association of Framingham risk factors with on cardiovascular events, reported biased prediction of cardiovascular events in non-white (Gijsberts *et al.,* 2015). Other challenges raised by respondents related to data include its inherent biases and lack of representativeness which affects application and performance in populations outside those which it was trained on, this has also been reported in the literature (Wartman and Combs, 2018). Another issue is the black box phenomenon exhibited by some AI technologies such as Convolutional Neural Networks whereby the features used in making decisions are unknown making interpretation and explainability are difficult to achieve (Singh *et al*., 2020). This has resulted in concerns about accountability, transparency, and the possibility of human control of AI technologies (Doshi-Velez *et al.*, 2017).

7.6.2. Finance-related challenges

Finance related challenges are those challenges associated with lack of funds. Though this challenge was consistent across locations there was some variation; while funding problem appears to be limited to the private healthcare sector for the UK, it appears to affect both the private and public healthcare sector in Nigeria. Challenges for the UK included high costs for private sector adopters of AI who may not have access to funding, lack of cost-effective and trustworthy implementation partner. The high financial implication of implementing AI and the lack of funding due to the poor economic situation were the main finance-related challenges for Nigeria. The respondents mentioned lack of healthcare funding in the country's healthcare system including private and public health sectors. Private healthcare providers struggle for adequate funding, as they must fund themselves out of pocket. They have little or no access to funding for basic healthcare requirements due to the poor economic situation of the country worse still funding for AI adoption. The challenge of funding in the Nigerian healthcare sector and other healthcare resource-constrained settings have also been mentioned in the literature specifically the high cost of data acquisition and preparation; hardware and computing resources and system maintenance and upgrading (Meskó, Hetényi and Győrffy, 2018; Owoyemi *et al.,* 2020). Lack of funding for AI may slow down adoption of AI in resource-constrained healthcare settings and further increase global healthcare disparities (Hosny and Hugo, 2019). It may be necessary for the government to consider the lack of funding in Nigeria as a state of emergency requiring immediate action.

7.6.3. Healthcare-related challenges

These are challenges that are specific to the healthcare sector. This challenge was highlighted by UK respondent who highlighted the bureaucratic nature of healthcare relating to several stringent approval requirements and processes, the lack of risk awareness and risk preparedness, conservative nature of the sector which appears to be slowing down AI adoption (The public health service). Similarly, some studies have reported that the healthcare sector is being hampered by slow AI adoption and this may prevent the sector from enjoying the benefits of the technology (Lai, 2020; Pumplun, 2021; Sunarti *et al.,* 2021). Healthcare organisations and systems may need to adopt a more risk-aware and risk prepared approach in terms of adopting innovations such as AI that can help mitigate emergency situations such as the Covid-19 pandemic. Although healthcare systems are required to go through stringent quality control and other approval processes. The removal of unnecessary bureaucratic processes may improve AI adoption.

7.6.4. Infrastructure-related challenges

These are challenges that are related to lack of infrastructure necessary for AI adoption. Infrastructure related challenges were cited by respondents from Nigeria only and include lack of power supply e.g., electricity, lack of water supply, lack of efficient internet technology, which are all basic requirements for AI adoption. The lack of infrastructure in the Nigerian healthcare sector has been cited in literature as a barrier to the adoption and implementation of AI in the healthcare sector (Owoyemi *et al.*, 2020). Without appropriate infrastructure such as power, water supply, internet, maintenance for healthcare service locations it may be difficult and even impossible to adopt and deploy AI. Although most private healthcare organisations aim to provide infrastructure to support their operations without relying on the government. The public healthcare organisations are left stranded and left to run without some basic infrastructure which should be made available to support the adoption of AI for improved OP in healthcare.

7.6.5. Resistance-related challenges

Resistance related challenges relate to lack of support and acceptance for AI in healthcare. Respondents mentioned repulsion to AI due to the human factor of wanting to do things in the conventional way. This has been observed in healthcare professionals particularly clinicians who usually spend several years to attain competence in their areas of specialty. Generally, respondents reported resistance to AI by healthcare professionals. Reasons cited for resistance included perception as non-useful, repulsion to new technology, lack of validation, threat to clinicians' livelihoods, legitimacy, rights, and judgements. Some of these reasons have also been cited in literature; threat to the livelihoods, legitimacy, and rights of healthcare professionals (Chiwome *et al.,* 2020). Naturally healthcare professionals show resistance to technologies like AI even when they have been tested and trusted and passed through regulatory approval (Laï, Brian, and Mamzer, 2020), resulting in non-adoption of AI e.g., the case of IBM Watson AI adopted into hospitals but not applied by doctors because it was not found to be efficient at diagnosing cancer (Lohr, 2021). It is therefore important for AI developers, management, and other stake holders to involve healthcare professionals in the design and decision making as this will encourage adoption and prevent wastage of resources.

7.6.6. Technology-related challenges

These are challenges related to lack of technological requirements for AI adoption. The main technology related challenge for the Nigeria were a lack of the basic requirements for AI adoption such as adoption of computers at scale within the entire healthcare system, as automated systems are not available in every healthcare facility especially in the public ones. This challenge is one that appears to be limited to resource-constrained healthcare settings. Another technology related challenge was the lack of transparency, explainability and interpretability of AI or the black box issue. This is one of the most prevalent challenges that negatively affect healthcare AI adoption and has been cited by several researchers (Sun and Medaglia, 2019; Ambagteesher *et al.*, 2020; Singh *et al.*, 2020; Pumplun *et al.*, 2021). It is important for AI to be explainable and interpretable so that healthcare professionals can understand the process of decision making for AI technologies as this appears important for scientific reasons and ethical practice and will enable them to accept AI and justify healthcare decisions made for healthcare customers or patients.

7.6.7. Skills-related challenges

Skills related challenges are those challenges linked to a lack of skills such as lack of general awareness, knowledge and understanding of AI skills, lack of training, education and competence, lack of technical manpower such as data management skills amongst healthcare professionals, lack of healthcare experts with AI competence to contribute to development of AI solutions for healthcare. Industry research raises concerns about an AI skills gap during the phase of early AI adoption (Deloitte, 2020), the skills challenge has also been reported as important by academic researchers (Sun and Medaglia, 2019; Singh *et al.,* 2020). Consequently, an AI skills gap may negatively impact AI adoption and development in healthcare and highlights the need to consider solutions.

Like the results of this research, Lee and Yoon, (2021) investigated the challenges of healthcare AI adoption have been cited in the literature to include challenges related to data, cost/ economic, regulatory, technological amongst other challenges (Lee and Yoon, 2021). Sun *et al.,* (2019) investigated the challenges of AI in the Public healthcare sector. They reported the following challenges; social challenges such as societal norms and attitudes; economic challenges such as profitability and economic stability; ethical challenges such as moral principles and factor; political, legal and policy challenges such as public political, legal and public policy related issues; organisational and management challenges such as strategy, human resource and management; data challenges such as data quality, quantity and standards and lastly technological challenges such as the nature and characteristics of AI technologies (Sun *et al.,* 2019).

Bajwa *et al.,* 2021, identified the following challenges in healthcare sector adoption and implementation of AI; data, technical infrastructure, organisational, ethical, safety and regulatory issues (Bajwa *et al.,* 2021). Their results are also like Lee and Yoon, (2021); Sun *et al.,* (2019); which are all consistent with the results of this Research in terms of the Challenges of AI adoption reported. All though not all the studies identified all the challenges of AI identified in this Research most common challenges are those related to Data, regulation, skills, and technology. With variance to the results of this research, Antwi *et al.,* 2021 conducted a qualitative investigation of radiographer's perspectives of AI application, adoption, and implementation. They reported the following barriers to AI adoption some similarities to this research; career insecurity such as potential job loss; cost of technology such as high acquisition and implementation costs; equipment preservation and data insecurity such as poor maintenance culture in Africa and negative implications of data insecurity for the patients (Antwi *et al.,* 2021). Another study by Robinson 2020, used quantitative methods to evaluate the knowledge, practices, and perceptions of AI in healthcare amongst healthcare care providers in Nigeria. The following were listed as challenges; Poor IT knowledge, Lack of legislation, and promotion of self-medication were the anticipated challenges (Robinson, 2020). The challenges were like the results of this research but differed based on identification of self-medication challenge.

7.7. Key Factors in AI Healthcare Adoption

The Researcher has identified eight key factors for AI healthcare adoption identified from the thematic analysis of the interviews with the Key informants: Acceptance, Data, Finances, Management, Organisational priorities, Regulation, Skills, and Technology factors are discussed. These factors have significant implications for managers of healthcare organisations adopting AI and have therefore been addressed by the Researcher as key elements within the internal and the external environments. Core aspects of these internal and external factors critical to the AI-OP adoption framework, are discussed. The Figure 7.6 below illustrates the factors that respondents identified as key for the adoption of AI in healthcare.

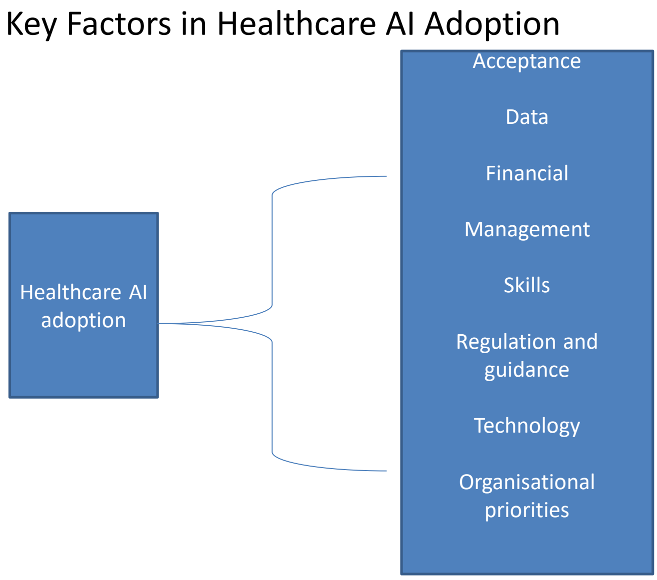


Figure 7.6: Key Factors in Healthcare AI adoption

Source: The Researcher

7.7.1. Acceptance factor

Acceptance has been cited as important in the adoption and implementation of AI in healthcare (Meskó, Hetényi and Győrffy, 2018; Laï, Brian, and Mamzer, 2020). Acceptance refers to the buy-in for AI by healthcare organisations. Respondents pointed out that healthcare professionals are more likely to accept and adopt AI if they understand how AI makes its decisions i.e., if it is more transparent and explainable. This reasoning is replicated in literature; transparency and Explainability are important because of scientific and ethical reasons; scientifically transparency may reveal unknown correlations and the likelihood of causation and ethically, transparency may improve healthcare professionals' decision making and protect them from exposing individuals to harm, making decisions based on bias, discrimination, violation of privacy (Ploug and Holm, 2020). It is therefore important to carry healthcare professionals and all members of the organisation (who are the end adopters in this case) along in the adoption process to ensure that AI is adopted applied to solving healthcare problems rather than left lying fallow. Based on justification from the research and literature it can be implied that acceptance is a key factor in AI adoption in healthcare.

7.7.2. Data factor

Data was cited by respondents across both locations as one of the most important factors for AI adoption. Data for training models must be both relevant and in the right quantity to be able to perform accurately (Agrawal, Gans, and Goldfarb, 2017; Kruse *et al.,* 2019). The importance of data was emphasized, specifically the need for data flows, clean data, good quality data, data engineering, the right data (such as longitudinal view of patient data from electronic health records that covers at least a period of one year) to support the adoption of AI by healthcare organisations. Furthermore, emphasis was laid on the need for data specific to the healthcare setting e.g., data required in health and social care settings may differ from data required in hospital settings and relevant to the population of interest for instance AI trained on data from Caucasian population may not perform effectively when deployed in African populations. Additional data factor included Data quality (determines how the data is developed), data ethics (should consider ethical use case for the development of solutions based on the data) and data governance (management of the data; privacy, dissemination), data quantity (large amounts of appropriate patient data are required to train some AI technologies e.g., ML systems) (Pumplun *et al.,* 2021). These issues of data quality, data ethics and data governance have been cited as important by other researchers as crucial in healthcare AI adoption (Mittelstadt and Floridi, 2015; Jiang *et al.,* 2021; Murdoch, 2021).

7.7.3. Financial factor

Financial factors refer to those financial resources that healthcare organisations require or allocate to invest in new technologies such as AI (Van de Weerd, Mangula and Brinkkemper, 2016; Pumplun *et al,* 2019). Funding was cited as important especially in the Nigerian healthcare sector and more so in the UK healthcare sector. The high cost of certain AI technologies makes it imperative to properly consider the cost and sustainability of AI adoption especially since the financial impacts of AI adoption such as ROI may not be immediately visible. Financial factors have been cited as important in all settings and even more in resource limited settings like Nigeria in Africa (Hosny and Aerts, 2019).

