FRAMEWORK TO DEVELOP A DATA-DRIVEN RESILIENT AND SUSTAINABLE HEALTH INFORMATION SYSTEM FOR HEALTH CARE APPLICATIONS

by

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DECLARATION BY STUDENT

I, AYOGEBOH EPIZITONE, declare that this thesis represents my work, from conception to execution. The thesis is succumbed to DUT only and no university or institution of higher learning for another degree. All material from published or unpublished works has been recognized.

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DECLARATION 2 – PUBLICATIONS

These are the candidate's contributions to scientific knowledge and development in the course of this study. The output presented in this section is published journal articles directly and indirectly associated with the professional and academic development of the candidate produced during the course of the project.

DHET ACCREDITED PUBLISHED JOURNAL ARTICLES

1. **Epizitone, Ayogeboh.** "Framework to Develop a Resilient and Sustainable Integrated Information System for Health Care Applications: A Review." *Framework.* In *International Journal of Advanced Computer Science and Applications"* 13, no. 7 (2022). DHET Accredited Journals - WOS & SCOPUS
2. **Epizitone, Ayogeboh,** Smangele Pretty Moyane, and Israel Edem Agbehadji. "Health Information System and Health Care Applications Performance in the Healthcare Arena: A Bibliometric Analysis." In *Healthcare*, vol. 10, no. 11, p. 2273. MDPI, 2022. DHET Accredited Journals - WOS & SCOPUS
3. **Epizitone, Ayogeboh.**, Smangele Pretty Moyane, and Israel Edem Agbehadji., 2023, March. A Systematic Literature Review of Health Information Systems for Healthcare. In *Healthcare* (Vol. 11, No. 7, p. 959). MDPI - WOS.
4. **Epizitone, Ayogeboh.** "The Simulation of Big Data to revolutionize the Effectiveness of Corporate Policy." *Interdisciplinary Journal of Economics and Business Law* 11, no. 4 86-104, 2022. http://www.ijebl.co.uk/ijebl_subscribersonly.html. DHET Accredited Journals - SCOPUS
5. **Epizitone, Ayogeboh**, Smangele Pretty Moyane, and Israel Edem Agbehadji., 2023. A Data-Driven Paradigm for a Resilient and Sustainable Integrated Health Information Systems for Health Care Applications. *Journal of Multidisciplinary Healthcare*. 2023; 16:4015-4025 https://doi.org/10.2147/JMDH.S433299.
6. Adeliyi, Timothy T., Lawrence Oyewusi, **Ayogeboh Epizitone,** and Damilola Oyewusi. "Analysing Factors Influencing Women Unemployment Using a Random Forest

Model." *Hong Kong Journal of Social Sciences* (2022). DHET Accredited Journals - SCOPUS

7. Nketsiah, R.N., Millham, R.C., Agbehadji, I.E., Freeman, E. and **Epizitone, A**., 2023, October. Optimising a Formulated Cost Model to Minimise Labour Cost of Computer Networking Infrastructure: A Systematic Review. In *International Conference on Advanced Research in Technologies, Information, Innovation and Sustainability* (pp. 427-442). Cham: Springer Nature Switzerland.

JOURNAL ARTICLES TO BE PUBLISHED

Epizitone, A., and Moyane, S.P., 2023. A conceptual study annotation for sustainable and resilient Health Information Systems for health care applications

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DEDICATION

I dedicate my thesis to my loved ones who are asleep, especially my late mom, Sally Enaga (2022), who left to be with my other loved ones at the onset of my PhD journey. Mummy, the thought of not having you here with me drove me to uncover my potential to complete this project soon. I miss you every moment and appreciate your unconditional support in my life and that of Joshua and Liam. I will always treasure you and carry your life lessons anywhere I go. Like you always say, “It is not going to be well. It is already well”. To my Dad, Joshua Mekang Epiezitone (2017), your little queen of Mpako has grown up to fulfil your dream and currently envisions holding the title you always envisioned her to possess. To my only little brother, Franz Agbonaga Epizitone (2018), whose words of comfort and courage sustained me, Tzey rest on, and lastly, to Stephen Ebot Eta (2014), thank you for your genuine love that wrote a significant part of my life.

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ABSTRACT

As the world advances, the population increases and many economic gradients are impacted in several sectors. The need for an information system that affords intelligent and valuable insights is a potential upshot to targeting some of the challenges of the current global transformation. In the healthcare sector, an integrated information system that is salient in augmenting and enabling healthcare is highly demanded. Thus, a sustainable and resilient Health Information System (HIS) for quality health care applications in the healthcare space is paramount. This premise is substantiated by the need for real-time elucidations from an information system like the HIS that is transient between time and space to enable healthcare applications for all healthcare stakeholders. However, the current HIS has been posited in extant literature to be flawed in affording enhanced healthcare. Accordingly, deploying HIS practically has been challenging with isolated stakeholders' involvement.

Although HIS is inadequate, it still maintains a firm position in the healthcare systems. The WHO acknowledges its disposition as a core enabling constituent of healthcare and a vital tool to realise pressing healthcare agendas. Extant literature further asserts the potential of HIS in realising the sustainable development goal related to health and well-being. Recognising the value and benefits of HIS necessitates harnessing technological advancement to augment its capabilities and leverage its weaknesses. Thus, this thesis investigates the HIS for heathcare applications via a data-driven paradigm with maximum inferences to the stakeholders within the healthcare arena. This thesis pinpoints and constructs the development of sustainable and resilient HIS from a data-driven angle as necessary for healthcare augmentation.

The thesis uses a research methodology that traversed the study's main aim at the intersection of design science research and data sciences in conjunction with a socio-technological concept to afford a resilient and sustainable HIS for health care applications. To uncover the knowledge-creation capabilities of health data within the HIS environment and revolutionise healthcare. Additionally, it highlights data science techniques that have been deployed in the health arena for health care applications. The thesis also illustrates the importance of data sciences serialisation and its implementation within the healthcare arena. This study develops a novel framework for HIS for healthcare that takes advantage of data to provide a resolution to counter the challenges experience with their deployment and utilisation.

The concerns of HIS juxtaposition that have resulted in inadequate healthcare and impermanence among stakeholders are also considered in this thesis. The proposed framework integrates the socio-technical stance in the face of digitalisation and globalisation.

The thesis' findings stem from a deeper delve into extant literature to substantiate the knowledge, constraints, and perception of HIS deliverables. In the course of this study, the performance of HIS and health care applications was uncovered from the analysis of the extant body of gen on healthcare to highlight the significance of HIS within the healthcare space. The findings substantiated the value of HIS and unveiled its untapped benefits to the healthcare arena. It also highlights an overview of the existing HIS framework, which established the data-driven paradigm for HIS sustainability and resiliency. It further discusses data sources, actions and decisions within the healthcare arena. Demonstrating a pragmatic application of generated insights from data sciences techniques urgently needed to transmute the healthcare systems and respond to its associated dares. A practical enactment of this efficient and effective holistic model framework that incorporates data sciences to attain a robust, resilient and sustainable HIS for health care applications is envisioned to benefit healthcare stakeholders significantly. In addition, deploying and implementing the proposed framework would benefit the global healthcare stakeholders to attain its goal of universal healthcare coverage at a minimal cost.

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LIST OF ACRONYMS AND ABBREVIATIONS

ABC	Ada Boosting Classifier
AI	Artificial Intelligent
ANN	Artificial Neural Networks
AUC	Area Under the Curve
BC	Bagging Classifier
CIS	Clinical Information Systems
DS	Data Science
DSR	Design Science Research
DT	Decision Tree
EHR	Electronic Health Record
EHREDA	Electronic Health Record Exploratory Data Analysis
ETC	Extra Trees Classifier

GBC	Gradient Boosting Classifier
HIIS	Health Institutions Information Systems
HIS	Health Information System
HoIS	hospital information systems
HOPT	Human, Organization, Process and Technology
HOT	Human, Organization and Technology
ICT	Information Communication Technology
IS	Information System
ISSM	Information Success System Model
IT	Information Technology
KNN	K-Nearest Neighbour
LDA	Linear Discriminant Analysis
LR	Logistic Regression
MIS	Mortality Information System
ML	Machine Leaning

MLP	Multi-Layer Perceptron
NB	Naïve Bayes
NN	Neural Network
PHR	Personal Health Record
RF	Random Forrest
ROC	Receiver Operating Characteristic curve
SDG	Sustainable Development Goals
SVC	Support Vector machines Classifier
TAM	Technological Acceptance Model
TAM	Technology Acceptance Model
TTF	Task-Technology Fit
UTAUT	Unified Theory of Acceptance and Use of Technology
WHO	World Health Organisation

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CHAPTER ONE: STUDY INTRODUCTION AND BACKGROUND

1.1 Introduction

The current Health Information System (HIS) is considered the core enabling support that implements digitalisation within healthcare (Tummers *et al.* 2021a). The deployment of HIS has enabled remarkable permeation of technological advancement within the healthcare arena. Overcoming hurdles that included usability and compatibility concerns to fit perfectly in attaining enhanced health care applications (Gamal, Barakat and Rezk 2021). Many reports assert the potential of HIS and posit its tremendous support for the healthcare system (Tangcharoensathien, Mills and Palu 2015; Sahay, Nielsen and Latifov 2018; Gamal, Barakat and Rezk 2021; Nicol *et al.* 2021). Evidence that asserts this premise is visible in the role of HIS in attending to the pandemic as well as unifying and digitising information within the global space (Al-Marsy, Chaudhary and Rodger 2021; Ye 2021; Feteira-Santos *et al.* 2022).

The current position of HIS today within the healthcare system features an information system that is absorbing and enacting current technology such as blockchain, cloud and data sciences (Al-Marsy, Chaudhary and Rodger 2021; Gamal, Barakat and Rezk 2021; Tummers *et al.* 2021a; Mnyawi *et al.* 2022). However, the progress and development of HIS have led to increasing challenges associated with the demand for enhanced HIS for health care applications. Hypothetically, the extolled HIS is acclaimed for its essential role in enabling gen flow and facilitating integration and interoperability for several units within the healthcare arena (English *et al.* 2011; Kien *et al.* 2018; Alahmar, Crupi and Benlamri 2020; Al-Marsy, Chaudhary and Rodger 2021). In practice, on the other hand, HIS is considered fragmented and symmetrical, resulting in distorted functions and even death (Sahay, Nielsen and Latifov 2018; Mejia Medina *et al.* 2019; Epizitone 2022). Thus emphasizing the demand for proficient strategic management and improvement of current HIS. Additionally, several prior studies identified the meagreness of HIS in addressing international healthcare systems transformation (Sahay, Rashidian and Doctor 2020; Ostern *et al.* 2021; Epizitone 2022). The aforementioned phenomena confronting HIS posit a gap that necessitates more studies. Thus, through an integrated data science approach, this study seeks to present a framework to develop a resilient and sustainable HIS that will enhance the current HIS and provide empirical findings that realign the global healthcare transformation.