7.7.4. Management factor

Management factors refer to those factors that support the establishment of organisational norms and impact efficiency and outcomes including AI adoption (Alhashmi *et al.*, 2019).

Respondents mentioned the importance of creating a team, unit, or department for management of all aspects of AI adoption such as decision making, strategy formulation and implementation, performance management, monitoring and evaluation etc. In practice these should be persons with management expertise and clinical orientation such as transformation, implementation and change management experts. Respondents also cited the need for top management support as an organisational factor for AI adoption. Management factors are important in AI adoption; change management may help to support healthcare management through the process of adoption ((Enholm *et al*., 2021; Wiljer *et al*, 2021). Top management support refers to the inclination of top management towards support AI related initiatives across the organisation. It is crucial for successful AI adoption because it signals an organisation-wide signal which drives other members to commit AI projects (Johnk *et al.*, 2021). Similarly, other studies have cited top management support as important in AI adoption (Alkhater *et al.*, 2014; Alsheibani *et al.,* 2020). For AI to be successfully adopted in healthcare, it is important that management set into motion the core functions of management by planning, organising, directing, and controlling all activities in the process of AI adoption.

7.7.5. Regulation

Regulation refers to interventions such as compulsory standard setting, monitoring and sanctioning by regulators in target population's activities (Koop and Lodge, 2015), in this case the activity is AI and the target population is the healthcare sector. All respondents considered the issue of regulation in all forms including, ethics and laws to be of key importance in the adoption of AI. They acknowledged the availability and application of certain regulatory provisions but highlighted the need for clarity in the regulatory landscape. The regulatory requirements for AI adoption varied across both locations. Several regulatory provisions were highlighted for the UK with the main ones being the GDPR (General data protection regulation), and the DPA (Data protection act) 2018. The need to comply with these and sector specific regulations such as the Data ethics framework for public organisations as well as relevant legislation and codes of practice have been raised in the literature and health sector publications (Forcier *et al.*, 2019; Smeaton and Christie, 2021; Data Ethics Framework, no date). Currently the UK is working on developing clear and innovative regulation centred with input from the 12 key regulators for AI in health and care (NHS Digital, 2020).

In the Nigerian context, mention was made of the availability of legislature applicable to AI, as well as other regulatory provisions currently under development such as the e-health policy and the need for proper regulation around AI in healthcare. Certain areas of AI regulation are covered by the Nigeria Data Protection Regulation (NDPR) (similar to the GDPR) which applies to the processing of personal data within and outside Nigeria covers data protection in Nigeria and is applicable to AI (KPMG, 2019).The need to pay attention to law, policy and the regulatory environment, improvement of AI knowledge, practice, and perception amongst healthcare professionals in Nigeria and the developing world has been cited in the literature (Robinson, 2020; Ibeneme *et al.*, 2021). Another point raised is the lack of clarity over responsibility for decisions making lies when AI technologies support healthcare delivery or are autonomous in the delivery of healthcare. AI in healthcare will result in new risks with unexpected consequences, wherefore the need for clear cut regulation (Reed, 2018). It is important for regulatory authorities to consult with all healthcare stakeholders properly define the use of AI, its use, and the user (Marcus, 1981; Kingston, 2016; Cath, 2018).

According to Reed, (2018), AI is at infancy stage, and its development and implementation and as such it may be better to apply current legal and regulatory provisions which place responsibility and hence liability to persons (Reed, 2018). Globally, stakeholders such as governments, industry representatives, technical experts, academics, and the civil society continue to debate the need for standard regulatory/ legal/ ethical frameworks in the application of AI (Cath, 2018). The issues raised above may affect an organisation's willingness to adopt AI since there are no clear laws and guidelines that regulate and guide the application of the technology and therefore leaving the organisation in a vulnerable position and unable to protect itself and its stakeholders in the case of eventualities (Palmerini *et al.*, 2016; Laï, Brian, and Mamzer, 2020). It is therefore expedient for healthcare organisations using AI technologies to safeguard their patients, service users by researching, evaluating, understanding, and complying with current regulatory policies and practices that are in place wherever they operate.

7.7.6. Education, training, and skills

Skill refers to the ability developed through training and experience (Cambridge Dictionary, 2022). Education and training in addition to skills were cited as crucial to AI adoption in healthcare. In relation to AI and this includes AI awareness, knowledge and skills set such as statistics, data analysis, data management and engineering are crucial to successful AI knowledge, adoption, and practice in resource sufficient and resource limited settings like Nigeria (Pumplun *et al.,* 2019; Robinson, 2020). Respondents emphasized the need for healthcare professionals to have AI training, certification, education and most importantly AI skills set that are required for AI adoption. While some respondents felt that extensive digital and AI skills i.e., dual expertise of healthcare professionals would be beneficial to new developments to the AI healthcare field, some respondents did not agree. Although healthcare professionals require training and education most respondents did not feel it was necessary for them to be technology experts. This perception of dual expertise is also observed in literature (Stanfill and Mare*,* 2019) and more emphasis laid on AI education and the incorporation of AI, digital technology into the medical curriculum for healthcare professionals (Singh *et al.,* 2021). Respondents observed that training needs varied with age; older healthcare professionals appeared to be higher than that of younger ones. The importance of initial refresher training, technical and supervisory support are reported as critical development of AI skills and successful adoption of AI in Nigeria with a higher need for training in older healthcare professionals (Kelechi *et al.,* 2020). Therefore, training needs which are linked to development of AI skills appear to vary with age and should be addressed or considered when designing AI training for healthcare AI adoption.

7.7.7. Technology

Technology factors refer to those technological requirements that must be in place before AI can be adopted. Respondents mentioned the need to get the basic technology requirements right before getting the advanced technologies right. For instance, what is the appropriate AI for the specific organisational problem, is the technology readily available, does it require training? Also important is the basic technology requirements such as Computer hardware, CPUs, Cloud storage etc., the complexity of AI, network infrastructure for the healthcare organisation must be right e.g., the workflows, the processes, the people etc. Another technology consideration made was the need to integrate AI with the existing systems. The issue Integration and interoperability are cited as important when adopting AI technologies (Lehne *et al.,* 2019). When adopting AI technologies, healthcare organisations need to consider the options available to them in terms of adopting existing AI or developing their own AI from scratch; if they intend to adopt existing AI then they need to ensure meet their healthcare needs, has features for interoperability, and integration with their existing technological infrastructure (Pumplun *et al.,* 2021; Singh *et al.,* 2021). Another issue is the safety of AI on healthcare customers which must come first before AI is adopted, consideration of overall risks to HCC customers especially in early phase of AI adoption e.g., safeguarding issues and how these can be mitigated. This issue of safety is also cited in the literature; healthcare organisations should consider data quality, patient safety and potential bias against the benefits of AI (Ambagteesher *et al.*, 2020). It is important that healthcare organisations consider the cited technological factors and ensure that they are accounted for to support successful adoption of AI.

7.7.8. Organisational priorities

Organisational goals, objectives, problems, challenges for which AI is being adopted are priorities for the healthcare organistion. Respondent's recognised that it is important for healthcare organisations adopting AI to first identify specific needs, problems, challenges, and priorities as this will determine the appropriate AI to be adopted. It is important to also ensure that the AI solves the healthcare organisation's problems and meets their goals, objectives, and priorities. Lastly, it is important to justify the investment in AI against the organisation's goals, objectives, and priorities. These factors have been cited as important in the adoption and implementation of AI both in general and specific to the healthcare sector. To prevent wastage of resources, it should be ensured that AI is solving an organisational problem or providing new opportunities (Hofmann *et al,* 2020). It is also important to follow a strategic approach of strategic planning, business planning, clear understanding of the advantages and alignment of organisational objectives (Olsen and Tomlin, 2020; Raj *et al.,* 2020; Singh *et al.,* 2020). It is essential that healthcare organisations not only ensure that AI meets their needs, but they should align organisational objectives, goals, and priorities with AI strategy.

Pumplun *et al., (*2021), in their qualitative study investigated the factors that influence the adoption of machine learning systems for medical diagnostics in clinics. They reported the following factors Organisation; clinic size, medical directors support, strategy, and resources; Wider system; government regulations and medical ethics; Adopter system; physician acceptance, patient acceptance; Condition; physician and patient value through ML and patient data; availability of data (Pumplun *et al.,* 2021). The study reports some similar factors also reported in this research although classified under different headings. Another study by Liu *et al.,* (2021) investigated the critical factors for the implementation of healthcare AI based on the experience of a medical centre in Taiwan. The study reported the following critical factors for AI adoption in a healthcare setting: policies and regulation amendment, top executive support, clinical actual demand, user department consensus, dedicated AI analyst, Information system department support, concrete benefits, explainability, continuous optimization, easy to install and use, assistance rather than replacement, spontaneous rather than compulsory Liu *et al.,* (2021). Although some of the factors identified are similar those identified in this Research e.g., regulation, management, skills other factors mentioned differ from the results of this research and this may be because the report is based on the hospitals view and may reflect some of the challenges being experienced.

7.8. Perceived ease of use and Perceived usefulness

Respondents generally agreed that they are more likely to adopt AI if they perceived it as useful and easy to use. They felt that if it helps their practice and the learning curve is short, and if the safety of the AI for the HCC customer is not compromised, then they would be willing to adopt. This result resonates with the literature, as several studies have cited perceived ease of use and perceived usefulness as predictors of technology adoption (Chen *et al.*, 2017; Kennedy and Ghallego, 2021). In line with the results of this research, a study by Alhashmi *et al.*, (2019) investigated the implementation of AI in the United Arab Emirates healthcare sector using an extended TAM. The study reported among other incorporated factors, perceived usefulness, and perceived ease of use as predictors of actual use and adoption of AI in healthcare (Alhashmi *et al.*, 2019). The study though quantitative, supports the results of this research that perceived usefulness and perceived ease of use are predictors AI adoption.

7.9. Testing of the AI-OP Adoption Framework

The focus of this section is to examine the changes to the theoretical AI-OP adoption framework developed in chapter 4, regarding the results from the qualitative research. The Researcher therefore performed a gap analysis that resulted to verification of the key elements of the framework.

The framework presented in Chapter 4, Figure 4.2, was developed from key findings from academic and industry research contributions, with the focus being to tackle the literature gap

(Chapter 3, Section 3.1) that led to the need for the need for the AI-OP adoption framework to support the adoption of AI for healthcare performance.

Therefore, the Researcher first defined key factors fundamental to AI adoption in healthcare sector (Chapter) and validated the importance of these factors based on qualitative research (Chapter 6 and 7), next the Researcher defined OP elements for the healthcare sector (Chapter 4) originally adopted from the Balanced score card then validated their importance through qualitative research (Chapter 6 and 7).

The last step is the provision of practical guidance on the adoption of AI for improved performance to healthcare sector professionals and academics. The theoretical framework presented in chapter 4, section 4.3 was established upon internal and external factors for AI adoption in the healthcare context and perspectives of healthcare performance.

The Researcher assumes that healthcare organisations are influenced by changes to the external factors such as cultural, economic, financial, political, and regulatory. The key factors identified from the literature review are Data, Education and training, Acceptance, Organisational, and Technological considerations while external factors are legal, ethical, regulatory, and environmental (Chapter 4, Section 4.3.2). The healthcare performance perspectives are healthcare financial performance, healthcare customer performance, healthcare internal business performance and healthcare Innovation and Learning performance.

Following the presentation of the conceptual underpinning from literature of the theoretical AI-OP adoption framework, the Researcher proceeded to validate the significance of the key factors affecting its implementation through qualitative research (qualitative).