1.2 Study background

The benefits of an integrated information system in healthcare have been acknowledged in the literature, with several scholars authenticating the capital accumulation it brings to the domain (Lluch 2011; Nguyen 2015; Dehnavieh *et al.* 2019; Najimudeen, Aldheleai and Ubaidullah 2021; Ostern *et al.* 2021; Epizitone 2022). According to English *et al.* (2011), for healthcare delivery to be worthwhile, an astute integrated information system (IS) is crucial. Several scholars have rendered tributes to the efficacious placement of HIS, especially in these times (Kivinen and Lammintakanen 2013; Sahay, Rashidian and Doctor 2020; Najimudeen, Aldheleai and Ubaidullah 2021; Ostern *et al.* 2021; Epizitone 2022). Nonetheless, there are numerous ongoing challenges centred on institutional and technological optics that limit the potential of HIS to deliver quality healthcare (English *et al.* 2011; Kivinen and Lammintakanen 2013; Waterson, Hoonakker and Carayon 2013; Park 2016; Chen, Baird and Straub 2019; Sahay, Rashidian and Doctor 2020; Ostern *et al.* 2021; Epizitone 2022).

According to these scholars, exploration of HIS is regarded as crucial for the attainment of two exigent primacies of global health, namely, ‘universal health coverage’ and ‘civil registration’ and ‘vital statistics systems’ (Dye, Reeder and Terry 2013; WHO 2013; Anwar *et al.* 2018; Boerma *et al.* 2018; Sahay, Nielsen and Latifov 2018; Nicol *et al.* 2021; Epizitone 2022). Moreover, the realisation of the sustainable development goals focus on healthcare and IT infrastructure by 2030 is dependent on HIS revisions (AbouZahr and Boerma 2005; Haux 2006; Sahay, Nielsen and Latifov 2018; Mills, Lee and Rassekh 2019; Sahay, Rashidian and Doctor 2020; Epizitone 2022). Nevertheless, existing insights on HIS research state otherwise regarding the position of the HIS research offerings (Epizitone 2022). Several authors also alleged the shortfall of previous studies in ameliorating evolving and foreseen revolution to the complex healthcare system (Chen, Baird and Straub 2019; Sahay, Rashidian and Doctor 2020; Ostern *et al.* 2021; Tummers *et al.* 2021a; Epizitone 2022). Ostern *et al.* (2021) complain about the concentration of HIS exploration on trivial issues and the lack of acknowledgement of transformative apprehensions within the healthcare arena. Additionally, several scholars express disappointing apprehensions on the attainment of long-lasting vicissitudes in the healthcare industries (Eslami Andargoli *et al.* 2017; Chen, Baird and Straub 2019; Ostern *et al.* 2021; Epizitone 2022).

A critical assessment of extant literature further emphasizes the necessity for prescient HIS investigation to leverage its ability to unravel systemic healthcare flaws (Epizitone 2022). In a bid to supply viable elucidations suited for the healthcare systems and its numerous actors, such as healthcare professionals, authorities, and technology providers (Ostern *et al.* 2021; Epizitone 2022). Lluch (2011) stresses the demand for auxiliary investigation for HIS prime augmentation and viable applications. Additionally, several authors query the adequacy of the current HIS in delivering quality healthcare (Sahay, Rashidian and Doctor 2020; Najimudeen, Aldheleai and Ubaidullah 2021; Epizitone 2022). According to Najimudeen, Aldheleai and Ubaidullah (2021), the restricted usage of HIS is attributed to impediments such as the lack of basic amenities, specialists, healthcare workers' e-readiness, and analytical intricacies. Dehnavieh *et al.* (2019) categorise these HIS' dares as operational, accentuating them on the experiences of the healthcare stakeholders. Tummers *et al.* (2021a) study on HIS identified 69 associated obstacles cited in extant literature. These writers advocate for further studies to bolster the HIS and improve healthcare applications (English *et al.* 2011; Dehnavieh *et al.* 2019; Sahay, Rashidian and Doctor 2020; Epizitone 2022). A hiatus that this thesis seeks to fill by proposing appropriate improvements to make the current HIS resilient and sustainable.

Furthermore, HIS investigation in extant literature disclosed the lack of empirical rigour (Sahay, Nielsen and Latifov 2018; Sahay, Rashidian and Doctor 2020; Ostern *et al.* 2021; Epizitone 2022). These findings highlight the need for scientific "HIS" research and serve as the basis for this thesis. Additionally, many other investigations globally reveal a high amount of HIS dares encountered in developing countries where they are adopted (Najimudeen, Aldheleai and Ubaidullah 2021). Whereas in developed nations, numerous advances have been realised. Several authors insisted that these dares are one of the main reasons for stunted HIS growth, affecting decision-making (Dehnavieh *et al.* 2019; Delnord *et al.* 2021; Epizitone 2022). With decision making being critical within the healthcare system, the chaotic and fragmented state of HIS has been proven to be problematic (Karuri *et al.* 2014; Gatta *et al.* 2020). Thus the demand for more investigations that embraces these concerns is paramount.

1.3 Practical motivation

The need to strengthen the HIS has been enthused by aspects such as the lack of evidence base decision making in the healthcare pitch (Farnham *et al.* 2020; Saigi-Rubio *et al.* 2021; Chanyalew *et al.* 2022). A strengthened HIS goes a long way to improving healthcare service delivery and quality (Nadri *et al.* 2017; Benbrahim, Hachimi and Amine 2018; Moghaddasi *et al.* 2018; Rudd *et al.* 2019; Biru *et al.* 2022). Undoubtedly, the lack of a resilient and sustainable HIS resulting from the existing challenges confronting the HIS infrastructure is affecting its stakeholders (Mejia Medina *et al.* 2019). Grosjean, Bate and Mestre (2020) contend that HIS deployed technologies have wielded adverse outcomes on its stakeholders. Many countries still suffer from eerie challenges regardless of the numerous benefits of an efficacious HIS. Grosjean *et al.* (2022) attribute these dares to the primary focus of technological solutions that are responsive rather than pre-emptive, indicating the need for a conventional approach that develops strategies that curb these challenges rather than providing solutions as they occur.

Additionally, several authors highlight the dithering fragmentation of HIS within the local, national and global settings as a significant challenge (Braa and Sahay 2012; Sahay, Nielsen and Latifov 2018; Sahay, Rashidian and Doctor 2020). These issues confronting the HIS have limited the benefits that can be harnessed from their deployment. Necessitating the need for scientific cutting-edge design research intensive methods to generate pertinent, astute and valuable strategic solutions to critical problems facing the HIS enactment and application globally.

1.4 Theoretical motivation

In the midst of the fourth industrial revolution, the modernization of the healthcare industry has been met with a great deal of resistance and difficulty. Among these are the lack of active stakeholders' engagement and the complexity of the technical deployment in the healthcare sector. The realization and construction of a reliable healthcare information system have been linked to the significant role play of technology. Benefits such as improved healthcare, longevity and more efficient information transmission have been linked to technological advancements (Epizitone 2022). However, despite the widespread adoption of digital technologies throughout the healthcare industry, a number of obstacles, including integration and fragmentation, have been wreaking havoc on the structure of the HIS, which in turn has influenced decision-making and the distribution of resources (Kien *et al.* 2018; Murad 2018; Epizitone 2022). Theoretically, there have been several studies that primarily focus on the deployment and benefits of HIS on healthcare applications (Sahay, Nielsen and Latifov 2018; Dehnavieh *et al.* 2019; Sahay, Rashidian and Doctor 2020; Ostern *et al.* 2021). Many studies that have been conducted adopted the theoretical lens that employs the evidence base research and practice (Paré and Kitsiou 2017) to afford elucidations on information systems phenomena. Limited studies have embraced the socio-technical components in developing HIS (Palojoki *et al.* 2017; Pavão *et al.* 2017). This theory postulates that stakeholders and technologies are equally valuable; hence stakeholder perspectives should be incorporated into the design of Information and Communication Technology (ICT).

Additionally, extant literature reveals the lack of stakeholders' perspectives in the development of technological solutions for healthcare applications (Pavão *et al.* 2017; Grosjean, Bate and Mestre 2020). Pavão *et al.* (2017) argue that despite HISs' potential, it remained underutilized by healthcare stakeholders. These studies identify a gap in research that employs the socio-technical lens, indicating the need for a theoretical approach that explores the socio-technical components in the development of ameliorations. As a result, studies that tackle HIS phenomena via the deployment of design science that incorporates the socio-technical components (actors, institutions and the technological infrastructure) are required (Gregor 2006; Kalong and Yusof 2017; Baskerville *et al.* 2018; Grosjean, Bate and Mestre 2020; Grosjean *et al.* 2022). Therefore, this study proposes to develop a "resilient and sustainable information system for Health Care applications"; and enhance the knowledge of HIS's implementation through the novel integration of data science and machine learning techniques in the traction of "Design Science Research" (DSR). It is envisaged that the realisation of the objectives of this study will contribute toward the attainment of a strengthened HIS, and the artefact developed by this study will be used to create and drive initiatives that strengthen the healthcare capabilities and effective utilisation by stakeholders.

1.5 Statement of the problem

Over the course of the past few decades, information technology (IT) has offered a variety of fields, not only opportunities but also obstacles of similar magnitude. In point of fact, within the realm of healthcare, IT applications, specifically HISs, have been instrumental in expediting many benefits and revolutions, such as eHealth, telehealth and mHealth (Momany *et al.* 2017; Ammenwerth *et al.* 2020; Ostern *et al.* 2021; Persano *et al.* 2021; Epizitone 2022; Mnyawi *et al.* 2022). In addition, the accurate decision-making capabilities made possible by HIS are a large part of the reasons why so many countries have invested in and adopted these systems (Park 2016; Jeffery *et al.* 2018; Murad 2018; Chen, Baird and Straub 2019; Jabareen, Khader and Taweel 2020; Ostern *et al.* 2021; Epizitone, Moyane and Agbehadji 2022). Regrettably, in the midst of all of this digitalization in the healthcare industry, there have been a variety of obstacles proffered, including integration, data quality, and the composition of the HIS (Sahay, Nielsen and Latifov 2018; Farnham *et al.* 2020; Najimudeen, Aldheleai and Ubaidullah 2021; Ostern *et al.* 2021; Epizitone 2022; Epizitone, Moyane and Agbehadji 2022). According to the researchers, this can be attributed to a lack of apprehension regarding the revolutionary changes occurring in the healthcare system and the requirement for a more robust HIS (Sahay, Nielsen and Latifov 2018; Chen, Baird and Straub 2019; Sahay, Rashidian and Doctor 2020; Ostern *et al.* 2021; Epizitone 2022; Epizitone, Moyane and Agbehadji 2022). As a result, it is crucial and essential for the improvement of a nation's HIS that studies be conducted that focus on addressing these concerns.

1.6 Research aim

This investigation aims to develop a resilient and sustainable integrated IS for Health Care applications and to enhance the knowledge of its implementation, which can be used to create and drives initiatives that strengthen its capabilities and effective utilisation by stakeholders. It is therefore expected to respond to the succeeding main research question: "*How can knowledge generated from an analyse integrated information system be used to attain a resilient and sustainable integrated information system for Health Care applications?*" Hence, the following overarching objectives have been defined in order to ensure that the purpose of this study is met.