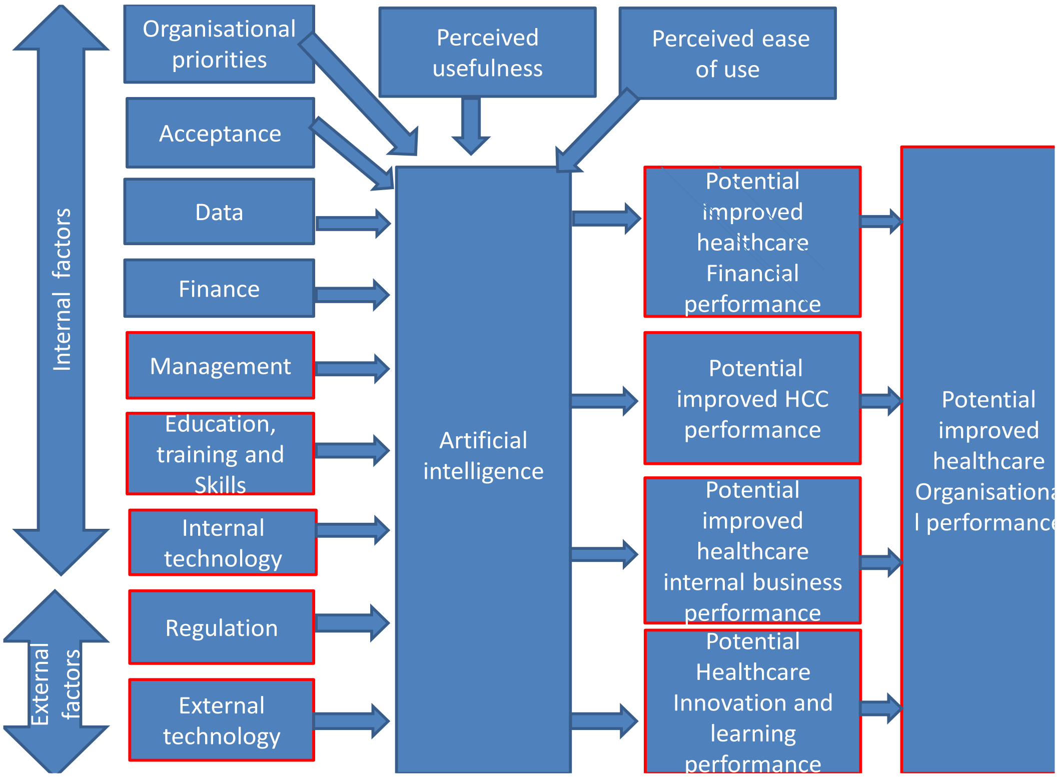


Figure 7.7: The Tested Strategic AI-OP Adoption Framework

Source: The Researcher

Figure 7.7 shows the tested Strategic AI-OP Adoption Framework. This final framework results from changes made to the theoretical AI-OP adoption framework presented in Chapter 4, figure 4.2 based on the results of qualitative research. The newly presented tested framework has undergone some significant changes which have occurred as a result of the qualitative findings. The components of the framework that have changed due to the result of the qualitative investigation are highlighted in red. When Figures 4.2 and 7.7 are compared, it can be observed that the framework component that encountered the highest level of change due to the results of qualitative investigation presented in Chapter 6, are the key factors for AI adoption.

Management: This was previously listed as a sub-factor of organisational factors under key factors for AI adoption in the theoretical AI-OP adoption framework. The reason for this is that respondent's perceived management as a factor that should have a separate structure because it is not only a key factor for AI adoption, but it is also a factor that is critical to the success of the adoption process.

Regulation: Another change made to the key factors for AI adoption component of the theoretical AI-OP adoption framework is the merging of ethical, legal, and regulatory factors, to give rise to the Regulation factor in the Strategic AI-OP adoption framework. The result of thematic analysis reveals that respondents perceived ethical, legal, and regulatory factors as different forms of regulation of AI and belonging to the AI regulatory landscape.

Technology: Another important modification to the key factors for AI adoption component of the theoretical framework, is the splitting of technology factor into internal and external. This change occurred due to results of thematic analysis which showed that respondents recognised technology for AI adoption as either internal or an external factor.

Education, training, and skills: Another change made to the key factors for AI adoption component of the theoretical AI adoption framework was to the Education and training factor which was expanded to Education, training and skills based on the results of the qualitative research. Respondents highlighted the need for practical AI experience in addition to training and education as this will lead to the development of AI skills which will support the adoption of AI.

Environmental: An additional change made was the removal of the environmental factor from the key factors for healthcare AI adoption. This is due to the lack of support for this factor as a key factor for AI adoption. Respondents' generally felt that it is good to consider the environmental factors such as carbon impact of AI, impact on other hospital systems but they believed the impacts are not of high significance as to drive or act as a barrier to adoption. Another environmental factor that was considered is the competitive terrain. The general perception was that there is that many organisations are interested in AI because it appears sexy and is being promoted (AI hype) but this is not at the level where it is driving competition in healthcare because AI in healthcare is in early phase of adoption. Therefore, it was not perceived to be a key factor in AI adoption.

Potential improved healthcare OP: On analysing the qualitative interviews, respondents generally argued that the impact of AI in healthcare is visible through the different elements of OP. These impacts are however potential since the adoption of AI in healthcare is in the early phase characterised mainly by non-scale deployments, and therefore presenting a challenge for measurement and quantification. Therefore, the four elements of OP and OP have been adjusted to a state of potentiality reflecting that AI has the capacity to fully improve these elements of performance and ultimately OP in the future or when deployed to scale. These components of the theoretical AI-OP adoption framework changed to potential improved financial performance, potential improved HCC performance, potential improved internal business performance and potential improved Innovation and Learning performance.

The factors perceived ease of use and perceived usefulness retained their position in the new Strategic AI-OP adoption framework as separate factors not considered by the qualitative research as key for adoption but as predictors of AI adoption. This implies that perceived usefulness and perceived ease of use of AI by healthcare professionals will support AI adoption but are not key determinants of AI adoption.

Consequent to the analysis and interpretation of the qualitative interviews (Chapter 7), the Researcher recommends that the following steps be considered by healthcare organisations as continuous rather than separate during the implementation process: The following section presents practical guidelines for implementing the AI-OP adoption framework based on combination of contributions from academic research and results of qualitative research.

7.9.1. Practical guidelines for implementation of the AI-OP adoption Framework

This section discusses the Researcher's proposed guidelines for implementing the Strategic AI-OP Adoption Framework (Figure 7.7), which is developed from analysis of primary and secondary data. The ongoing application, adoption, implementation of new technologies such as AI has culminated in the need for technology-related strategies, therefore experts and researchers introduced strategic planning relevant to such technologies (Yeh *et al.,* 2012; Kitsios and Kamariotou, 2021). According to pertinent research, it is important for organisations to combine technology with effective strategy planning and implementation for OP (Kihara *et al.*, 2016; Kitsios and Kamariotou, 2021). Therefore, an effective implementation strategy is important to help ensure that technologies (A1) addresses performance issues in healthcare and to avoid duplication of efforts (Keyworth *et al.*, 2018; Klaic *et al.,* 2022). Effective implementation has been emphasized as important for supporting the translation of effective interventions or innovations from research to real world settings and reducing waste globally to an estimated annual US$85 billion (Klaic *et al.,* 2022).

It is recommended that managers put into consideration, key questions relevant to the organisational context:

- What are the goals and objectives of the healthcare organisation and how can they be aligned with AI strategy?
- How can healthcare professionals be supported to accept AI?
- How can the healthcare organisation develop appropriate or comprehensive data infrastructure for AI adoption?
- What are the financial requirements for AI adoption?
- How can the change that occurs due to adoption of AI in healthcare be managed?
- How can healthcare organisations meet the skills requirements for AI adoption?
- What technology requirements do healthcare organisations need to meet for AI adoption?
- What regulatory requirements do healthcare organisations need to meet for AI adoption?

The Researcher considers the above questions as critical to the AI-OP adoption framework and provision of implementation guidance.

7.9.2. Management responsibilities:

Management needs to define the organisational structure then decide how AI can be incorporated into it. Irrespective of the specific strategic path the organisation takes, it is important that management understands and defines the aims of the AI programme and effectively communicate it across the organisation. Management should also ensure that all employees understand the vision and the mission of the organisation as well as the main organisational objectives as linked to their performance objectives while remaining conversant with the organisation's strategic direction. Therefore, based on the actions presented above, the Researcher recommends the following implementation steps:

1) Establishment of the external environment by putting in place key factors of the external environment as listed: Regulation, External technology and any other factors deemed relevant.

2) Establishment of the internal environment by putting in place key factors of the internal environment as listed: Organisational priorities, Acceptance, Data, Finances, Management, Education, training and skills, Internal technology and other internal factors deemed relevant.

3) Establishment of perceived usefulness and perceived ease of use of AI

4) Definition of OP elements

5) Mitigation of Challenges in healthcare AI adoption.

To support effective implementation, the Researcher proposes that the following actions should be considered to support each step of the implementation process:

- Define
- Plan
- Communicate
- Enable feedback
- Monitor
- Evaluate

The following subsections offer guidance on each key implementation step outlined above.

7.9.3. Establish the external context.

This section emphasizes the importance of establishing the external context in which healthcare organisations operate as a first step in developing the AI-OP Adoption Framework (Figure 7.1). Healthcare organisations operate in a complex business environment and are therefore exposed to the dynamics of this external context (Zinovieva *et al.,* 2016). This external context includes various regulatory, political, financial, socio-cultural, economic factors, physical, etc. which influence the environment in which healthcare organisations operate (Ziemann *et al.,* 2019). The dynamic nature of these factors in the external environment are beyond the control of the organisation and may therefore affect it and drive it towards realigning or adjusting to remain competitive (Sammut-Bonnici, 2015) this effect may also be extended to the internal organisational context. The Researcher recommends that management establishes first establishes the external context when developing an AI-OP adoption framework. This is because the healthcare organisations exist within a complex healthcare sector or system where there are stringent and dynamic macro factors that may affect the performance of the healthcare organisations (Zinovieva *et al.,* 2016). It is therefore important that management monitor both the external and internal contexts by understanding the component factors, likely changes that occur and develop effective strategies to mitigate any negative effects. There are several tools available to managers for analysis and management of the external environment such as PESTEL (political, economic, socio-cultural, technological, environmental, and legal), SWOT (strengths-weakness-opportunities-threats), Porters five forces, key success factor analysis, scenario analysis etc. (Qehaja, Kutllovci and Shiroka Pula, 2017).

Table 7.1: Sample SWOT for Healthcare organisations

Strengths • What are the advantages of the healthcare organisation? • What can the healthcare organisation do better than others? • What are the unique services that can be provided to healthcare customers (HCCs)? • What do HCCs in the sector see as the healthcare organisation's strength? Magazines	**Weaknesses** • What are the factors that can facilitate improvement? • What are HCCs likely to see as the healthcare organisations weakness? • What lack of services makes the healthcare organisation loose HCCs?
Opportunities • What are the potential beneficial opportunities available to the organisation? • What are new and exciting trends is the healthcare organisation open to e.g., technological? • What are the new changes to governmental regulation/policy that the organisation may benefit from?	**Threats** • What are the healthcare organisations problems challenges? • What is the basis of your competitor’s competitive advantage? • Do new technologies and new services pose a threat to the organisation's position in terms of HCCs loyalty? • Are there any financial or cash flow issues? • Are there any organisational weaknesses that could threaten the quality of care received by HCC?

A situation analysis can be conducted by combining the PESTEL and the SWOT to provide a snapshot view of the organisation's positioning. The PESTEL framework facilitates identification of the macro-environmental factors and the influences that they may exert on the implementation of the AI-OP adoption framework and other management activities. While the SWOT analysis helps to identify the areas of strength, weakness, opportunities, and threats for the healthcare organisation such that the strengths and opportunities are maximised, and the weaknesses and threats are mitigated through the appropriation of organisational resources. Table 7.1 above shows a sample SWOT for healthcare organisations and Steps for SWOT Analysis and questions to consider for SWOT in a healthcare context. These can be applied to develop the SWOT analysis.

Steps in SWOT Analysis and questions to consider.

i. Strengths: Identify areas where the healthcare organisation is doing well that can distinguish it from the competition such as in terms of assets, people, products, services, processes, unique selling points.

ii. Weaknesses: Identify areas where the healthcare organisation is vulnerable and requires change.

iii. Opportunities: Research opportunities, trends, technological advancements that can project the healthcare organisation forward in terms of brand, healthcare sector and internal processes.

iv. Threats: Identify external factors that can exert a negative impact on the healthcare organisation by conducting a PESTEL analysis to understand these factors and conduct benchmarking to reveal competitor activities Source: (Teoli *et al.*, 2022).

7.9.4. Step 2: Definition of the key factors for AI adoption

On establishment of the external environment, the Researcher recommends that managers develop an understanding of the internal environment and align its components (step 2). Key internal factors identified as critical to developing and implementing the framework (figure 8.1) are: Organisational priorities, Acceptance, Data, Finances, Management, Skills, Internal technology and other internal factors deemed relevant. The key factors discussed should be clearly understood, appropriately defined, measured, and aligned with AI.

7.9.4.1. Organisational priorities

After analysis of the healthcare organisation's situation, the next step is definition of the organisation's priorities. Healthcare organisations vary regarding their goals, objective, priorities (DalleMule and Davenport, 2017; Alami *et al.*, 2020) consequently it is necessary to identify the goals, objectives, and priorities for which the organisation is adopting AI. Not only should these be identified, but it must also be ensured that AI adoption is justified as the most suitable or beneficial solution (Alami *et al.*, 2020). When it is established that there is need for AI, the organisational priorities should be presented as goals and objectives. This can be outlined using the SMART approach (specific, measurable, attainable, realistic, and time-bound) so that they are clear, logically structured, and open to effective monitoring and evaluation (Ogbeiwi, 2017).

7.9.4.2. Data

The Researcher recommends that healthcare organisations adopting AI get their data infrastructure right by ensuring effective data collection, standardization and management. Healthcare data are usually unstructured and may also be from multiple sources (e.g., EHR patient data and medical databases). Appropriate methods of standardization should be applied, or standardized data collected instead. The costs of acquiring and managing such data should also be put into consideration. Healthcare organisations should ensure that the AI they apply is free of bias e.g., has been trained on data that is relevant and representative, trained that does not exclude minorities or certain groups of people unconsciously (Chua *et al.,* 2021). As the accuracy of prediction and diagnosis by AI is as good as the training data. Healthcare organisations may choose to apply a Data openness approach which proposes adoption of open science approaches used in education, data sharing, research, and software development for AI to enable access to data as well as openness of mechanisms and clinical effectiveness, thereby supporting a safety-critical healthcare context (Kobayashi and Paton, 2019).The adoption and evolvement of data governance principles can help organisations efficiently manage AI by clear, consistent and standardized policies and procedures (Mioto *et al,* 2018) that ensure people, processes, and systems involved in AI initiatives are held accountable for ethical use and deployment, the process is transparent, the result has integrity, the information is protected, the approach is compliant with organisational and legal practices, the technology is available, the method of AI development is retained, and when appropriate the healthcare data is disposed of properly (Stahl, 2021) thereby minimizing risk to patients, providers, developers, and healthcare organisations. It is imperative for healthcare organisations to develop a data infrastructure that covers all the structures necessary for AI to support the provision of healthcare across the care continuum within an organisation, across other organisations while improving efficiency and ensuring safety (Davenport, 2019; Panch, Mattie, and Celi, 2019).

7.9.4.3. Education, training, and skills

Regarding developing AI skills, healthcare organisations should appropriately introduce AI to stakeholders (e.g., through training, two-way communication, and other methods) by providing appropriate training and education to healthcare professionals (Alami *et al.,* 2020) so they can understand AI and integrate into their practice. Training should be extended to other users such as health system administrators and mangers of information systems should be trained on the demands and impacts of AI technologies (Chua *et al.,* 2021) so they can appropriately support healthcare professionals. An assessment of the knowledge and skills level of healthcare professionals should be conducted before planning AI training they should also conduct user evaluation post-training and use to identify any extra training needs (Banerjee *et al*, 2021).

7.9.4.4. Regulation

The Regulatory landscape which includes regulation, law, ethics are important in AI adoption and the absence of these will hamper the adoption of AI in healthcare (Pumplun *et al.*, 2021). Although currently the regulation of AI technologies including law, ethics and guidelines are not well defined, (Chua *et al.,* 2021). It is important that healthcare organisations research understand and comply with all existing provisions as well as stay conversant to changes in the regulatory environment so that they can provide qualitative and safe care. In the UK, healthcare organisations adopting AI are required to comply with the major regulations relating to AI which are the GDPR (General data protection regulation) and the Data protection act 2018, Common Law Duty of Confidentiality, Caldecott Principles and sector specific regulatory requirements such as NHSX DTAC specific to the NHS, CQC registration for health and social care organisations, guidance such as the Data ethics framework for government and public sector organisations, NICE guidelines among others. In Nigeria, the main regulatory provisions are the National information technology development agency act, 2007, the Nigeria Data Protection Regulation (NDPR) and legislation that intersect with AI such as the Medical and dental practitioners act.

7.9.4.5. Management

It is recommended that AI and its adoption be allocated dedicated management or department as this is supported qualitatively and, in the literature, (Pumplun *et al.*, 2021). Management should determine the strategic direction of the healthcare organisation and then align with AI to facilitate OP. This can be done following a strategic approach of flexible business planning, objectives setting, identification of performance elements and then alignment with the organisation's goals, objectives, and priorities (Singh *et al.*, 2020).

Management may need to create new roles specific to AI such as champions or create a team with diverse expertise for AI such as AI/ Digital lead etc. The adoption and implementation of AI in healthcare is reported to be facilitated by AI champions, as they can significantly help overcome lack of acceptance (Strohm *et al.,* 2019; Morrison and Exworthy, 2020). These champions should be competent subject matter experts that can educate and support healthcare professionals at all organisational levels on AI/ related matters. Managers should also apply change management to the adoption process, communicating consistent messages to support all stakeholders to envision, accept AI and co-own AI (Alami *et al.*, 2020). It may also be necessary to develop and implement AI policy, clarify professional jurisdiction, and revisit remuneration and professional jurisdiction. Top management has a part to play by offering, trust, help, resources, support (Hsu *et al,* 2019) and ensuring the organisation is ready for AI (Olawumi and Chan, 2020; Johnk *et al,* 2020). Top management should provide a supportive environment for AI adoption by providing explicit directions to avoid uncertainty, clarify objectives and allocate the resources required for AI adoption.

7.9.4.6. Technology

AI like other technologies should be approached at a functional level being aligned with the healthcare organisations strategy (Kitsios and Kamariotou, 2021). Healthcare organisations vary in typology of specialty, size, challenges, priorities, and resources, and as such need to identify the most suitable approach for technology. It is therefore recommended to ensure that the internal technological requirements are met e.g., computers, CPU, etc. before preparing the external more advanced technologies such as cloud platform, EHR etc. It is also recommended to check integration and interoperability of the AI with existing or other technologies, organisational processes, and that it is adaptable to needs of complex systems such as healthcare organisations (Cresswell and Sheikh, 2013). Healthcare organisations such as hospitals for instance with a good EHR system may be able to add-on AI capabilities through EHR vendors that enable system connection and data exchange. There is also the option of working with a technology firm and an EHR vendor to provide a suitable solution. In healthcare adoptions where crucial processes are involved, it is necessary to conduct onsite pilot implementation and validation is conducted to ensure as well as on-going monitoring of system performance to ensure safety and effectiveness (Chen and Decary, 2019) of AI for the end users.

7.9.4.7. Finance

Healthcare organisations may require substantial investment when adopting AI due to validation and adaptation of the AI to the organisation's local context. Finances should be made available to cover several costs such as data cleaning e.g., from EHR and standardization, interoperability, AI maintenance and monitoring which may include software updating, IT infrastructure updating, cost of regular equipment maintenance, cost of assessing performance, security of AI as well as human resource recruitment and training. Healthcare organisations should ensure that they have sufficient resources to sustain adoption and integration of the AI (Alami *et al.*, 2020).

7.9.4.8. Acceptance

Acceptance of AI has been cited as important in literature (Papadopoulos *et al.*, 2018) and from the qualitative results of this Research. To ensure that healthcare professionals accept and adopt AI, issues linked to AI acceptance should be resolved. Healthcare professionals' acceptance AI should be improved by making them understand the benefits and challenges of AI as well as the process of decision making by which it supports healthcare (Shinners *et al.*, 2019). Also, healthcare professionals should be involved in the adoption process from start to finish i.e., from design to implementation stage to ensure that issues that are important to them are highlighted and considered when planning to adopt AI.

7.9.5. Establishment of perceived usefulness and perceived ease of use as predictors of AI adoption

Perceived usefulness and perceived ease of use were identified both in literature (Singh *et al,* 2020; Kennedy and Ghallego, 2021) and by the qualitative research as predictors of AI adoption. It is recommended that Managers consider the healthcare professional's perception of usefulness and ease of use of AI before adopting AI. This is important because healthcare professionals are more likely to adopt AI if they perceive it as useful to their practice and that the technology has a short learning curve and will not increase their workload rather than if perceived as not useful and creating additional workload, it is likely that it will not be adopted regardless of the establishment of key factors for adoption. Healthcare professionals may resist technological systems including AI if they are perceived as inadequate deficient or constraining to their values, objectives, and the way they conduct their work (Beckman and Gross, 2015, pg. 477; Ali *et al.*, 2016). Managers can consult with healthcare professionals to understand challenging areas of healthcare where AI can support to make processes faster, more accurate and efficient. They should also understand the healthcare professional's perspective on how AI can be incorporated into their workflow without significant increases in workload.

7.9.6. Definition of OP elements

7.9.6.1. Definition of OP elements that best assess or measure performance in the healthcare.

For this study, the BSC is proposed to potentially measure and improve performance multi dimensionally across four perspectives or domains namely financial, customer, internal business and Innovation and Learning. Potential Improved financial performance; is proposed to occur when factors for AI adoption are aligned with AI and linked to financial elements of OP. Potential Improved is proposed to occur when factors for AI adoption are aligned with AI and linked to HCC elements OP. Potential Improved internal business performance is proposed to occur when factors for AI adoption are aligned with AI and linked to internal business elements OP. Potential Improved Innovation and Learning performance is proposed to occur when factors for AI adoption are aligned with AI and linked to Innovation and Learning elements of OP.

Steps in implementing performance measurement.

- Identify the healthcare organisations strategic elements (conducted earlier) which will lead to identification of key performance indicators for performance measurement by the BSC.

- All metrics are clearly defined, targets are established, performance thresholds defined, and reporting requirements detailed.

- Frequency for KPIs updating is identified e.g., daily, bi-weekly, monthly, or quarterly and results.

- Individuals should be allocated to collect and analyse data for the BSC.

- Baseline data should be collected and recorded to enable establishment of targets for each performance measure and to serve as reference point to compare and determine level of performance (Enwere, Keating and Weber*,* 2014). In addition to all the implementation steps outlined, it is recommended that challenges in healthcare AI adoption be understood and mitigated for. These include but may not be limited to: Data-related challenges, Finance-related challenges, Healthcare specific challenges, Infrastructure-related challenges, Resistance-related challenges, Technology-related challenges, Skills-related challenges.

7.9.7. Strengths of the AI-OP Adoption Framework

As previously noted in Chapter 2, the complexity of AI adoption in healthcare, calls for the development of a framework to identify and describe the elements critical to AI adoption and implementation. The results from the qualitative investigation (Chapter 6) demonstrate the need for changes to the theoretical AI-OP adoption framework proposed in Chapter 4 towards achievement of the research aims and objectives presented in Chapter 1 (Section 1.6). The purpose of the resultant framework is to serve as a practical tool to the healthcare sector and academia for improvement of the understanding of the complexities of AI adoption, to identify key factors for adoption of AI to improve organisational performance in healthcare.

7.9.8. The main strengths of the Strategic AI-OP adoption framework are presented:

7.9.8.1. Reliance on academic literature

The literature review in Chapter 2 indicates the nature of components that are involved in AI adoption. The Framework is supported by a well-grounded theoretical and research-based underpinning of literature and existing knowledge and relies upon proven methods to explain strategic AI adoption for OP in healthcare.

7.9.9. The development of interaction between AI and various internal and external factors that affect healthcare organisations.

The Framework identifies and accounts for changes in the internal and external environment of healthcare organisations. Based on its focus on AI as a strategy for OP, the framework is expected to improve different aspects OP, thereby improving competitive advantage, survival, and long-term sustainability.

7.9.10. Development of a Strategic AI-OP framework aligned with key factors for adoption.

Research on AI adoption of AI on OP in healthcare focuses more on the AI model and its technical components. This Research identified key themes from AI and technology adoption which were qualitatively investigated and culminated into a strategic framework that incorporates key factors for AI adoption and links them to improving OP in healthcare.

7.9.11. Development of a Strategic AI-OP adoption framework that accounts for the effects of the internal and external environments.

AI adoption frameworks may not account for changes in the environment that exist in real world situations. This framework puts differentiates which key factors are internal and external, and how they may affect AI adoption.

The study identifies four output factors driven by the implementation of the strategic AI-OP framework. These are the OP in healthcare perspectives that are improved by incorporating the key factors for AI adoption: Potential Improved financial performance, potential improved customer performance, potential improved internal business performance and potential improved Innovation and Learning performance. These are discussed in detail in Chapter 7. The Researcher is of the opinion that the strategic nature of the Strategic AI-OP adoption Framework, has the potential to support improved OP in healthcare. The researcher claims that the developed framework can support the successful adoption of AI and improvement of OP in healthcare settings.

7.9.12. Limitations of the AI-OP adoption Framework

In this section, significant limitations of the Strategic AI adoption Framework are discussed:

7.9.13. Complexity of the Strategic AI-OP adoption framework

Based on the complexity of AI and the interaction of various elements in the Strategic AI-OP adoption framework (Figure 7.7), the Researcher acknowledges that the framework may initially appear challenging to manage. However, availability of the components of the framework and support from the implementation guidance can mitigate this complexity.