1.7 Research objectives

The primary impetus of this thesis is to examine the health information system using the data-driven track to enhance its resilience and sustainability. In attending to this aim, the succeeding objectives are defined. To:

- Ascertain the knowledge, constraints, and perceptions of the Health Information Systems deliverables.
- Explore knowledge creation that addresses ill-defined problems in the Integrated Health Information System.
- Investigate the performance of Health information systems for health care applications.
- Structure an efficient and effective holistic model framework for a robust, resilient, and sustainable integrated Health Information System.
- Empirically validate data science techniques for achieving a resilient and sustainable HIS and evaluate the developed machine learning model with other models using well-known metrics.
- Enact the best deployment model for enhancing the healthcare information system.
- Provide theoretical and practical reflections from the study that may be used to implement a resilient and sustainable HIS.

Following the realisation of these objectives, the study's findings are expected to be used to present recommendations and suggestions tailored to the interests and needs of the stakeholders. Five research questions are designed to facilitate the achievement of the following research objectives.

1.8 Research questions

This thesis expands on the inquiry to apprehend the data-driven paradigm in attaining a resilient and sustainable integrated information system such as the HIS. Following through the thesis objectives, the study, therefore, answers the following designed research questions:

- What are the knowledge, constraints and perceptions of the Health Information Systems deliverables?
- How can Knowledge creation address ill-defined problems in the Integrated Health Information System?
- What is the performance of the health information systems and health care applications within the healthcare domain?
- What framework can be used to achieve a robust, resilient, and sustainable integrated Health Information System?
- How can data science techniques empirically validate HIS resilience and sustainability, and how can the developed machine learning model be evaluated relative to different models using well-known metrics?
- How can the best model be deployed to achieve a resilient and sustainable integrated information system for health care applications?
- How can the study's findings be used to implement a resilient and sustainable HIS?

1.9 Validity and reliability

This study made sure that the information and data used were accurate in terms of validity and reliability concerns. A data-driven practical enactment using a machine learning technique was also employed and evaluated to validate the proposed "framework to develop a resilient and sustainable integrated information system for health care applications." It is also entirely feasible to have access to a comprehensive, detailed approach that reveals the data source, as well as a choice of data science techniques and analyses used in this study. To indicate the robustness of this study's methodology and the validity of the findings, it is realistic that the study can be replicated by adhering to the same approach, using the reproduce pipeline that is presented in the study. Confirming the reliability concern that asserts the ability of the study method to yield the same result. In addition, the use of a variety of outlooks in alignment with the study objectives helps to ensure that the findings of this study are accurate, consistent, valid, and reliable. Thus the reliability and validity concerns were pleased as the study can be replicated using the reproduce pipeline presented in the study.

1.10 Limitations of the study

Every single research study has its own unique set of limitations, and every single researcher has to contend with those limitations. Within the scope of this investigation, three fundamental concepts were investigated, namely integrated IT (HIS), health care applications, and data. As the study progressed, it became blatantly apparent that the keywords for this study were ambiguous and needed definitions within the frame of reference of the healthcare domain. Defining the scope of the keywords of this study was one of the limitations of this study.

Another limitation was finding data that could be employed in this study. Although there were many choices and open sources for obtaining the data needed, finding the appropriate data for this study was challenging. Lastly, this study's overall scope was limited to the development of a data-driven paradigm for a "resilient and sustainable HIS" for health care applications. Incorporating this designed model into implemented HIS was out of the scope and not executed.

1.11 Findings of the study

This study presents an ample amount of insight to its stakeholders regarding the development of a resilient and sustainable HIS for its stakeholders. The model developed, and the experiment afforded some real-world solutions to dares currently facing the health system globally. A probable application of these offerings might be the direct implementation into an existing system where HIS is deployed for health care applications. These findings would contribute to the optimization of integrated information systems in the healthcare arenas as well as enhance their applications. In addition, the results provided also answered the demand and the requirement for a strengthened HIS that can anticipate and tackle global transformations in order to enhance healthcare applications. Using the developed model in the existing healthcare system will increase the satisfaction of stakeholders as well as solidify the positioning of HIS in improving healthcare.

Overall the findings assert and encourage the use of data science techniques such as machine learning to revolutionise healthcare. The developed framework serves as a point of reference to all stakeholders, and the insight generated from an analysed electronic health record serves as evidence of the potential of data science to transform HIS to be resilient and sustainable. Deployment of the model incorporated in HIS will considerably enhance healthcare and the efficient healthcare system processes.

1.12 Study contributions

From this study, both theoretical and practical contributions are provided. In chapter six, the specifics of these contributions are broken down and extensively discussed. The detail of these contributions is discussed at length in chapter six. These contributions to the research areas, both theoretically and pragmatically, as well as a summary of the significance, are presented in the sections that follow below.

1.12.1 Theoretical contributions

The researcher's theoretical contributions emanating from this study were established at the accumulation of HIS, health care applications and data sciences implemented using the DSR methodology. This summarises the body of gen added to the existing core areas of emphasis. Epizitone (2022) and Epizitone, Moyane and Agbehadji (2022) present the theoretical insights in this regard that is available in international journals reporting healthcare and IS core concepts.

Mainly contributing to theory in the following ways:

- Identifying the potential of "resilient and sustainable" HIS in enhancing health care applications globally.

- Positing the critical need to ascertain HIS scalability in order to capitalize on opportunities in settings where they are deployed for health care applications
- Highlighting the need for resilience and sustainable HIS for health care applications framework paramount position in the healthcare pitch and asserting that the adoption and implementation of the resilience and sustainable capabilities of HIS can afford long-term ameliorations.
- Depicting vividly the equal role of the stakeholders and technology in the up-and-coming enactment of HIS for health care applications and relating the concepts of social–technical theory to the "sustainability and resilience" of HIS for health care applications.
- Proposing the enactment of a data-driven paradigm for "resilient and sustainable health information systems for health care applications".
- Contributing to the fortification of HIS through developing and enacting a "resilient and sustainable" HIS for health care applications that are unparalleled in this digitalisation era and endowment of an integrated footing for data analytics to support and assist health care delivery.

1.12.2 Practical contributions

The applied concessions of this study were based on the research work done and the findings. These contributions were accentuated on considerations concomitant to the strengthening of HIS and to establishing a "resilient and sustainable Health Information System for health care applications"(Epizitone 2022; Epizitone, Moyane and Agbehadji 2022). The utmost relevance of these contributions is first to leverage the impact of weakening HIS and work on strengthening it using data sciences. HIS inadequacy is identified as the root cause of healthcare errors that can be remedied by identifying incidents and events that occurred during the provision of healthcare (Mejia Medina *et al.* 2019; Mohd Yusof *et al.* 2020; Salleh, Abdullah and Zakaria 2020). The first unique practical contribution of this thesis in line with the demands of stakeholders is the findings of this study that anchor on data sciences offering. The insights from data analysis using data sciences techniques like machine learning can enable data-driven actions needed at the identified incidence and events as they occur. Secondly, using the insights this study offers to revolutionize healthcare by instituting the consideration at all levels, from local to national to international, will significantly enhance healthcare. A summary of the practical contributions is:

- Consider reviewing existing HISs to identify their weaknesses and consider employing insights from data analytics to leverage the deficiencies identified without compromising on the health care delivery.
- Consider implications of the socio-technical stance of HIS within the entire organisation/practices.
- Consider the need for both humans and technology to share value and responsibility equally.
- Leverage the potential of data sciences to mine health data.
- Ensure that there is flexibility to model amelioration within the contexts of the set-up.
- Implement the proposed framework from local to national and globally to benefit from its enhanced health care applications capabilities.
- Evaluate the performance and adopt practical measures to anticipate future occurrences from the present lessons and insights.

1.13 Definitions of terms

Health Informatics is the field that studies medical practice, education, and research's cognitive, information processing, and communication tasks and their supporting information science and technology (Bouhaddou, Bennani Othmani and Diouny 2013; Ammenwerth *et al.* 2017; Aziz 2017).

Health Informatics Tools consist of computers, clinical guidelines, formal medical terminologies, and information and communication systems (Anshari and Almunawar 2015).

Health Information Technology is an information processing application that involves computer hardware and software. It deals with storing, retrieving, sharing, and using health care information, data, and knowledge for communication and decision making (Ghaffari *et al.* 2021; Malik, Kazi and Hussain 2021).

Electronic Medical Record (EMR) refers to a medical record stored in a digital format (Almunawar and Anshari 2012).

Electronic Health Record (EHR) refers to an individual patient's medical record in a digital format (Almunawar and Anshari 2012; Negro-Calduch *et al.* 2021).

Electronic Patient Record (EPR) is electronically stored health information about one individual uniquely identified by an identifier (Almunawar and Anshari 2012).

A personal Health Record (PHR) is an internet-based set of tools that allows people to access and coordinate their lifelong health information while making appropriate parts available to those who need them (Negro-Calduch *et al.* 2021).

Health Information System is a set of interrelated components that collect, process, store and distribute information to support decision-making and assist in controlling health organizations (Lippeveld 2001; Malaquias and Filho 2021)

Health Information System Stakeholders refer to all HIS beneficiaries and users, including but not limited to physicians, nurses, admin and technical staff, health information managers, patients, visitors, suppliers, and global health bodies (Tummers *et al.* 2021a).

Health Information Network refers to an internet-based interchange of health data by medical providers to enhance health care, automated prescriptions and patient information accuracy nationally, regionally and globally (Mayer *et al.* 2017; Ammenwerth *et al.* 2020).

Health care is the maintenance of the well-being of a person (Tummers *et al.* 2021b; Epizitone, Moyane and Agbehadji 2022).

Healthcare is the encapsulated representation of all the businesses, institutions, or activities offering medical services (Tummers *et al.* 2021b; Epizitone 2022; Epizitone, Moyane and Agbehadji 2022).

Healthcare/health care application is the mode of care employed for delivering health services within the healthcare arena (Epizitone, Moyane and Agbehadji 2022).

Research Ontology is the researcher's conception of the nature of reality (Epizitone and Olugbara 2020).

Research Epistemology is the relationship between the knower and what is being studied (Epizitone and Olugbara 2020).

Research Axiology is the role of values in research and the researcher's stance, and methodology refers to how the researcher can discover knowledge (Epizitone and Olugbara 2020).

Positivism is a branch of research philosophy that relies solely on observable phenomena to provide credible data and facts, focusing on causality and law-like generalities to reduce phenomena to their most basic elements (Epizitone and Olugbara 2020).

Post-positivism is parallel to positivism or thought to have replaced positivism, naive rationalism to critical realism concentrates on explicating within a context or contexts, separating the existence of an objective from human thoughts, beliefs, or knowledge (Epizitone and Olugbara 2020).

Interpretivism is based on the notion and the sense that a simple occurrence is pertinent for every research problem since the true essence of actuality cannot be established, and it is driven toward constructivism and interpretivism, which retain that reality is constructed or interpreted through perception (Epizitone and Olugbara 2020).