7.9.14. Focus on Healthcare sector.

The Strategic AI-OP adoption framework (Figure 8.1) has been developed to address adoption of AI in healthcare organisations and is based on the characteristics of this group of organisations therefore it may not be applicable to other sectors. However further research may be conducted by incorporating characteristics of other organisational sectors and making changes to components of the framework as required.

8. CHAPTER EIGHT: CONCLUSION AND RECOMMENDATIONS

8.1. Introduction

This chapter presents the research contributions, establishes that the aims and objectives of the research have been achieved and that the research questions have been answered. Subsequently conclusions are drawn from the research and the need for more studies of AI and OP in healthcare demonstrated while simultaneously addressing the research gap revealed in Chapter 3. The chapter begins by reviewing the research aims, objectives and research questions with regards to the results. Section 8.3 discusses the research limitations while Section 8.4 discusses contributions of the research to knowledge and practice. In section 8.5, the scope for further research is discussed and finally Section 8.6 presents the conclusions from the research results and makes practical recommendations for implementation of the Validated AI-OP adoption Framework in the healthcare sector, healthcare settings and academia.

8.2. Aims, objectives and research questions.

This section of the chapter reviews research aims, objectives and research questions as presented in Chapter 1 (Sections 1.6 and 1.7), to demonstrate that they have been achieved. The overall aims of this research are stated below:

- To investigate the impact of Artificial Intelligence (AI) on Organisational Performance (OP) in the Healthcare sector
- To develop a framework for the adoption of AI for OP in the Healthcare sector supported by implementation guidance.

The two aims presented above have been achieved. While reviewing the literature in (Chapters 2 and 3) academic research contributions on Artificial intelligence and Organisational performance were identified, and this enabled discussion of the application, adoption and implementation of AI in healthcare and provided theoretical and qualitative bases to support development of the AI-OP adoption framework developed in chapter 4.

The development of the theoretical AI-OP Adoption Framework (Figure 4.2) is based on the identified literature gap and depicts an understanding of various components that have a direct influence on the design, adoption and implementation. Additionally, Figure 7.7 presented in Chapter 7, reflects findings from the qualitative research, and provides the stepwise guidance for AI adoption and implementation in the healthcare sector and in academic research.

In addition to the research aims, the following research objectives were set:

1. To critically review the literature on the application of AI to Organisational performance in the General and the Nigerian healthcare sector.

2. To identify the challenges and benefits of artificial AI for the healthcare sector.

3. To evaluate current frameworks of Artificial intelligence

4. To investigate the impact of AI on OP in the Nigerian and the UK healthcare sectors.

5. To investigate the challenges of AI adoption in the Nigerian and the UK healthcare sectors.

6. To investigate factors for the adoption of Artificial intelligence for organisational performance in the Nigerian and the UK healthcare sectors.

Chapter 2 is a comprehensive review of related theories and relevant research contributions to the research area. Theories and models relating to AI, OP and adoption were evaluated and the relevant elements contributed to development of the theoretical AI-OP adoption Framework. The theoretical Framework (Chapter 4, Figure 4.2) was developed based on the theoretical aspect of the research (Chapters 2 and 4). As highlighted in Chapter 6, the theoretical AI-OP Adoption Framework was adjusted after the qualitative field research focusing on identification of internal and external key factors and other factors identified as relevant to AI healthcare adoption. On this account, the theoretical AI-OP Adoption Framework transitioned to the Tested AI-OP adoption Framework for the healthcare sector (Figure 7.7).

8.2.1. Research Questions Answered by Desk Research

The research aims and objectives have been attained by answering the six research questions outlined in Section 1.7 of Chapter 1. The six research questions are discussed in the subsection below.

1. What is the current literature on the application of AI to OP in the general and Nigerian healthcare sector?

The body of literature on the subject appears to be emerging with most studies on AI application focusing on different OP related issues in the healthcare sector and resulting mainly in positive impacts. Despite the wide application of AI to OP in healthcare, only a limited number of studies directly linked, measured, or assessed variables or elements of OP in healthcare (e.g., efficiency, health outcomes, financial performance, improved health outcomes etc.). Without specific linkage of AI to OP elements in healthcare, the actual impact of AI in healthcare cannot be ascertained. AI was applied to improving different areas of performance including: predictive and diagnostic accuracy such as in the prediction of decision making in clinical settings, prediction of brain cancer, prediction of periodontal diseases, interpretation of pathology slides, diagnosis of Crohn's disease; improved revenue recovery and cost savings; reducing risk of falls and improving care management; improved social presence and therefore social health outcomes for older people with dementia; improved service quality, patient care and well-being; improved healthcare outcomes in the management of Covid-19 and other diseases by decreasing morbidity, mortality; improved patient wellbeing; improved resource management and reduced pathologist's workload. The studies reviewed on the application of AI to OP in the Nigerian healthcare sector applied AI to different aspects of OP in healthcare such as in the diagnosis of communicable diseases such as typhoid fever; Ebola disease; paediatric diagnosis of birth asphyxia and improved decision making. Having reviewed the literature on the application of AI to OP in the general healthcare sector it can be inferred that there is a high interest by researchers on the application of AI to different aspects of OP and in different healthcare settings. Having reviewed the literature on the application of AI to OP in the general Healthcare sector and in Nigerian healthcare sector, it can be concluded that the concept of AI is not new and has been applied to different aspects of healthcare OP. Most of the studies did not show any specific links to variables or elements of OP specific to healthcare. Further investigation of the literature by evaluation using the four-quadrant framework reveals that there is a scarcity of AI studies with a focus on practical guidelines adoption and implementation of AI in the healthcare sector.

2. What are the challenges and benefits of artificial intelligence on the healthcare sector?

From the literature reviewed it can be inferred that AI can benefit healthcare in many ways such as in improving medical research, improving management of healthcare resources, improvement of patient access to care, and improvement of diagnostic processes in many healthcare specialties such as radiology and imaging, genetics and genomics, pathology, dermatology, oncology, neurology, health and social care, ophthalmology, diabetes, critical care, public health resulting in reduced treatment and associated costs, more efficient management of diseases reduced morbidity, mortality and health outcomes. These have been discussed with greater detail in Chapter 2. The literature review also revealed that AI can be applied widely in healthcare but with several imminent challenges. These challenges can pose barriers and prevent the application, adoption, and implementation of AI in healthcare. Some of the challenges identified include reliability and safety issues, legal liability, lack of transparency and explainability, data privacy and security issues, unethical and malicious use, bias, issues with equity and fairness of data, resistance from healthcare professionals, profitability issue, issue of over-reliance on AI, mental health implications and lack of evidence base to support AI.

3. How effective are current AI frameworks in healthcare?

Having reviewed several healthcare AI frameworks it can be concluded that most of them focused on the AI, describing their components and the performance. There was little focus on the factors for adoption of AI apart from data.

For healthcare organisations to apply and adopt AI for performance improvement, there is need to not only ensure the performance of AI but there it is important to identify the key factors for AI adoption. One of the frameworks reviewed (Hadley *et al*, 2020) identified all the factors required to apply the framework and provided implementation guidance. The framework proposes important considerations for AI adoption in global health initiatives vaccine delivery and community healthcare worker routes (which can be transitioned to local public health settings). Factors for AI adoption include the type of AI models, processes, personnel and infrastructure are also identified. In addition, a guide is provided to support development of a pre-implementation strategy. One framework by Ashfaq *et al.,* (2019) accurately predicted readmission risk, linked AI to OP by measuring cost savings therefore improving efficiency and OP in healthcare, additionally, it showed the input of patients' data such as demographics, diagnosis, procedures, and lab data but did not show or identify any other factors involved in AI applying the framework. All the other frameworks evaluated showed AI components, identified data as a factor in AI adoption but failed to identify any other factors required to adopt AI for OP.

8.2.2. Research Questions Answered by Field Research

4. How does Artificial intelligence impact OP in healthcare in the Nigerian and the UK healthcare sector?

The results of the qualitative research in Chapters 6 reveals that AI improves four perspectives of OP in healthcare as outlined below. Firstly, AI potentially improves healthcare financial performance through Improved cost efficiency, improved cost savings, improved financial profit and revenue generation. This result was consistent across all themes for both Nigeria and the UK healthcare sectors. Secondly, AI potentially improves Healthcare customer performance through Improved healthcare customer (HCC) satisfaction, Improved healthcare quality, Improved access to healthcare, Improved HCC engagement, Improved health outcomes, Improved patient safety. The result was consistent across majority of themes except improved HCC engagement which was identified for the UK but not Nigeria and implying that there may be need to improve apply AI to improve HCC engagement in the Nigerian healthcare sector. Thirdly, AI potentially improves Internal business performance in healthcare through Decreased disease burden, Decreased workforce crisis, Decreased workload, Decreased wastage of resources, Improved efficiency, Improved productivity. This result was consistent across all themes for both Nigeria and the UK healthcare sectors. Lastly, AI potentially improves Innovation and Learning performance in healthcare through Improved learning, Improved Innovation, Improved processes, Improved research and development. The result was consistent across all themes for the UK and Nigeria. The need for improved data for research and development was highlighted for Nigeria. This implies that there may be need to apply AI to improving research and development in the Nigerian healthcare sector. Based on the four perspectives of OP assessed, it can be implied that AI impacts OP in healthcare by potentially improving financial performance, HCC performance, internal business performance and leaning and growth perspective of performance.

5. What are the challenges of AI adoption in healthcare and in the Nigerian and the UK healthcare sectors?

Eight typologies of challenges were identified for AI adoption in healthcare these are: Skills-related challenges, Data-related challenges, Finance-related challenges, Healthcare specific challenges, Infrastructure-related challenges, Resistance-related challenges, Technology-related challenges, Skills-related challenges. Three of the challenges Skills, Infrastructure, and Resistance were consistent across research locations of Nigeria and the UK while the remaining five challenges varied. These are outlined below.

Regulation-related challenges were highlighted as lacking clarity and structure for both Nigeria and the UK, however with the UK current regulatory provision appearing to be more comprehensive than what is obtainable in Nigeria. Finance-related challenges were identified for both locations but appeared limited to the UK private healthcare sector while more prominent in the Nigerian healthcare sector where it affects both private and public healthcare sectors due to the poor economic situation. The data challenges also appeared to vary based on location, with respondents from Nigeria highlighting more primary data challenges related to basic infrastructure for data collection and management while UK respondents mentioned secondary related data challenges related to data appropriateness and technical data challenges. Healthcare specific challenges appeared to be limited to the UK healthcare sector only. Technology and Infrastructure related challenges were also limited to the Nigerian healthcare sector.

6. What are the factors for the adoption of Artificial intelligence in the Nigerian and the UK healthcare sectors?

Eight key factors for Healthcare AI adoption were identified from the analysis of the interviews with the Key informants (Healthcare managers, Healthcare professionals, Healthcare technologists). These are: Acceptance, Data, Finances, Management, Organisational priorities, Regulation, Skills, and Technology factors. Seven factors remained consistent for Nigeria and the UK while one varied regarding location. Regulation was cited as important for both locations but observed to have variable requirements across both locations as presented in Chapter 7. The skills factor, which is composed of training, education, competence was consistent across locations with respondents from both Nigeria and the UK identifying it as important. It however appears that training needs vary with age with older healthcare professionals showing higher training needs than younger ones.

8.3. Research limitations

Several limitations have been identified for this research as follows.

I. It is important to mention that the Covid-19 pandemic affected this Research around data collection. Many of the organisations contacted to participate in the research were not operating due to lock down and travel restrictions imposed by the UK government. Although some of these organisations were expected to be operational, they were hardly available for business and operating minimally. On easing of lockdown, most of the private healthcare organisations contacted for research were non-responsive while most of the public ones were operational but also not open to research and related purposes. The Researcher was able to mitigate the effects of the pandemic on data collection by using networks to privately contact healthcare professionals working in healthcare organisations and by making contacts within her academic and professional networks. Most potential research participants contacted were unavailable to participate in research due to either due to lockdown or because of shielding. Some potential participants appeared not just enthusiastic to participate in research and the Researcher contacted well over a hundred potential participants before securing interested participants that agreed to participate. There appeared to be reduced availability of women to participate in research during the pre and immediately post lockdown and this was notable in the reduced number of female respondents in this research.

II. The literature search was restricted to published articles from a limited number of databases due to the Research word limit and the emerging nature of AI in healthcare. Also, there were no searches in grey literature this means that many other literatures could not be included in the review.

III. One of the main limitations is that this Research evaluates AI from the strategic point of view rather than the technological point of view.