Pragmatism is a research philosophy constituent that concedes that there are no deterministic constructs or theories that sculpt truth or insight, and thus it is not dedicated to any one system, reality, or philosophy (Epizitone and Olugbara 2020).

1.14 Thesis organisation

This thesis is organised chronologically, with the core research discussions presented in chapters that detail the discourse in alignment with the study context. A brief description of each chapter in this thesis is presented below.

1.14.1 Thesis chapters

Chapter One: Introduces the thesis topic and the foremost overview of this study. These include the study background, theoretical and practical motivations, and the problem statement. The research's aim, objectives and questions that the thesis seeks to address. The validity and reliability. The study's limitations, findings and contributions (theoretical and practical). Finally, the definition of keywords used, the thesis structure and a fleeting summary of chapter one (study introduction and background).

Chapter Two: presents an overview of the existing problems in integrated information systems related to the health sector. Also, related work associated with the study will be detailed in this chapter from the extant literature. The chapter defines the health information system in the study context, featuring the HIS instances enacted in healthcare, the role of information systems and knowledge management in attaining HIS resilience and sustainability. The evolution of the HIS with its current benefits. The interoperability, data quality, scalability, implementation and design of HIS in the healthcare sector. The Internet health information and the HIS global disposition in developed and developing countries. HIS and health equity is discussed with the availability of functional infrastructure. The chapter ended with the conceptual annotation for resilient and sustainable HIS for healthcare (Literature Review).

Chapter Three: Focus on the study's methodology and structure case analysis elements constructed in the research design phases. The problem overview establishing the data-driven design is discussed with the research's method, multiphase design, strategy, data, and material used (Research Methodology).

Chapter Four: The data-driven paradigm for a resilient and sustainable integrated information system is presented in this chapter. The HIS-implemented framework in the extant literature is discussed in the chapter and helps to rationalize the proposed data-driven framework. The elements that make up the data-driven paradigm are discussed in detail. The data source, actions, decisions, and state-of-act

Chapter Five: The data preparation and analysis of a health dataset will be presented in this chapter, along with the subsequent discussion and findings reporting. This chapter will demonstrate a practical application of a data science technique that can be incorporated in a HIS environment to renter it sustainable and resilient in the provision of healthcare (The research analysis, Results and Discussion of a Health dataset).

Chapter Six: The research, theoretical and practical contributions of this study are discussed. Theoretical findings that add to the body of knowledge are provided in this chapter. Practical contributions for consideration are also presented to healthcare stakeholders (Research Theoretical and Practical Contributions of this study).

Chapter Seven: The consolidated study findings under the headings: research summary, recommendation and Conclusion are discussed. Future research directions are also provided for stakeholders to facilitate the continuous development of the concepts presented in this study.

1.15 Summary of the chapter

The general outline of this study's background, motivation and rationale for undertaking this project is explicated in this chapter. An overview of digitalization (HIS) within healthcare is presented in this chapter with the constraints that necessitate an enhanced health care application system with the advent of technological breakthroughs such as the use of blockchain, cloud, and data sciences. The research objectives and questions that guide this thesis were also outlined. Furthermore, this study's validity and reliability concerns were also discussed, along with the abstract of the findings and contributions of the study. Finally, this chapter described the definitions of key concepts used in this study and thesis organisation. The ensuing chapter presented the extant literature in the study area.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

Chapter two of this study presents an overview of the existing problems in integrated information systems related to the health sector. Also, related work associated with the study is detailed in this chapter from the extant literature. The review presents the theoretical and conceptual framework that underpins this research study and, subsequently, affords the foundation for attaining the research objectives. It is essential to point out that in spite of the surplus of research work conducted on health information systems, there are still many challenges confronted in the healthcare area that necessitate the need for this study(Flora, Margaret and Dan 2017). Therefore, extant literature is explored in this chapter to uncover current and pertinent challenges within the deployment of the HIS, an integrated IS.

2.2 Health Information Systems (HIS)

The HIS are critical systems deployed to help organisations and all stakeholders within the healthcare arena eradicate disjointed information and modernize health processes by integrating different health functions and departments across the healthcare arena for better healthcare delivery (English *et al.* 2011; Flora, Margaret and Dan 2017; Sahay, Nielsen and Latifov 2018; Bagayoko *et al.* 2020; Berrueta *et al.* 2020; Rachmani *et al.* 2020). Over time, the HIS has transformed significantly amidst several players, such as political, economic, socio-technical and technological actors that influence its ability to afford quality healthcare services

(Almunawar and Anshari 2012). The unification of health-related processes and information systems in the healthcare arena has been realised by HIS. HIS has often been contextualised as a system that improves healthcare services quality by supporting management and operation processes to afford vital information and unifying process, technology and people (Almunawar and Anshari 2012; Haule, Muhanga and Ngowi 2022). Haux (2006) modestly chronicled HIS as a system that handles data to convey knowledge and insights in the healthcare environment. Almunawar and Anshari (2012) incorporated this construed to describe HIS to be any system within the healthcare arena that processes data and affords information and knowledge. Malaquias and Filho (2021) accentuate the importance of HIS in the same light, highlighting its emergence to tackle the need to store, process and extract information from the system data for the optimisation of processes, enhancing services provided and supporting decisions making.

The definition of HIS was popularised by Lippeveld (2001), who reported HIS to be an *"integrated effort to collect, process, report and use health information and knowledge to influence policy-making, programme action and research"*. Over the course of time, this definition has been adopted and contextualised countlessly by many authors and WHO (AbouZahr and Boerma 2005; Bogaert and Van Oyen 2017; Bogaert, van Oers and Van Oyen 2018; Bagayoko *et al.* 2020; Haule, Muhanga and Ngowi 2022). Although Haule, Muhanga and Ngowi (2022) claimed the definition of HIS varies globally, in actuality, the definition has never changed from its inception, but on the contrary, conceptualised over various contexts. Malaquias and Filho (2021) reiterated the definition in the extant literature. These scholars reported HIS as *"a set of interrelated components that collect, process, store and distribute information to support the decision-making process and assist in the control of health organizations"* (Malaquias and Filho 2021). The same definition is adopted for this study, and

HIS is construed as *"a system of interrelated constituents that collect, process, store and distribute data and information to support the decision-making process, assist in the control of health organizations and enhance healthcare applications"*. However, it is paramount to note that HIS is broad. In many instances, the definition is of minimal relevance due to its incorporation of external applications related to health developments and policy-making (Panerai 2014). Hence, emphasis should not be enforced on the definition but on its contribution to all facets of health development.

HIS's unified front is geared toward assimilating and disseminating health gen to enhance healthcare delivery. HIS consists of different sub-systems that serve several actors within the healthcare arena (Taye 2021). These sub-systems are dedicated to specific tasks that perform various agendas such as civil registrations, disease surveillance, outbreak notices, interventions and health information sharing within the healthcare arena. It also supports and links many functions and activities within the healthcare environment, such as recording various data and information for stakeholders, scheduling, billing and managing. Stakeholders are furnished with health information from diverse HIS instances. These include but are not limited to information systems for hospitals and patients, health Institution systems and internet information systems. Sligo *et al.* (2017) regard HIS as a panacea within the healthcare ground that improves health care applications. Despite all the limitless capabilities of HIS, it has been reported to be asymmetrical, lacking interactions within subsystems (Sahay, Nielsen and Latifov 2018; Epizitone 2022). Many decision making and policies are reliance on good health information (Bosch-Capblanch *et al.* 2021). According to Suresh and Singh (2014), the HIS enables stakeholders such as the government and all other players in the healthcare arena to have access to health information which influences the delivery of healthcare. Sundry literature further reveals accurate health information to be the foundation of decision making and highlights the decisive role to be a human constituent (Jeffery *et al.* 2018; Isleyen and Ulgu 2020; Bosch-Capblanch *et al.* 2021; Taye 2021).

Furthermore, HIS can be classified into two cogs in today's era: the computer-related constituent that employs ICT-related tools and the non-computer component, which both operate at different levels. These levels include strategic, tactical and operational **(Figure 2-1)**. The deployment of HIS at the strategic level offers intelligence functions such as decision support, financial estimation, performance assessment and simulation system (Bagayoko *et al.* 2020; Sawadogo-Lewis *et al.* 2021). At the tactical level, managerial functions are performed within the system, while at the operational level, functions include recording, invoicing, scheduling, administrative, procurement, automation and even payroll.

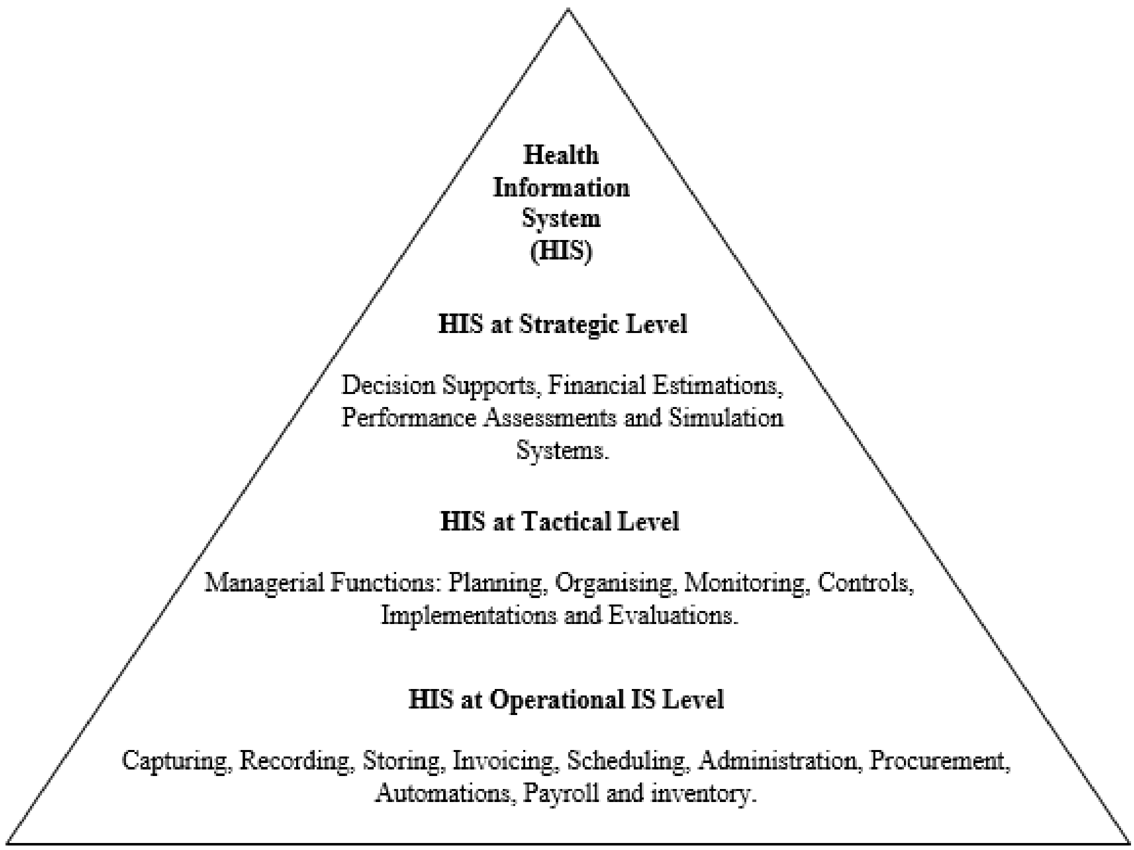

Figure 2-1 HIS Levels: Source Author

2.3 Instances of health information system

The health information system is an extensive system that includes several instances within the healthcare environment. Some known examples include hospital information systems (HoIS), health institutions information systems (HIIS), Mortality Information Systems (MIS) and Clinical Information systems (CIS) (Almunawar and Anshari 2012; Moghaddasi *et al.* 2018; Combi and Pozzi 2019). Some studies consider these instances one and the same, with literature claiming that HIS is frequently used interchangeably (Vaganova *et al.* 2017). This notation is a contrary delineation of the HIS that holistically houses these instances are dedicated for specific use. While unique, these instances within the HIS aggregate several functions that serve different purposes to better healthcare deliveries (Gouda *et al.* 2017; Vaganova *et al.* 2017). An effective HIS is revealed in literature to be associated with a collection of communal efforts of several forces (Vaganova *et al.* 2017; Taye 2021). An integrated enabler within the HIS is paramount for the attainment of the HIS's objective to afford quality and better service in the healthcare arena (Haule, Muhanga and Ngowi 2022). In many sectors in the healthcare arena, one or more of these instances are deployed to strengthen and enhance health care applications and enable sound decision making (Al-Shorbaji *et al.* 2018; Jabareen, Khader and Taweel 2020; Biru *et al.* 2022). Jabareen, Khader and Taweel (2020) aver HIS is a multidisciplinary purview that employs health information technology (HIT) to enhance health care services through any amalgamation of increased effectiveness, improved quality and new opportunities. Resultantly these HIS instances enable digitalised medicine, health, and patient records to serve stakeholders (Ajami and Arab-Chadegani 2013; Moghaddasi *et al.* 2018).

2.4 Information System and knowledge management in the healthcare Arena

The presence of Information systems (IS) modernization in the healthcare arena is alleged by scholars to be a congested domain that seldom fosters stakeholders' multifaceted and disputed relationships (Bernardi, Constantinides and Nandhakumar 2017). On the other hand, it is believed that a significant amount of newly acquired knowledge in the field of healthcare is required for the improvement of health care (Liu, Tsui and Kianto 2022). Ascertaining and establishing the role of IS and knowledge management is an important step in the development of HIS for healthcare. Flora, Margaret and Dan (2017) posited that efficient 'IS' and data usage are crucial for an effective healthcare system. Bernardi (2017) alleges that the underpinning inkling of a "robust and efficient" HIS enables healthcare stakeholders such as managers and providers to leverage health information to plan commendably and regulate healthcare, which could result in enhanced survival rates. As a result, it is imperative to ground these ideas within the context of the healthcare industry to provide a foundation for developing a robust and sustainable HIS for use in the context of health care applications.

2.4.1 Information system

Information systems (IS) in the healthcare setting play a significant role in the assimilation and dissimilation of health information. Many continents endorse the deployment of IS mainly to consolidate mutable information from different sources within the systems. Although the primary objective for these systems deployment has been centred on bringing together the unique and different components such as institutions, people, processes and technology in the system under one umbrella (Flora, Margaret and Dan 2017; Epizitone 2021).

An overview of the extant literature reveals this has rarely been easy, as integration within this system has always been difficult in many contexts. In the context of HIS, many reported the integration phenomena to be problematic, attributing these to the global transformation within the healthcare arena (Farnham *et al.* 2020; Ostern *et al.* 2021). This revolution, coupled with the advancement of the healthcare arena, has resulted in the need for robust allied health IS systems that incorporate different IS and information technology (Flora, Margaret and Dan 2017; Vaganova *et al.* 2017). These allied health information systems are necessary to consolidate independent information systems within the healthcare arena to enhance healthcare applications (Faujdar *et al.* 2020; Jabareen, Khader and Taweel 2020). Organisations in the healthcare arena are expected these systems to be sustainable and resilient; however, in order to satisfy these requirements, an integrated information system is needed to unify all independent, agile and flexible health IS to mitigate HIS dares(Ayabakan *et al.* 2017)

An aligned HIS akin-allied is essential as it supports Health Information Networks (HIN) that subsequently enhance and improve healthcare applications (Mayer *et al.* 2017; Ammenwerth *et al.* 2020). Thus, many organisation within the healthcare settings are fine-tuning their HIS to be resilient and sustainable. However, the realisation of a robust information system within the healthcare arena is challenging and is depended on the flow of information as a crucial constituent for suave and efficient functioning (Seo, Kim and Kim 2019; Soltysik-Piorunkiewicz and Morawiec 2022).

2.4.2 Knowledge management

The process of constructing value and generation maintainable edge for an industry with capitalisation on building, communicating and knowledge applications procedures to realise set aspirations is denoted as knowledge management (Mahendrawathi 2015). Literature reveals knowledge management as an important contributor to organisational performance through its knowledge-sharing capabilities (Kim, Newby-Bennett and Song 2012). In the healthcare industry, there is a high demand for knowledge to enhance healthcare applications (Nwankwo and Sambo 2020; Liu, Tsui and Kianto 2022). Several studies reported the deployment of knowledge management in the healthcare arena is set to enhance healthcare treatment effectiveness (Kim, Newby-Bennett and Song 2012; Liu, Tsui and Kianto 2022; Soltysik-Piorunkiewicz and Morawiec 2022). Many stakeholders such as the government, World Health Organisation (WHO) and healthcare workers rely on the management of healthcare knowledge to complement healthcare applications. According to Kim, Newby-Bennett and Song (2012), the focus of knowledge management is to expedite knowledge sharing efficaciously. However, integrating knowledge from different sources is challenging and requires an enabler (Kim, Newby-Bennett and Song 2012).

The HIS is an indispensable enabler of health knowledge generated from amalgamated health information within the healthcare arena (Benis *et al.* 2018; Khader *et al.* 2018; Delnord *et al.* 2021). Dixon, McGowan and Cravens (2009) aver that efficacious modifications in the healthcare arena are made possible by knowledge codification and collaboration from information technologies. Similarly, some Authors pinpoint information and communication technologies within the healthcare arena to be a major determinant in the attainment of a sustainable health system development (Soltysik-Piorunkiewicz and Morawiec 2022). The knowledge management relationship with HIS is considered complementary and balanced as it enables the availability of knowledge that can be shared. The importance of knowledge management is relevant for the realisation of an enhanced healthcare application via HIS. Soltysik-Piorunkiewicz and Morawiec (2022) claim that the information society effectively uses HIS as an information system for management, patient knowledge, health knowledge, healthcare unit knowledge, and drug knowledge. The authors herein demonstrate how 'HIS' facilitates knowledge management in the healthcare sector to improve healthcare applications.

2.5 The evolution of health information systems

The concept of enhancing healthcare applications has always been the foundation of HIS, which posit that the intercession of information systems with business processes affords better healthcare services (Almunawar and Anshari 2012; Tossy 2014). According to Almunawar and Anshari (2012), many determinants, such as technological, political, social and economic, have enormously influenced the nature of the healthcare industry. The technological determinant, particularly the computerised component, is thought to be deeply ingrained in the enactment and functioning of HIS. According to Panerai (2014), this single attribute can be held solely responsible for HIS let-downs more than its accomplishment.

The ownership of HIS has been contested in literature, with some authors claiming that HIS belongs to the IT industries (Vaganova *et al.* 2017). While IT has enabled many developments in various industries, it has also resulted in dissatisfaction. Recently, there has been an insurgent from many industries, particularly the healthcare industries, who acknowledge the role of IT in optimising and enhancing health initiatives but want appropriation of their integrated IS. However, according to the definition of HIS, it is presented to the healthcare sector as *"a set of interconnected components that collect, process, store, and distribute information to support decision-making and aid in the control of health organisations"*. The disposition of HIS was established in its definition without bias; the development of HIS was conceived due to unavoidable changes and transformations within the global space.

A good representation and consolidation of this dispute are within the realisation that there is a co-existence of different related and non-related components in a system. And in this case, the HIS is an entrenched system with several features, including technologies. Panerai (2014) support this notion and theorizes HIS to be broad and states the relevance of its definition is contextual. In the study, HIS was reiterated as any kind of "structured repository of data, information, or knowledge" that can be used to support health care delivery or promote health development (Panerai 2014). Thus, maintaining a rigid definition is of minimal practical use because many HIS instances are not directly associated with health development, such as the financial and human resource modules. Moreover, several different HIS examples are categorised according to the functions they are dedicated to serving within the healthcare arena. They highlight the existence of outliers' instances that are not regarded as the normal HIS even though they contain health determinants data such as socioeconomic and environmental, which can be used to formulate health policies.

The development of HIS over the years has led many to believe they are solely computer technology. This notion has contributed dramatically to the misconception of the origin of HIS and the lack of peculiarity between the HIS conceptual structure and HIS implemented technology. Extant literature dates back the origin of HIS to be associated with the first record of mortality in the 18^{th} century, revealing their existence to be 200 years or older than the invention of computers (Panerai 2014). This demonstrates the emergence of digitalised HIS from the availability of commercialised episodes of "electronic medical records" EMR records in the 1970s (Thomas *et al.* 2022). Namageyo-Funa *et al.* (2018) commend the advancement of technologies in the healthcare arena, recounting the implementation of digitalised HIS that has significantly revolutionised the recording and accessing of health information. A study by Lindberg *et al.* (2019) highlight an instance of HIS transition from paper-based to digital-based, revealing a streamlined workflow that revolutionises health care applications in the healthcare arena. This HIS transition over the course of time has led to increased adoption of it within the health care arena. Tummers *et al.* (2021a) highlight the landmark of HIS from its transition to digitalisation and report a current trend in healthcare that has now extended with the inclusion of blockchain technology within the healthcare arena. Malik, Kazi and Hussain (2021) assessed HIS adoption in terms of technological, organisational, human and environmental determinants and reported a variation of different degrees of utilisation. Despite these facts, extant literature maintained the need for a resilience and sustainable HIS for health care applications within the healthcare arena at all levels (de Carvalho Junior and Bandiera-Paiva 2018; Malik, Kazi and Hussain 2021; Epizitone 2022).

Figure 2-2 illustrates the successful adoption of HIS amidst the significant determinants of its effectiveness. From the figure, the technological, organisational, human and environmental determinants are the defining concepts with individual sub-determinants in each domain that influences HIS adoption. At the technological level, the need for digitalisation drives HIS adoption, especially for stakeholders such as clinicians and decision-makers. The administrative, management and planning functions are the driving actors within the organisation level that endorse the implementation of HIS. The environmental and human determinants are more concerned with the socio-technical components that have been regarded as complex drivers for HIS adoptions. The perceptions, literacy, and usability are known forces within these categories that necessitate the adoption of HIS in many healthcare arenas.