IV. However, the application, adoption and implementation of AI and ML to OP is a topic that is newly emerging and therefore many of the AI technologies evaluated in the literature and those experienced by respondents in the qualitative research have not been fully deployed to scale in healthcare settings therefore have not gone through external validation or prospective testing. Potential improved performance based on AI technologies that have been internally validated or which have undergone prospective testing, may not culminate in applications in the real-world healthcare settings.

V. Interviews were conducted with respondents from 2 countries; Nigeria and the United Kingdom because there is variation in the healthcare sector across countries which could make the results differ. Nevertheless, the research results were substantiated with the help of literature on studies from the contexts of other countries in addition to these countries.

VI. Data saturation was reached, at a smaller sample size than planned. In addition to this, there were more respondents from the UK than Nigeria even though this was not intentional. Although the number of qualified potential participants from Nigeria appeared to be less than the UK, many of the potential Nigerian correspondents contacted did not participate. Also, there were more males than females probably due to women being less represented within health/technology/management field. Although the results of the Research are internally consistent, it is possible that a more balanced and diverse sample would have enhanced it more.

VII. This Research focused only on the healthcare sector but was generalised to different settings of healthcare. Across cases, the professionals interviewed varied in terms of role, position, experience, and knowledge due to the early stage of adoption and implementation of AI in healthcare. Therefore, the sample of respondents is likely biased towards individuals having specific interests and high interest in AI application, adoption, and implementation in healthcare.

8.4. Contributions to Knowledge and practice

This section presents key contributions made by this research to the literature and to practice. Firstly, this Research provides in-depth review of concepts and themes relevant to AI and OP in healthcare, supported by a detailed review of the academic literature, and by the recognition of important factors and challenges in the adoption and implementation of AI. To the Researcher's knowledge, this research is one of the few that have investigated the impact of AI on OP (with assessment of OP elements) in the healthcare sector. As highlighted in Chapter 3, this research identified a gap in the literature on the application, adoption, implementation of OP in healthcare which, to the best of the Researcher's knowledge, has not been empirically investigated in this context (the Nigeria and UK context and linkage to elements of OP) in previous research. Secondly, this research makes a considerable contribution to literature by developing the Strategic AI-OP Adoption Framework for the healthcare sector. This framework is considered unique in the sense that it clearly illustrates the key factors for adoption of AI for improved OP in the healthcare sector. Key changes to the theoretical AI-OP Adoption Framework that were introduced to the Strategic AI-OP Adoption Framework are: Identification of Management as a key factor for AI adoption; Merging of regulation, ethics and law into Regulation factor as they all belong to the regulatory landscape; Expansion of the Technology factor to Internal technology and external technology as a key factors for AI adoption and Expansion of the Education and training factor to Education, training and skills.

The sample selected for the interviews comprised 19 Key Informants from private and public healthcare settings within Nigeria and the UK who are theoretically and practically competent in the AI/ healthcare intersection. Consequent to the investigation, the Researcher concluded that AI impacts OP in healthcare, but the impact is potential at this time due to low level of adoption and non-scale deployment which hamper proper impact measurement. This research contributes to a better understanding of the role and importance of AI to improve OP in healthcare organisations. It highlights the key factors and challenges of AI adoption and offers guidance on the achievement of AI adoption and implementation. This Research relies on the theoretical and empirical investigations conducted and upon the Researcher's years of professional experience in the healthcare sector. The study thus contributes to the literature by combining qualitative methods taking into consideration the value of rich descriptions of and contexts offered by qualitative research. The table 8.1 below summarizes the main contributions of this research.

Table 8.1: Summary of Research contributions

Contribution	Description	Chapter/ Figure
Development of Theoretical AI-OP Adoption Framework	Theoretical AI-OP Adoption Framework	Chapter 4, Figure 4.2
	Key factors for Healthcare AI adoption	Chapter 4
	Technology acceptance factors	Chapter 4
	Organisational performance measures	Chapter 4
Strategic AI-OP Adoption Framework	Development of the Strategic AI-OP Adoption Framework which	Chapter 7, Figure 7.7
	Identification of Management as a key factor for AI adoption	Chapter 7
	Merging of regulation, ethics and law into Regulation factor as they all belong to the regulatory landscape.	Chapter 7
	Expansion of the Technology factor to Internal technology and external technology as a key factors for AI adoption	Chapter 7
	Expansion of the Education and training factor to Education, training and skills	Chapter 7
Practical guidelines	Practical guidelines for	Chapter 7

Source: The Researcher

8.5. Recommendations and Managerial implications

Regarding management implications, it is recommended that the management of healthcare organisations carefully put into consideration the current state of the organisation, its wider goals, aims and objectives to determine that AI is a good fit. If AI is identified as a good fit, then the Strategic AI-OP can be used as a guide for Adopting AI as a strategy to improving

OP in healthcare by first identifying the key factors identified in the study in addition to other factors considered as important in the specific healthcare setting. The challenges that may act as barriers to AI adoption in the specific healthcare setting can also be identified and mitigated. Over time, the adoption of AI can lead to improved financial performance, improved performance in relation to healthcare customers or the patients in healthcare, improved performance in relation to the internal business and improved performance in the Innovation and Learning aspect of the organisation's performance.

8.5.1. Recommendations

I. In addition to education and training of healthcare professionals, greater awareness of AI should be promoted to healthcare organisations in terms of its knowledge, practicality, profitability, efficiency.

II. Healthcare organisations should adopt AI early to improve OP.

III. Healthcare organisations should engage in partnerships, collaborations with other organisations, academic and research institutions to promote AI innovation.

IV. AI should be used to augment humans in healthcare for optimisation of healthcare systems.

V. Healthcare professionals and all stakeholders should be involved and engaged from the design stage to implementation to understand how to appropriately design these technologies with the interest of the users and their practice in mind. It is also recommended that clinical champions be identified to support AI adoption.

VI. The challenge of financial requirements and funding for AI adoption should be looked into for private healthcare organisations in resource-sufficient settings and more so in resource constrained settings by improvement of access to funding by governments and private investors. It may also be worthwhile for both private and public health organisations to enter business partnerships with capable local and foreign investors to support the adoption of AI in the country.

VII. The issue of infrastructure common to resource-constrained settings like Nigeria should be urgently addressed by government.

VIII. Healthcare organisations should mitigate healthcare challenges to improve adoption and OP in the sector.

8.6. Scope for future research

While this Research, has been exploratory in nature, focusing on qualitative assessment of the impact of AI on different perspectives in a combination of experimental and real-world settings resulting in linkage of AI to OP and an understanding of the areas of potential impact of AI on OP. In order to achieve better generalizability of the results, further research should investigate the under-listed.

- Quantitatively measure the impact of AI technologies on performance in real world healthcare setting as this will further conceptualize and strengthen the adoption of AI in healthcare organisations.

- Investigate the impact of AI on OP with focus on other elements of performance more specific to various healthcare settings.

- Investigate AI from the technological point of view by measuring the impact of specific subfields e.g., ML, DL, ANN of AI on Healthcare performance with a view to establishing causation rather than association and correlation.

- Research on the application of AI should focus less on propagating the performance of AI in terms of accuracy, area under the curve (AUC), sensitivity and specificity and more on their actual impacts they have on healthcare performance in real world settings.

8.7. Conclusion

The Researcher concludes that the application of AI to OP in healthcare has been researched and can currently be described as an emerging area of study. It appears that healthcare organisations may not be benefiting from the application and adoption of AI as there is a lack of literature on the key factors, challenges of adopting AI for the improvement of Organisational performance. This Research has revealed that AI is known to the healthcare sector, but application and adoption is not aimed at improving performance as AI is not directly linked to OP measures and elements and therefore the actual impact of AI cannot be assessed or measured, and improvements cannot be made. Healthcare organisations and the healthcare sector can improve performance if AI is adopted at scale and linked to performance.

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10. APPENDIX

10.1. Appendix 1

10.1.1. INVESTIGATION OF THE IMPACT OF ARTIFICIAL INTELLIGENCE (AI) ON ORGANISATIONAL PERFORMANCE (OP) IN THE HEALTHCARE SECTOR

Answers to the following questions can be based on direct examples from the organisation and experiences observed in other organisations.

Date: 16th June 2021

Time: 11:30

Location: Conference call

Name of the interviewee (code): RE13

Question/ Respondent's Answer

1. R: Describe the healthcare organisation where you have applied, adopted or implemented AI?

RE: Yes, I'm a consultant surgeon. I work in a large teaching hospital in the UK.

2. R: Describe your role in the organisation?

RE: So I'm a consultant neurological surgeon, so I'm responsible for looking after patients with neurological conditions and cancer from the acute setting on the hospital, on the ward and also as an outpatient. In addition to that, I perform surgeries. So I operate on patients with conditions as well, and manage the junior teams in our department on a clerical and administrative basis for many things.

3. R: Define Artificial Intelligence?

RE: For me, it's quite clear that if you speak to the general lay person, everyone thinks AI is a computer that just makes decision for you magically, and does something clever and it does things that humans can't do. But actually, we're far from that. That's Hollywood. The reality is

AI is multifaceted. So you've got starting with the basic things, we've got rules based systems. So you train the computer with a fixed set of rules, and the computer even those the rule or not, and it says yes or no, and that's the basic AI, if you want to call it AI, then you've got an expert systems that are trained by humans. And it just only recognises one thing, if you put something else in it can't recognise it, because it doesn't understand the input. Then you've got moving through that you've got, you've got machine learning, where you give the rules, and you get the data. And you train the computer how to learn. And then it goes through the data using the rules that's been predefined and, and learns and picks things up basically, it gives outcomes. So that's machine learning. And then you've got the neural networks, which are the blue sky stuff, where you don't give the computer rules. You don't give it any real give it data. And it forms its own opinions and outcomes. But that's a Hollywood that's we're not even there yet.

4. R: How does AI impact your role?

RE: NHS is quite a, it's quite a bureaucratic organisation. Look, I put my computer on it took me 15 minutes to put my computer on how can you sit? How can an organisation deal with AI without getting the hardware straight? So on a day to day shop, from NHS, role, AI doesn't mean very much, it means very little in my trust. There are hospitals where they use AI. So I know Royal free in North London, use an AI centre to analyse patients. Again, it's a kidney failure. So it is rules based, there are set parameters. Anyone with a kidney percentage of x, it will alert the system that they potentially can go into renal failure or let the doctors and nurses basis that's AI and machine learning. But that's experimental. But as far as I'm concerned, in the NHS no one's doing it. No one's using these systems as routine standard of care. They're still part of trials or experimental system, basically, or research. So I might be wrong. But that's my understanding. So most of what is happening at the moment is still experimental, though In the NHS, and there might be pockets. Yeah, there might be pockets of things that are running national.

Yeah. So we've got the analysis of kidney function. The biggest use of AI and NHS is in diagnostics in radiology. So there are AI systems I know during COVID are experimenting with people with chest x rays, and trying to use AI to work off the chest X ray had COVID, the patient had COVID based on the appearance of the chest X ray. So that's the kind of or for abnormalities in the lung. So that's pretty much the biggest use of AI in NHS is also companies using it for breast mammography. So using AI to identify the mammogram and if there's any abnormal lesions for them to be presented to see doctors basically so pockets of use. So I was saying that there's different systems in NHS, but they're all very experimental, the government has invested 150 million pounds in AI in NHS, especially with COVID that the priorities COVID recovery. So we're seeing more patients more cancer patients. So how can we do things better and efficient, more efficiently? Well, we're certainly not in widespread adoption in the NHS at present.

5. R: What subfield(s) of AI have you applied in your organisation?

RE: The reality is AI is multifaceted. We've got the rule based systems, expert systems, machine learning and neural networks. Basically, in healthcare at the moment we're still in is rules based, we'll have a bit of machine learning basically. Well, that's why AI means to me but you're getting it you're getting an answer from someone is doing this.

6. R: How does AI impact your organisations performance in terms of the following variables of OP?

Probe: Financial perspective e.g. financial performance, financial health, cost optimization, customer base.

RE: Well, the theory is, again, this hasn't really been proven, because the studies on them the thinking is if we can be more efficient with our time, so AI is about how to help doctors do what they need to do quicker and efficiently so we can see more patients. So for example, the projects I'm doing on the prostate cancer decision support system, we discussed about 100 patients a week and our meeting, that meeting has 10 doctors and 10 consultants, admin staff, the amount of time it takes to prepare that meeting so much, that time I'm sitting in drinking coffee and looking at scans, I can be actually seeing in real life patient treating them. So it's very inefficient use of my time.

So how can AI help with that? Could AI be used to then run through those lists? Pull out who needs to be discussed and reduce that list by say, 30% 40%? How many hours of manpower that reduces, its cost efficiency and from a cost point of view, for example, a patient waiting for hip surgery comes to A&E they get seen by a doctor, they get medication, there's a cost for that for the service for them presenting. And it gets the point where they turn up so many times it's cheaper to do the operation, than have them wait and then have more and then strictly treat the complications of that waiting. So AI has a role. But again, I keep saying it needs to be evaluated, but there's a lot of potential.