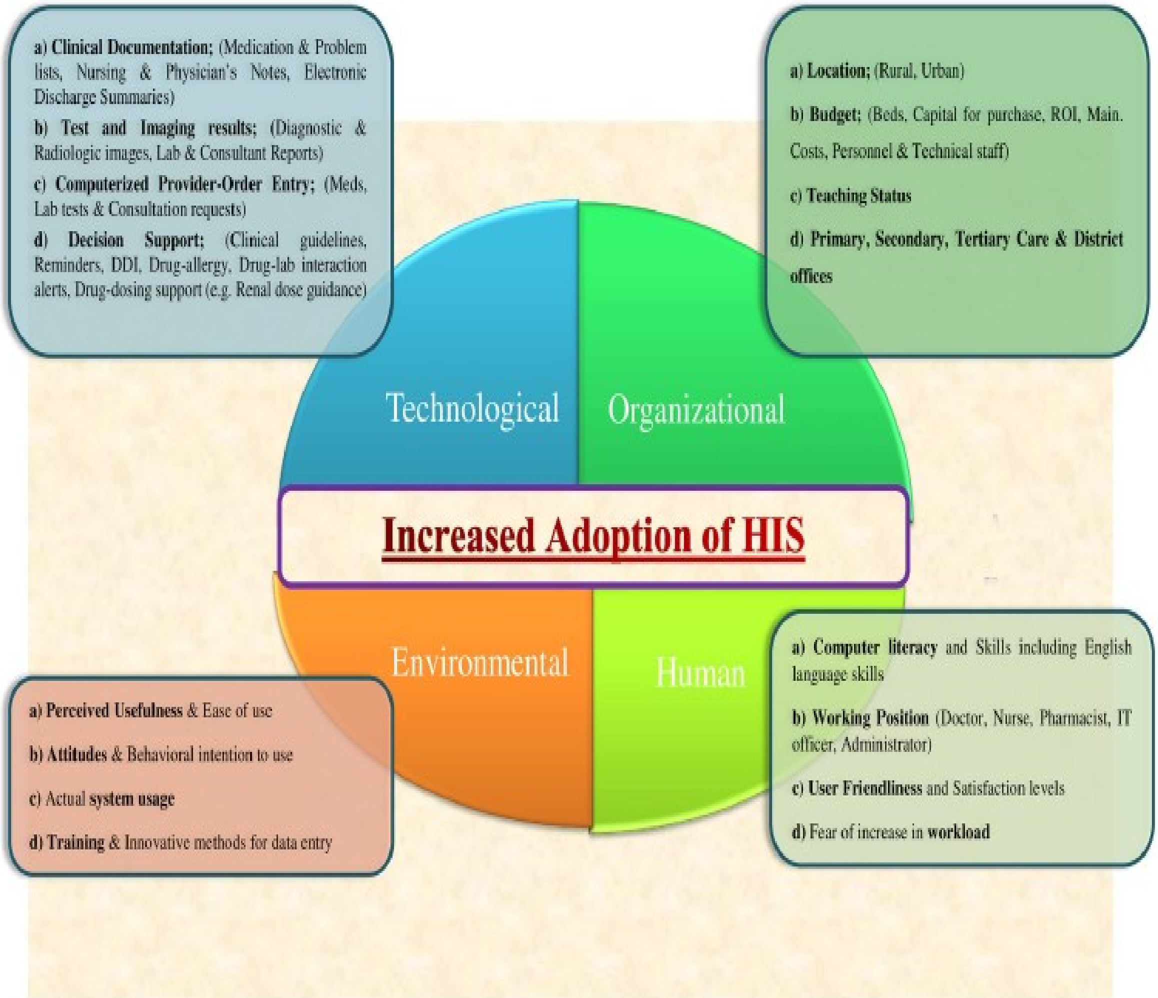

Figure 2-2 Effective health information system associations with the driving adoption determinants

Source : (Malik, Kazi and Hussain 2021)

2.6 Health information systems benefits

HIS, as an interrelated system, houses several core processes and branches in the healthcare arena to afford many benefits. Among these includes the ease of access to patients and medical records, reduction of costs and time, and evidence-based health policies and interventions (Tossy 2014; Ker, Wang and Hajli 2018; Kpobi, Swartz and Ofori-Atta 2018; Feteira-Santos *et al.* 2022; Haule, Muhanga and Ngowi 2022). Several authors reveal the benefits of HIS to widely known and influential within the healthcare domain (Ker, Wang and Hajli 2018). Furthermore, many health organisations are drawn to HIS because of these numerous advantages (Vaganova *et al.* 2017; Alahmar, AlMousa and Benlamri 2022). Moreover, investment in HIS has enabled effective decision making, real time comprehensive health information for quality health care applications, effective policies in the healthcare arena, scale-up monitoring and evaluation, health innovations, resource allocations, surveillance services, enhanced governance and accountability (Kpobi, Swartz and Ofori-Atta 2018; Dunn *et al.* 2021; Krasuska *et al.* 2021; See *et al.* 2021). Ideally, HIS is pertinent for data, information, and knowledge sharing broadly in the healthcare environment. HIS critical features are now cherished due to its incorporation with diverse technology (Panerai 2014; Nyangena *et al.* 2021). Extant literature reveals the role of HIS to extend beyond its reimbursement. **Table 2-1** presents a summarised extract of various HIS benefits captured in literature and some of its core enabling components or instances.

Table 2-1 HIS core enabling components and its Benefits

Source: Authors	**Core enabling HIS Components**	**Benefits**
Malaquias and Filho (2021)	Health ER eHealth mHealth	Ease of access to patient and medical information from records. Cost reduction Enhance efficiency in patients' data recovery and management. Enable stakeholders' health information centralisation and remote access.
Ammenwerth *et al.* (2020)	eHealth	Upsurge care efficacy and quality. Condense costs for clinical services. Lessen the health care system's administrative costs. Facilitate novel models of health care delivery.
Tummers *et al.* (2021c)	HIS	Patient Information Management. Enable communication within the healthcare arena. Afford high-quality and efficient care.
Steil *et al.* (2019)	HIS	Enable inter and multidisciplinary collaboration between humans and machines. Afford autonomous and intelligent decision capabilities for health care applications.
Nyangena *et al.* (2021)	HIS	Enable seamless information exchange within the healthcare arena.
Sik, Aydinoglu and Son (2021)	HIS	Support precision medicine approaches and decision support.

2.7 Interoperability of health information System

Interoperability is inferred by Malaquias and Filho (2021) to represent “the degree to which two or more systems can exchange information through interfaces in a specific context”. HIS interoperability within the context of healthcare applications has been revealed in literature to be critically indefensible due to the heterogeneity of data generated from the system (Jayaratne *et al.* 2019; Weber and Ho 2020; Malaquias and Filho 2021; Nyangena *et al.* 2021; Ladas *et al.* 2022). Kuo and Kuo (2017) posited interoperability as an HIS necessity that addresses issues such as deferral, recurrent blunders and cost within the healthcare arena. Several authors argued that many countries are confronted with HIS that are not interoperable (Kapepo and Yashik 2018; Mejia Medina *et al.* 2019; Tummers *et al.* 2021c). The current HIS is plaque with the influx of heterogeneous data that need to be integrated to aid core processes within healthcare, such as clinical decision making, patient care and real-time information availability (Ayeni *et al.* 2018; Malaquias and Filho 2021; Feteira-Santos *et al.* 2022). Jayaratne *et al.* (2019) argue that the upsurge of heterogeneity of generated HIS data has affected integration within HIS adversely.

Similarly, other authors associated the accumulation of heterogeneous data with different solutions deployed in the healthcare arena (Malaquias and Filho 2021). Mejia Medina *et al.* (2019) posit that problems with interoperability and communication contribute to resistance to using HIS. Additionally, interoperability challenges can be attributed to other determinants such as rapid developments of vast Health Information Systems technologies (HIIT) and unprecedented pressures within the wake of the 4IR and the emergences of pandemics such as the COVID-19 (Feteira-Santos *et al.* 2022). These determinants have created many benefits as well as challenges with the delivery of healthcare that are directly related to the interoperability of HIS (Nyangena *et al.* 2021). Moreover, Paul *et al.* (2015) reveal the amassed challenges associated with the lack of interoperability which impedes ambulatory care within the healthcare arena. Malaquias and Filho (2021) propose using middleware for health to tackle integration challenges that will subsequently enable interoperability within HIS. Whilst, Feteira-Santos *et al.* (2022) recommend the integration of independent IS within the healthcare arena.

2.8 Data quality of health information system

Data has been established as a core enabling component in the healthcare system. Stimulated by the advancement of technological applications within the healthcare arena, many benefits from data have been achieved. An empirical example of these includes better management of hospitals' and clinics' tests, administration, and biographical and epidemiological data (Jinabhai *et al.* 2021; Malaquias and Filho 2021; Pineros *et al.* 2021). Panerai (2014) regards data as an important constituent of HIS that contributes to health development. A major need arising from these advancements stems from the challenges of storing, processing, and extracting information from these data (Malaquias and Filho 2021; Taye 2021). According to Bogaert, van Oers and Van Oyen (2018), the attainment of a sustainable HIS is partly reliant on easy access to the superior quality of comparable data that can serve the purpose of health information generation, management, exchange and translation. At the same time, Ahmadi (2017) identify data quality within HIS to be integral in the attainment of decision, planning and insights of healthcare stakeholders. Several authors posit that the underpinning actions of quality data are paramount to health management decisions which, as a result, are crucial to governance, management and leadership effectiveness within the healthcare arena (Chaudhry *et al.* 2006; Riley *et al.* 2012; Dixon-Woods *et al.* 2013; Willis *et al.* 2013; Faridah *et al.* 2020). Jeffery *et al.* (2018) highlight the fundamental role of data quality within healthcare to be indefensible. Whilst this may seem easy, the nature and sources of this health data make it difficult to ensure its quality. Several authors emphasised the heterogeneity of health information data as a common phenomenon in HIS data (Bhattacharya *et al.* 2019; Malaquias and Filho 2021). This phenomenon is one of the main contributors to the HIS integration challenges. Mandacaru *et al.* (2017) associate poor data quality with the privation of linkage between different sources of health information data and highlight the importance of linking and integrating various health data sources. Paul *et al.* (2015) report the lack of variable data quality in HIS as a challenge within the healthcare arena.

Another concern associated with the quality of health data is related to the sources. Although the majority of health data emanates from different technologies that enable the capturing, retrieval, storing and transmission (Almunawar and Anshari 2012; Malaquias and Filho 2021) of the data, there are issues of replications of the same information across the HIS network. Additionally, this results in health data proliferation, adversely influencing data quality. Farnham *et al.* (2020) confirm data quality and wholeness' issues to be problematic due to many factors, such as solitary HIS instances within the healthcare systems that impair integration resulting in the dearth of integration of current digital health interventions. Hence in other to optimise processes and support decisions, the quality of the data in the HIS is more imperative than the quantity of the data. Additionally, several authors proposed using minimum data sets in HIS to reduce data redundancy and mend information quality and efficacy (Abbasi, Khajouei and Mirzaee 2019). As a result, pertinent data would be accumulated, permitting unnecessary data communication mitigation.

2.9 Usability of health information systems

HIS, from its definition, affords evidentiary-based medical care to stakeholders in the healthcare arena by assimilating and disseminating information (Crepaldi *et al.* 2018; Ebnehoseini *et al.* 2018; Kpobi, Swartz and Ofori-Atta 2018; Hyppönen *et al.* 2019; Nicol *et al.* 2021; Tummers *et al.* 2021c). Panerai (2014) posit HIS development and utilisation to be evidentiary based, implying that apart from its definition, emphasis should be on its contribution. Several studies attributed HIS contributions to the efficiencies of health care applications highlighting feats such as ease of use, efficiency, and helpfulness with its usability in many settings (Hypponen *et al.* 2019; Jeddi *et al.* 2020). Farrahi *et al.* (2019) highlight the fundamental role played by HIS in managing many hospital tasks, such as treatment procedures and appointments. The need and use of HIS stem beyond the affordability of quality health care applications to the deployment of medical care via robotic interventions in surgical procedures (Steil *et al.* 2019).

Extant literature reveals HIS to be a fundamental block in the establishment of many benefits, such as universal health courage and health care applications (Nicol *et al.* 2021). Steil *et al.* (2019) accentuate the emergence of intelligent and autonomous capabilities of HIS and warn on the implications of hybrid clinical team machine interactions. According to their study, there is a need to envision human and machine interactions within the healthcare arena, especially where actions and decisions are shared between the two parties (Steil *et al.* 2019). Several authors highlight the importance of frameworks such as "cognitive" walkthroughs in ascertaining the usability of HIS in a different context (Ghalibaf *et al.* 2018; Farzandipour, Nabovati and Sadeqi Jabali 2022).

Farzandipour, Nabovati and Sadeqi Jabali (2022) recommended the deployment of "heuristic" appraisal and "cognitive" walkthrough to optimise HIS and identify impediments associated with HISs' usability. Additionally, Crepaldi *et al.* (2018) express concern about HIS usability in association with its attributes, execution time and managerial benefits. However, in spite of these concerns, extant literature posits the usability of HIS to be easy and straightforward (Crepaldi *et al.* 2017; Crepaldi *et al.* 2018; Hypponen *et al.* 2019). Moreover, several scholars assert the usability of HIS to be satisfactory in many health care applications and recommend continuous development of HIS to facilitate the services of the stakeholders (Crepaldi *et al.* 2017; Hypponen *et al.* 2019).

2.10 Scalability of health information systems

The scalability of HIS is considered to be the capacity of the system to transform its size and scale to produce a range of capabilities. There are several developmental steps of HIS, which consist of Geographical management information system GIS, information system CIS and MIS (Murad 2018). Depending on the environment could be scaled up or down. The scaling-up of HIS extends to cover a broad range of services, while its scaling-down delimits its capabilities to offer an extensive range of services (Hochgesang *et al.* 2017; Beck *et al.* 2018; Krasuska *et al.* 2021). Regardless of HIS scalability, it has been highly efficacious in the planning and allocating of healthcare services (Hochgesang *et al.* 2017; Murad 2018). According to Murad (2018), HIS lures the applications of many information systems within the healthcare arena to handle foremost concerns of health services such as the identification of facilities locations and distribution, levels of accessibility and needed density of the health services facility. Extant literature reports an increase in the emergences of HIS adoption within the healthcare arena for reasons associated with its ability to aid health data integration and the merger of extensive digital health information (Paul *et al.* 2015; Alahmar, AlMousa and Benlamri 2022).

The scalability features can be attributed to the resilience and sustainable capabilities of HIS. Scalability was echoed in the extant literature as vital and indispensable property of HIS in healthcare delivery (Lal *et al.* 2022). However, despite this appreciation, stunted progress is reported due to the low national reliance on HIS and diverted local emphasis on health innovations (Paul *et al.* 2015). Ebnehoseini *et al.* (2018) associate unsolved usability delinquent with HIS scalability enactment. Similarly, Negro-Calduch *et al.* (2021) associate HIS undertaking dares to be associated with its scalability. Although extant literature heralds HIS to be essential to stakeholder engagement in decision-making and planning for health care applications (Paul *et al.* 2015; Hurtado-Salgado *et al.* 2018; Murad 2018; Steil *et al.* 2019). It is imperative to ascertain the HIS scalability in order to tap from potentials in the settings where they are deployed for health care applications.

2.11 Implementation and design

The design and implementation of HIS have been structured to meet the healthcare arena needs to support and consolidate urgent health priorities and objectives, amongst which consist of the mortality registry, civil registry and many health development statistics. While most designs and implementations have accomplished a lot, there are still many known barriers to the attainment of HIS offerings (Faridah *et al.* 2020). Extant literature reveals HIS implementation and design to be complex undertaken that relies on aspects such as technological, organisational, structural and human factors (Cresswell and Sheikh 2013; Sligo *et al.* 2017; Malekzadeh *et al.* 2018; Steil *et al.* 2019; Faridah *et al.* 2020). According to Jeddi *et al.* (2020), considering different stakeholders' needs and characteristics in the design and analysis of HIS is essential to drive its usability. Additionally, extant literature highlights the need to envision machine interactions within HIS, especially in the case where human and machine actions and decision-making are shared (Steil *et al.* 2019). A study by Panerai (2014) identified the "lack of political will, resistance to embrace a culture of informed decision making, absence of a critical mass of trained professionals, stifling bureaucracy, and incompetent management" among other determinants as limiting agents. However, the study posits that generalising the identified limiting determinants can apply to some healthcare scenarios and further reveals a global concern with HIS implementations and designs.

A study by Kien *et al.* (2018) contends the positioning of HIS within the healthcare system framework to be an overlapping constituent with the high importance realisation of healthcare applications. Similarly, Weber and Ho (2020) argue that there is insufficient evidence in studies to guide HIS design and specific functionality, such as interoperability, which is an elusive goal. Nonetheless, Teixeira, de Pinho and Patricio (2019) suggested using the service design approach that includes visual models and tools to foster user adoption for an efficacious HIS development and enactment. Despite all these notions, several authors assert the infrastructure of HIS to be an amalgamation of information structures, information processes and information technology that supports many health care applications (Nadri *et al.* 2017; Benbrahim, Hachimi and Amine 2018; Jabareen, Khader and Taweel 2020).

2.12 Internet health information

Health information on the internet prevalence has been fostered by the growing reliance of many healthcare stakeholders. These stakeholders regard and use this information as a primary means of information inference. The principal concept of internet health information is dependent on the technologies directly associated with HIS instance. Among which is the e-health, m-health and telehealth, which emerge from the juncture of public health, medical informatics and business (Malaquias and Filho 2021). Primarily, these technologies employ the internet to improve health care services. The Personal Health Record (PHR) is a practical enactment to make appropriate personal lifelong health information available. The progression of 3G, 4G, and 5G mobile technologies has propelled these instances in the HIS network and as well as indorses many possibilities for healthcare solutions. A study by Grosjean, Bate and Mestre (2020) presents a practical application of m-health in managing Parkinson's disease.

Similarly, PHR affords integrated and comprehensive health information gestalt that includes but is not limited to disease symptoms, doctor's diagnoses, tests result, medical insurance, medication and pharmaceutical information. Ammenwerth *et al.* (2020) emphasize that this instance affords holistic and ubiquitous (regional and national) information logistics that potentially overcome data silos. This particular HIS instance affords a platform to enhance healthcare delivery to stakeholders by providing support for management and clinical data, monitoring and evaluating vital signs, alerting and predicting outcomes and managing medication administration (Malaquias and Filho 2021). However, the surge of health information and data on the internet has contributed dramatically to the distorted HIS concept resulting in the recurrent question mark on the quality and reliability of available health information (Panerai 2014). Nonetheless, the internet information instance is considered a classical HIS as it affords a base for health information and supports many stakeholders' decisions.

2.13 Health information systems for global healthcare disposition

The global healthcare representation of HIS deployment and utilisation varies with many admirations as well as aversion for several reasons. Many scholars have presented this view based on the functionality and infrastructure of HIS (Ahmadi 2017; Gouda *et al.* 2017; Ahmadi *et al.* 2018; Meribole *et al.* 2018; Mejia Medina *et al.* 2019; Al-Marsy, Chaudhary and Rodger 2021). Regardless of this premise, HIS is highly desirable globally, especially for assimilating and disseminating health information. Authors Ammenwerth *et al.* (2017) and Sik, Aydinoglu and Son (2021) reveal HIS to be fundamental in achieving precision medicine, health and biomedical informatics. Thus, to afford long-lasting resolution for HISs deployment, it is crucial to ascertain its global disposition.

2.13.1 Health information systems in developed countries

There have been significant progress and satisfaction derived from the deployment of HIS in developed countries. These rewards can be attributed to the fact that many developed countries have amassed inordinate experience in HIS enactments and, as such, have enjoyed a great benefit from HIS promises. Extant literature reveals that these nations have best practices and opportunities (Saigi-Rubio *et al.* 2021; Boikos *et al.* 2022). Yet that does not rule out challenges associated with the enactment of HIS for health care applications (Saigi-Rubio *et al.* 2021; Boikos *et al.* 2022). These nations have an established base for HIS at the central levels of their governments, such as social security, planning and developmental units and their ministry of health (Panerai 2014). Authors Malik, Kazi and Hussain (2021) argue that developed countries have active and high levels of HIS adoption and usability. Saigi-Rubio *et al.* (2021) postulate that HIS deployment has been employed to address several predictable health information needs. However, despite these advancements, these nations still encounter challenges with the HIS enactment (Sarmiento-Suárez *et al.* 2022). Literature reveals cases of segregated HIS that fail to function as a system but instead isolate health databases such as mortality data, infectious diseases, tropical incidence and chronic diseases, hospital admissions and health service structure (Panerai 2014; Ammenwerth *et al.* 2020; Salminen-Karlsson and Golay 2022; Sarmiento-Suárez *et al.* 2022).

Moreover, although these nations have developed capacities to harness HIS promises to enhance health care applications, there is still evidence of dares resulting from issues like data management and interoperability. Synthesized evidence of this HIS dares in developed nations is associated with underused. Other identified data-related issues were the long logistics involved in the assimilation and dissemination of the data (Panerai 2014). Similarly, several authors emphasise the importance of real-time information at all levels of HIS deployment, including local, provincial, and national (Aung and Whittaker 2013; Saigi-Rubio *et al.* 2021). Thus, even in developed nations, reform and strengthening HIS for health care applications is highly recommended even in their health settings. Another pertinent concern is the availability of health information that fluctuates globally, even with the presence of HIS for healthcare. Developed nations are still lagging in their degree of access to health information. According to Ammenwerth *et al.* (2020), Finland, South Korea, Japan, and Sweden are the only four countries that can fully access health record data. Insinuating that there are still HIS fissures that are practically and theoretically evident in developed nation context, thus the requisite desire for a resilience and sustainable HIS is highly relevant in this setting as well as developing nations or low-income countries (Bogaert, For and Hlth 2017; Bogaert, van Oers and Van Oyen 2018; Malik, Kazi and Hussain 2021; Epizitone 2022). Moreover, extant literature posits that the HIS dares are not the same in all nations (Ahmadi *et al.* 2018), indicating that the problems encountered in developed countries will differ from those in developing nations.