7. How does AI impact healthcare Customer performance?

Probe: e.g. safety, quality, accessibility, efficiency and healthcare customer or patient satisfaction

RE: In terms of patient satisfaction, there are not many studies about patients on AI. The problem is, is deep distrust with data, and AI, if people the public think that robots are huge, or computers are managing their care, there will be a big uproar, so let’s be quite careful about it. So there are studies at the moment, we're doing work with patients to look at patient accessibility of AI. And we just started some work on that we soon actually to see what patients think about what does AI mean to a patient or average on the street?

8. How does AI impact health Internal business performance?

Probe: e.g. operations, quality of care, productivity, volume, internal efficiency?

RE: Well, all I can say in terms your question is not the impact, we don't know the impact as nothing has been proven. What the presumed/ potential impact will be basically less wastage, less human time doing menial tasks, and a lot of things that like, for example, in our cancer meeting, I only found out the other month that one of our admin staff, she prints out 40 pieces of packs a day a week, for the meeting but its only two or three doctors actually reading it. But every time there is a meeting she spends all the time producing all these parts and then at the end of the meeting they get put into recycling. She spends three hours doing this in a week, it is a waste. Like there's so much time that's wasted that you know, that doesn't need to happen basically. So AI can potentially help reduce those menial tasks and there a lot of menial tasks in medicine that computers can do to save free up human time. So productivity we hope will improve. We hope that this has to be evaluated.

AI can also impact on things like backlog. Well, that's the presumption. Yes. So that's what we need to evaluate. Because we've COVID, now, like, for example, in theatre, the waiting list for an operation in UK is about 2 million people waiting. It's the highest on one of the highest in 20 years. And I met an AI company that can basically do that. At the moment, I have to go through a list of 200 patients and manually review them and decide who is in more critical condition, who needs more priority. It is labour intensive and it will take like half a day to do that. I've got other things that we do, and I've not got time to sit a computer. But as a tech company, basically, they can do this if they take the parameters from hospital EMR systems, and look at when the patient was booked, how long they've been waiting for. And if they've been to A&E or hospital in those times the same issue because their priority goes up, rapidly analyse that with AI and produce a list of the patients who needs to be prioritised. Now that can be brilliant for me, because I don't have to do that work and can use the time for other things. And based on the long hours I will spend, will be probably more accurate because it can take into account the factors rapidly. If we have two patients, waiting for hip surgery, for 19 months, one of them is stable and never seen a doctor not on painkillers. The other has been to A&E four times for hip pain. Who do you think you're going to operate on first? It will be the one has been to A&E even though they're both at A&E at the same time, we can see clearly the impact on that person's life is more.

9. How does AI impact healthcare Innovation and learning performance?

Probe: e.g. education, research and scholarship, innovation, organisational learning, process improvement RE: The impact on learning is massive because it's auditable. And you know, at the moment, we keep files of our training and all that. But again, if we can have like IR protocols, you can compare between hospitals and sites.

You can then use AI as a research tool, that research tool then generates money for the trust, because you're doing research in AI, so and there's a good international increase in the hospital international reputation, as you are seen to be leading the way in AI and because AI is in early development, it's just a matter of time. So there's a good upside from the organisational point of view in terms of your processes,

10. R: What are the challenges to adoption and implementation of AI for your organisation?

Probe: Cost, organisational, technical, technological, clinical, difficulty establishing a business case.

RE: organisational change NHS is a very slow commoner, it moves like, if you've got Goggles and apples that are like, you know, speed, like speed boats, they're nimble, they can move well, in the early stages, and they can adapt. NHS is like the tugboat to turn left, it takes so long, everything slow. Multiple managers, there's multiple, for example, our project just to get off the ground, I put out I had about 30 meetings now to meet with multiple different players, basically, just to get the thing off the ground, you want to be of it, you got to meet a governance, you've got to meet legal people, you've got to meet the clinical people. And it's just, there's so many stakeholders, and sometimes it's so inefficient, it doesn't foster the AI kind of learning, basically. So that's one frustration.

Cost, Yes, Yeah, the cost, obviously a big thing but I think people are coming around to that this funds like the one that government's doing, where the money helps bridge that cost organisation to people's biases.

So some doctors think it's all nonsense, and like, you know, big brother's watching and There's in from patients as well as usability because I guess we've COVID that people are more suspicious of government and healthcare. So you're telling them that a computer is going to analyse your notes and decide on your treatment, then, you know, it could blow up and more things like health disparities. So for example, in skin cancer, we found that when they were training the AI systems, they'll train it on Caucasians. So you got a black skin, the computer doesn't necessarily know skin and it is in that so you know, there's health disparities that it may open because if the coding is done by Caucasian, they may not bear in mind that ethnic minority so you've got to think about these things as multi factor, or people where English is not their first language, or elderly whether they may have bought smartphones. So you're excluding people. And you know, the young people that have Apple watches and smart phones may engage, the older people or people that are marginalised may not. Society argued that they are the ones who need to benefit. These are unintended consequences of adoption, you have to kind of think of a lot of things as well, not just the actual adoption, but the ethics as well and implementation.

11. R: What are the factors of importance for healthcare organisations when adopting AI?

Probe: important factors for successful AI adoption/ implementation for healthcare organisations.

Probe: Data Educational and training, Acceptance, Organisational considerations, Technological considerations, Legal, Ethical, Regulatory considerations, Environmental considerations

RE: There are a lot of considerations that, you know, we have to consider, I think the biggest one going forward in adoption is ethical considerations. Because even simple things like where's the data being stored? You know, in our hospital, the company we're working with, had the data stored in Ireland. And before Brexit, that wasn't a problem. But now in Brexit, there's a whole massive issue about sectors and data, go to European Union and come back to us. So we have to then think about we have to put the data in our own server. So and then, you know, so that's one thing. So these are things we never thought about the ethics of AI, as I've mentioned before, and except is there user acceptance from doctors and clinicians and from patients?

Environmental, you know, there's a lot of like, with all these extra servers, are you going to use more energy electricity, you're going to have more power requirements, taken away potentially from other areas in the hospital? Or is that going to cause more surges and damaged where you need generators when you know, and that's not a good idea in a hospital? So these are, yes, it's great saying AI, but there are unintended things that we just probably never even factor in until you do it and it is a problem, then you realise that they are opposite in time, in safety. Critical systems, like hospitals can't make those mistakes as lives maybe lost or it may be at a cost.

As for education and training of clinician, no doctor is the same, some are very tech savvy and very effective with AI, some don't actually know that we're talking about. So you got to bring everyone to the same level playing field to get user acceptance, because it's going to be the doctors who are going to be using these systems.

If you don't get clinical staff buy in early, it's not going to happen. Like, you can design the best system. But if you don't design it with doctors and nurses and physios in mind, they are not going to use and you'll have, you'll have a very expensive software that no one touches. So training, user testing concept designing at the heart of it when you are starting, because traditionally, software companies will make a product we think is great, make the product and then give it to Doctors. And then it may or may not get used. But that is back way of thinking

I think you should design it for the people who will use it in mind, start and reiterate constantly. And that's the way you get by and even before you get training, because trainings is once you have accepted it, then you're going to train everyone to use it.

Basically, I argue you get people in, in the earliest stage of design, which is not starting to happen now. But still very much as a product, we'll send it to you use it get one trend. Perceived usefulness and perceived ease of can be considered. Like, if Apple made if Apple ran a hospital and made computers and software systems, everyone would be happy because Apple products are easy to use. They're not clunky, you don't have to log in here and do their intuitive. So, absolutely it will be easier for clinicians to accept. But then the balance shown as easy to use, is it how secure is that basically. So you have to have that balance. And obviously, we've got personally identifiable information. So it's always about usability versus security is a challenge.

12. R: What recommendations can you make for healthcare organisations' when adopting AI to improve OP?

Prompt: strategic/ management, clinical, technological recommendations depending on expertise; Managers, Clinicians and IT/ AI experts respectively.

RE: Yeah, well, as I said, in my last words, I think when you're designing these software's have clinicians in mind, don't just create something you think will work and they will go use, it is not going to work that way. Involve them first in the initial stages and in that concept design and then when you're implementing it, have buy in from the staff. The problem is sometimes hospital buy things like in our hospital now we're moving to epic. There was no consultation when they just decide to use epic, which is fine, but that may bring resentment or people just don't feel they're listened to. So they're just, you know, they're above or they're not engaged in the process because they don't grow that fast. But the management, they're just deciding what we're using and the impact is some of the clinicians have never even touched the EHR system, let alone use them. You know, so and sometimes frustration where you feel that people are making decisions outside of your control. So having focus groups having usability discuss, why should we do this? And what's this one? What are the pitfalls of this? I think you'll get much more widespread adoption in the NHS this way since it's pseudo commercial, unlike the private sector.

KEY

R: Researcher

RE: Respondent

10.2. Appendix 2- Research Interview Guide

10.2.1. RESEARCH INTERVIEW GUIDE

THESIS TITLE: INVESTIGATION OF THE IMPACT OF ARTIFICIAL INTELLIGENCE (AI) ON ORGANISATIONAL PERFORMANCE (OP) IN THE HEALTHCARE SECTOR

Qualitative Interview Introduction

Format: Semi-Structured Interview

Type: Face-to-face/ Virtual/ Phone

Duration: 30-45 minutes

Primary goal: To understand the topic from the interviewee's perspective, a conversation with a focus on interviewees lived experience, opinions and feelings about the topic.

Verbal consent: Your participation in this study is on voluntary grounds and the responses that you provide will be kept confidential. Interview will be audio recorded, however your data will be de-identified; this means that the information you provide will not identify you as an individual or as an organisation. It will be used solely for the purpose of this research.

Background Information Overview: Interviewee will be invited to briefly talk about him/herself: General information about background… mostly about experiences and perspectives on Artificial Intelligence (AI), AI adoption and impact of AI on Organisational performance.

Some questions may be more relevant than others depending on the participant's role; Healthcare Manager, Healthcare practitioners/ Clinicians or IT/AI experts therefore questions may be omitted or probed further depending on appropriateness.

Interview Schedule

1. Describe your organisation?

Probe: (structure, business activities), location and history.

2. What is your role in the organisation?

Probe: professional background, role, tasks

3. Describe Artificial Intelligence?

Probe: your definition

4. How does AI impact your role?

Probe: impact of AI on role, tasks, changes and adjustments.

5. What subfield(s) of AI you have applied/ adopted/ implemented in healthcare?

Probe: Neural Networks, Evolutionary and Genetic Computing, Vision Recognition, Robotics, Expert systems, Speech processing, Natural language processing, Machine learning.

Why is this subfield important?

6. How does AI impact healthcare financial performance in terms of the following perspectives of OP?

Probe: In the Financial perspective e.g. financial performance, financial health, cost optimization, customer base.

7. How does AI impact healthcare Customer performance e.g. safety, quality, accessibility, efficiency and healthcare customer or patient satisfaction?

8. How does AI impact health Internal business performance e.g. operations, quality of care, productivity, volume, internal efficiency?

9. How does AI impact healthcare Innovation and learning performance e.g. education, research and scholarship, innovation, organizational learning, process improvement

10. What are the challenges to adoption and implementation of AI for healthcare organisations?

Probe: cost barrier, organisational barriers, technical barriers, technological barrier, clinical barriers, difficulty establishing a business case.

Probe: How do these factors affect adoption?

11. What are the key factors for healthcare organisations to consider when adopting AI?

Probe: Data factors, educational factors, Acceptance, Organisational factors, Technological factors, Legal, Ethical, Regulatory factors, Environmental factors, Perceived ease of use, Perceived usefulness.

12. What recommendations can you make for healthcare organisations' when adopting AI to improve OP?

Probe: strategic/ management, clinical, technological recommendations depending on expertise; Managers, Clinicians and IT/ AI experts respectively.

Thank you for agreeing to participate in this research.

10.3. Appendix 3 –Ethics Approval

UNIVERSITY OF THE WEST *of* SCOTLAND

UWS

15/01/2021

Dear Opeyemi Awonugba,

Your application 9661: Investigating the impact of Artificial intelligence on Organizational Performance in the Healthcare sector: Case of Nigeria, submission reference 11795, has been approved, with conditions, by the Business and Creative Industries SEC. **You may proceed with your study provided you meet the conditions outlined below**;

Title	Comment
How will the costs of the study be met?	Provide more detail on the specific external sources of funding. There needs to be clarity here in order to allow the reviewer to check whether there is any potential conflict of interest.
What measures will you put in place to ensure the confidentiality of personal data gathered during your study?	It is acknowledged earlier in the application that discussion of poor implementation of AI may be of a sensitive nature to some participants. With this in mind, the measures to protect confidentiality should be more clearly set out for the benefit of participants. Provide more information on how data are to be encrypted and password protected particularly if data is being transferred from a recording device to a personal computer.
Who will have access to the data collected during the study and how will you keep it confidential?	Are the interviews being recorded directly onto the password protected personal computer or are you using a mobile phone or dictaphone to record the interviews first then transferring them to the personal computer? If you are transferring them to personal computer later, how do ensure secure data protection of the interviews on the mobile phone or dictaphone before transfer? You need to state and justify the length of time you intend to retain the data after the project is complete and the secure method of destruction of that data once the data after the retention period ends.
Please upload any additional supporting documents you are submitting with this application	The Participant Information Sheet makes an erroneous reference the Data Protection Act 1998. This has been superseded by the Data Protection Act 2018 and the General Data Protection Regulations 2018 (GDPR). This must be amended to reflect the current legislation.

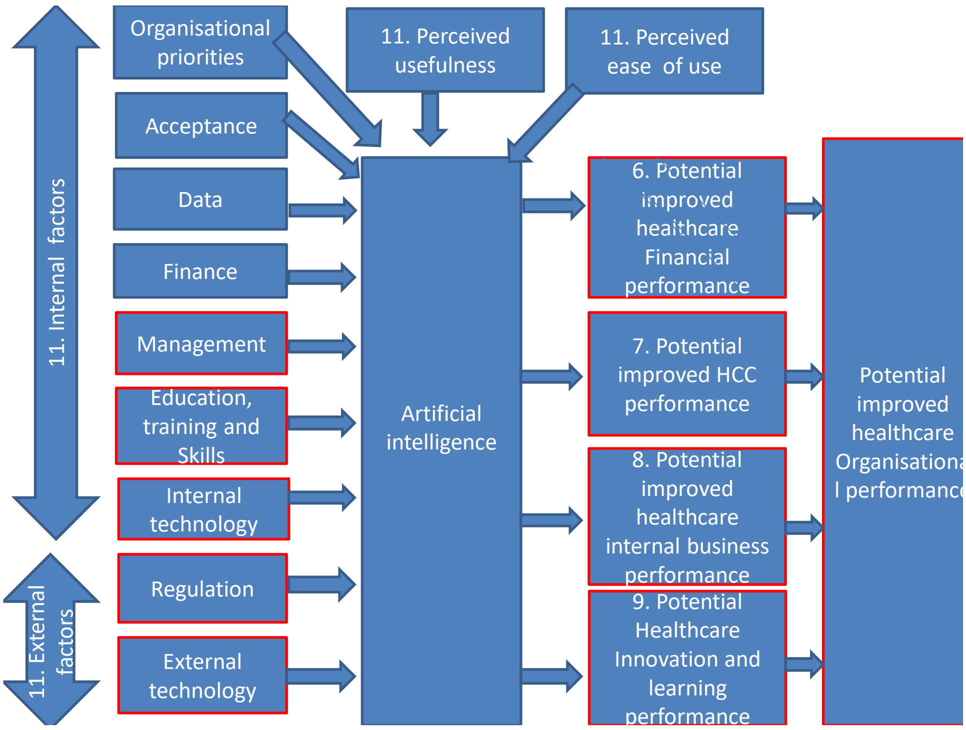
If you wish to make any significant changes to your study you must seek the committee's approval before actioning them.

Good luck with your research.

Dr D Turner

10.4. Appendix 4 –Strategic AI-OP Adoption Framework

Figure 10.4.1 Strategic AI-OP Adoption Framework showing the interview questions that yielded the components.



Source: The Researcher

10.5 Appendix 5: Summary of review of studies on the application of AI to OP in the healthcare sector

Table 2.2a Summary of review of studies on the application of AI to OP in the healthcare sector

Author/ year/ location	Study title	Contribution	Gap	Application of AI to OP
Amiri *et al.*, (2013)/ Iran	Assessing the Effect of Quantitative and Qualitative Predictors on Gastric Cancer Individuals Survival Using Hierarchical Artificial Neural Network Models	ANNs accurately predicted survival probability of gastric cancer patients more than Cox proportional models.	No specific link with elements or variables of OP. OP elements or variables not measured.	AI applied to improve diagnostic accuracy and efficiency.

Ciresan *et al.*, (2013)/ France	Mitosis Detection in Breast Cancer Histology Images with Deep Neural Networks	Deep neural network classifier successfully detected mitotic breast cancer in histology images with a higher accuracy than other approaches (statistical and CNN) in the mitotic detection of breast cancer.	Same as above	AI applied to improving diagnostic accuracy and efficiency.
Aragbol *et al., (*2013)/ Iran	ANN and GA can accurately predict and plan waste in healthcare settings	ANN and GA can accurately predict and plan waste in healthcare settings with higher accuracy of waste prediction than multi linear regression and mean square error approaches.	No specific link with elements or variables of OP. OP elements or variables not measured.	AI applied to improving improve accuracy and efficiency in healthcare waste management.
Bennet and Hausser, (2013)/ USA	Artificial Intelligence Framework for Simulating Clinical Decision-Making: A Markov Decision Process Approach.	Markov models achieved over 60% reduction in unit cost and 30-35% rise in patient outcome. It also outperformed the current treatment fee for healthcare	Measurement of financial element of OP.	AI applied to reducing cost and cost efficiency.
Papantonopoulous *et al., (*2013)/ Amaterdam	Artificial Neural Networks for the Diagnosis of Aggressive Periodontitis Trained by Immunologic Parameters	ANN had a 90 to 98% accuracy in diagnosis of aggressive periodontitis patients by their immune response profile into the AgP or CP class. AI can improve diagnostic accuracy and efficiency.	No specific link with elements or variables of OP. OP elements or variables not measured.	AI can improve diagnostic accuracy and efficiency.

Li *et al.*, (2014)/ USA	Deep learning-based imaging data completion for improved brain disease diagnosis	CNN model was successfully applied to improved brain disease diagnosis more accurately than, *K*-nearest neighbour (KNN) and Zero methods. AI can improve diagnostic accuracy and efficiency.	Same as above	AI can be applied to improving diagnostic accuracy and efficiency.
Ozden *et al.,* (2015)/ Turkey	Diagnosis of periodontal diseases using different classification algorithms: A preliminary study	SVM and DT had performance of 98% compared to SVM 46% and may be better in decision-making and diagnosis of periodontal disease.	No specific link with elements or variables of OP. OP elements or variables not measured.	AI can be applied to improving diagnostic accuracy and efficiency.
Shi *et al.*, (2015)/ USA	Adaptive Neuro-Fuzzy System with Semi-Supervised Learning as an Approach to Improving Data Classification of Bad Debt Recovery in Healthcare	Neuro-Fuzzy System with Semi-Supervised Learning successfully classified data as an approach to bad debt recovery in healthcare.	Same as above	AI can be applied to improving revenue recovery.
Litjens *et al.*, (2016)/ Netherlands	Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis	CNN improved the efficacy of prostate cancer diagnosis and breast cancer staging.	Same as above	AI can be applied to improving diagnostic accuracy and efficiency.

The table summary show that although most of the studies applied AI to different aspects of healthcare performance, most of them did not specifically link AI to elements of OP in healthcare.

10.6 Appendix 6: Summary of review of studies on the application of AI to OP in the healthcare sector

Table 2.2b: Summary of review of studies on the application of AI to OP in the healthcare sector (continuation of table 2.2a)

Author/ year/ location	Study title	Contribution	Gap	Application of AI to OP
Razmara *et al.*, (2018)/ Iran	Elderly fall risk prediction based on a physiological profile approach using artificial neural networks	ANN had approximately 91% higher accuracy than single datasets and can be applied effective management of falls.	No specific link with elements of OP. OP elements not measured.	AI can be applied to improving health outcomes.
Kwong *et al.*, (2018)/ Hong Kong	A prediction model of blood pressure for telemedicine	Prediction of systolic blood pressure by ANN with over 90% prediction of systolic B.P than stand-alone measurements.	Same as above	AI can be applied to improving diagnostic accuracy and efficiency.
Ahmed *et al.*, *(*2017)/ New Zealand	Effect of Fuzzy Partitioning in Crohn's Disease Classification: A Neuro-fuzzy based Approach	AI system had improved the classification of Crohn's disease with classification accuracy of 97.6% and sensitivity, specificity of 96.07% and 100% respectively.	No specific link with elements of OP. OP elements not measured.	AI can be applied to improving diagnostic accuracy and efficiency.

Desautel *et al., (*2017)/ UK	Prediction of early unplanned intensive care unit readmission in a UK tertiary care hospital: a cross-sectional machine learning approach	Accurate prediction of unplanned readmission by improved decision	Same as above	AI can be applied to improving efficiency.
Jahantigh *et al.*, (2018)/ Iran	The use of artificial intelligence techniques for the diagnosis of periodontal disease by clinical indices	Levenberg-Marquardet NN algorithm successfully diagnosed periodontal diseases with low time, minimal error and low iteration.	No specific link with elements of OP. OP elements not measured.	AI can be applied to improving diagnostic accuracy and efficiency.
Moyle *et al.,* (2018)/ Australia	Potential of telepresence robots to enhance social connectedness in older adults with dementia: an integrative review of feasibility	Social robots had positive social presence on older people with dementia.	Same as above	AI can be applied to improving engagement and health outcomes.
Gonel *et al.,* (2020)/ Turkey	Clinical biochemistry test eliminator providing cost-effectiveness with five algorithms	AI and rules-based systems to eliminate ratios of requested unnecessary tests and for cost-	AI linked to financial element of OP. Measurement of cost of healthcare.	AI can be applied to reducing cost of healthcare treatment.
Incze *et al.,* (2021)/ UK	Using machine learning tools to investigate factors associated with trends in 'no-shows' in outpatient appointments	ML successfully identified factors associated with missed appointments.	No specific link with elements of OP. OP elements not measured.	AI can be applied to improving efficiency and health outcomes in patients.

Yarbakhsh *et al.*, (2022)/ UK	Artificial intelligence effectively predicts the COVID-19 death rate in different UK cities	ML models effectively predicted Covid-19 death rate.	Same as above	AI can be applied to improving predictive efficiency. It can also be applied to improving health outcomes by identifying disease risk factors, prevention, treatment and management.

Source: The Researcher

The table summaries show that although most of the studies applied AI to different aspects of healthcare performance, most of them did not specifically link AI to elements of OP in healthcare.

10.6 Appendix 7: Summary of review of studies on the application of AI to OP in the Nigerian healthcare sector

Table 10.1: Summary of review of studies in the Nigerian healthcare sector

Author(s) and year/ Location	Study title	Contribution	Gap	Application of AI to OP
Samuel *et al.*, 2013/ Nigeria	A web-based decision support system driven by fuzzy logic for the diagnosis of typhoid fever	AI supports Typhoid diagnosis	No specific link with elements of OP. OP elements not measured.	AI applied to diagnostic accuracy and therefore OP

Oguntimilehin *et al.,* 2014/ Nigeria	A Machine Learning Based Clinical Decision Support System for Diagnosis and Treatment of Typhoid Fever	Machine Learning Based Clinical Decision Support System successfully used in the diagnosis and treatment of Typhoid Fever	Same as above	AI applied to diagnostic accuracy and therefore OP
Oyelere *et al.,* 2017/ Nigeria	Mobile Application for Pre-screening of Ebola virus disease	AI supports the creation awareness on early EVD detection, prevention and transmission	Same as above	AI applied to health promotion, improved health outcomes and OP.
Fashoto *et al.,* 2018/ Nigeria	Decision support model for supplier selection in healthcare service delivery using analytical hierarchy process and artificial neural network	Hybrid model used to evaluate and select suppliers in healthcare	AI linked to decision making but no identification of DM as an element of OP.	AI applied to decision-making and efficiency element of OP.
Ojugo and Otakore, 2018/ Nigeria	Improved Early Detection of Gestational Diabetes via Intelligent Classification Models: A Case of the Niger Delta Region in Nigeria	Intelligent system used for the detection of gestational diabetes.	No specific link with elements of OP. OP elements not measured.	AI applied to diagnostic accuracy and efficiency element of OP.
Onu *et al.*, 2019/ Nigeria	Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia	AI supports diagnosis of perinatal birth asphyxia	Same as above	AI is applicable to improving diagnostic accuracy and efficiency element of OP.

Source: The Researcher

The table summaries show that although most of the studies applied AI to different aspects of healthcare performance, only one study (Fashoto *et al*., 2018) linked AI to elements of OP in healthcare.