2.13.2 Health information system fissures in developing countries

The enactment of HIS in developing countries has been considered a fad supplementary to its enhancement of healthcare services and experiences of patients (Bernardi 2017; McPherson *et al.* 2017; Alsharo, Alnsour and Alabdallah 2020; Helwig *et al.* 2020). However, in spite of this, HIS in developing countries have been associated with many disappointments, amongst which include challenges ranging from data qualities, competent stakeholders and untapped capabilities (Hewapathirana and Sahay 2017; Hariyanto, Denison and Stillman 2018; Kapepo and Yashik 2018; Kumar *et al.* 2018; de Sanjose and Tsu 2019; Higman *et al.* 2019; Farnham *et al.* 2020; Fine *et al.* 2022). The HIS and health development have been considered very instrumental in attaining basic healthcare in many developing nations, supporting the main aim and purpose of the HIS in the enhancement of quality healthcare (Kpobi, Swartz and Ofori-Atta 2018; Malik, Kazi and Hussain 2021). However, many determinants are involved, such as environmental, genetics, demographic, behavioural, economics and social determinants that influence its enactment (Panerai 2014; Alsharo, Alnsour and Alabdallah 2020; Malik, Kazi and Hussain 2021). Reynolds *et al.* (2022) state that evidence and guidelines for HIS augmentation lag conventionally in these settings.

Within the healthcare arena, many effectors such as health policies, resource allocation and health service exert influences on HIS enactment for health care applications. The lack of reliable health information in developing countries is a major hindrance in developing strategies and policies that anchor HIS digitalisation in developing countries (Kumar *et al.* 2018; Koumamba *et al.* 2021). These highlight some of the flaws of HIS undertaking in developed nations and reveal the socio-technical component lagging in HISs' enactment in this setting (Kumar *et al.* 2018; Kumar, Mostafa and Ramaswamy 2018; Koumamba *et al.* 2021). Moreover, the stakeholder component, which represents the population's health levels, equity and satisfaction, is a curial health effector and a significant challenge to HIS undertakings in the developing nation context. Regardless, however, the association of these health effectors has a three-way influence on the data, health determinants and population, which interferes with decision-making within the healthcare arena. Thus, HIS enactment for health care applications within this context is a complex undertaking confronted with the challenged inherent nature of these nations.

According to Kpobi, Swartz and Ofori-Atta (2018) the lack of policies, personnel incompetency, and flawed workflow are prevalent with HIS implementation, especially in developing countries. In developing countries, improving the health care applications is an urgent need; even with the promised benefits of HIS, many developing countries still scuffle with decision making and planning in the healthcare arena (Bouhaddou, Bennani Othmani and Diouny 2013; Panerai 2014; Koumamba *et al.* 2021). However, few studies delve into the enactment of HIS in developing countries despite the great potential involved (Bawack and Kamdjoug 2018). Additionally, concerns with the data quality, integration and functionality of the HIS in developing counties persist (Bouhaddou, Bennani Othmani and Diouny 2013; Luna *et al.* 2014; Meribole *et al.* 2018). Tossy (2014) synthesises that integration in the HIS is considered a practical dare in developing countries, especially in Africa and other low-income countries. Correspondingly, Farnham *et al.* (2020) reveal data quality issues to be problematic, particularly in the African continent and argue that poor data quality impairs integration and renders the Sustainable Development Goals (SDG) ineffective. Hence, the HIS data challenge is painstakingly considered to be salient and needs to be redresses in order to aid the tracking of SDGs (Boerma *et al.* 2018; Bhattacharya *et al.* 2019; Hoxha *et al.* 2022). Extant literature identifies integration challenges in developing nations as a primary concern and urges the involvement of policymakers to readdress the deployment of HIS to compliments the huge investments and efforts vested in these systems (Tossy 2014). Another HIS challenge encountered in developing nations includes the instabilities concerns caused by political agendas and conflicts that influence and interfere with HIS enactment. Panerai (2014) associated these instabilities as a significant hindrance to delivering healthcare applications, as commitment and training cannot be afforded in such conditions.

Several studies have suggested a change in HIS deployment as a means to address the unyielding dare in developing nations (Luna *et al.* 2014; Steil *et al.* 2019). The “bottom-up” approach has been heralded in literature as it shifts the focus from the “top-down” course without any exclusion to promote transformation in the HIS development and utilisation (Luna *et al.* 2014; Panerai 2014). This approach champion the premise that recognised stakeholders at the local level have direct contact with health-related issues. Hence their proactive involvement can aid preventive and interceptive actions and the realisation of HIS offerings. Although this approach may be inexplicable in developing nations, its implementation could mitigate many of the HIS dares encountered in developing nations, like shortage of staff, death of equipment and installations, lack of drugs and other supplies, and service deliveries. Additionally, certain developing countries like China, India and Brazil have harnessed most of the limitless potentials of technology to strengthen their HIS for quality health care applications.

2.14 Health information system and health equity

Braveman (2014) define health equity as the “principle underlying a commitment to reduce and ultimately eliminate disparities in health and in its determinants, including social determinants” and health disparities as a “particular type of health difference closely linked with economic, social, or environmental disadvantage”. Although health equity and disparities are ambiguous and applied vaguely, it aligns with the objective of HIS to afford the highest possible standard of health for all stakeholders (Braveman 2014; Cotlear *et al.* 2015; Zhang *et al.* 2020). These studies highlight the need for special attention that tends to afford health care to high-risk stakeholders based on social and meagre conditions. Braveman (2014) contended that health disparities unsympathetically upset certain people who have analytically experienced greater social or economic obstacles to health. The bases of these disparities are not limited to racial, ethnicity, religion, demographic and cognitive determinants. All of these are transient in different health care applications and require a resilient and sustainable HIS to enhance health equity (Schmidt, Abboud and Bogaert 2021; Sarmiento-Suárez *et al.* 2022). Notwithstanding, in order to afford health care to all without compromising is vital to utilise the total capacity of HIS. The pertinent role of HIS in enhancing health care applications ameliorates many concerns with health equity and disparities (Al-Shorbaji *et al.* 2018; Gil-Borrelli *et al.* 2018; Khader *et al.* 2018; Kpobi, Swartz and Ofori-Atta 2018; Jabareen, Khader and Taweel 2020; Nicol *et al.* 2021).

2.15 Availability of functional infrastructure

The HIS functional infrastructure is instituted globally to afford different levels of aid to the stakeholders. Current literature reveals the importance of HIS' functional infrastructure and commends HIS as an integral building block in the delivery of health care (Gebre-Mariam and Fruijtier 2018; Roth *et al.* 2018; Samra, Li and Soh 2020; Tummers *et al.* 2021c). Roth *et al.* (2018) describe HIS functional infrastructure as value-added healthcare IS that emerges from a state-of-the-art business intelligence of prior integrated IS like enterprise resource planning. However, sundry extant literature alluded the evidence of meagre HIS' infrastructure associated with the health care applications (Mejia Medina *et al.* 2019; Khorshed *et al.* 2022). The development of HIS functional infrastructure for health care applications has been reported in extant literature to be vested with great potential to enhance healthcare applications (Tamm *et al.* 2022). Fernandes *et al.* (2019) describe it as an architecture for health systems for healthcare applications that support stakeholders such as patients. Jawa *et al.* (2020) share an architecture for HIS functionality that can be enacted for resource allocation and oversight of health concerns like COVID-19 within the healthcare arena. Nyangena *et al.* (2021) assert the isolation of HIS functionality and reported the maturity level to be in a nascent emerging stage. Jeffery *et al.* (2018) allege the presence of HIS structural flaws in healthcare coverage had produced a hiatus superfluous with health perils.

According to Nyangena *et al.* (2021) study, HIS functional infrastructure, mainly the digital component, has many health promises that need to be well defined to afford seamless data exchange and enhance the quality of health care applications. They are highlights of HIS functional infrastructure that enable integration and interoperability in the healthcare system. Sundry literature praises HIS integration and interoperability capabilities as a purposeful infrastructure delivery (Prasser *et al.* 2018; Nyangena *et al.* 2021; Santana *et al.* 2021). Prasser *et al.* (2018) posit that the future of medicine within the healthcare arena would be digital, participatory, preventive, predictive and personalised; thus, HIS architecture that integrates and harmonises and share big data should be envisioned in the future enactment of HIS for health care applications. These authors collectively reveal the existing and future HIS functional infrastructure to be embedded with many capabilities and abilities to address many dares within the healthcare arena and enhance health care applications (Prasser *et al.* 2018; Fernandes *et al.* 2019; Jawa *et al.* 2020; Nyangena *et al.* 2021).

2.16 The conceptual study annotation for sustainable and resilient Health information systems for health care applications

The aforementioned sundry discussion on the HIS established the existing global outlook of HIS for health care applications. According to scholars, the existing HISs aids healthcare systems and their beneficiaries in many ways (Tummers *et al.* 2021a; Tummers *et al.* 2021b; Tummers *et al.* 2021c; Epizitone 2022; Epizitone, Moyane and Agbehadji 2022). These benefits and reliance have led to increased deployment and adoption of HISs within the healthcare domain. Congruently, there have been increases in HISs' dares as well as dissatisfaction with some authors alleging that there is a need for a substantial expanse of efforts to be invested in HISs' deployment (Malekzadeh *et al.* 2018; Gamal, Barakat and Rezk 2021; Epizitone 2022; Epizitone, Moyane and Agbehadji 2022). Moreover, despite the unique design of HIS, several dares, such as constant transformation and evolution of technology, and increased cost, still maintain a tenacious presence with its enactment (Kumar *et al.* 2018; Gamal, Barakat and Rezk 2021). Although these dares vary across the healthcare system globally for several reasons related to their contextualisation, there seems to be a consensus in extant literature that associated these HISs' dares to its infrastructure, organisational and data culture (Ahmadi *et al.* 2018; Malekzadeh *et al.* 2018). However, a global united front calls for a strengthened HIS for health care applications to leverage its potential and enhance its applications.

2.16.1 Sustainable and resilient health information system for health care applications

Different dimensions of well-being have been said to be attainable by the availability of opportunities presented by the existence of sustainability and resilience of systems such as the HIS (Gardoni 2019). According to Gardoni (2019), the presence of sustainability and resilience within a system avail opportunities to current and future generations with minimal disruption and afford and address certain considerations. In the extant literature, there are several definitions of these concepts, with some being industry-specific (Doorn, Gardoni and Murphy 2019; Gardoni 2019; Koliou *et al.* 2020). In general, sustainability is considered as the ability to measure or deliver a balanced resource offering within an ecosystem while taking certain concerns into account as resources are generated, whereas resilience is defined as the ability to withstand peripheral trepidation, acclimate, and swiftly recover to the original state of functionality or a new one (Zhang and Lin 2010; Gardoni 2018; Gardoni 2019; Gardoni and Murphy 2020). While these two terms may be used interchangeably, they are two distinguishable terms. According to Zhang and Lin (2010), a merger of sustainability and resilience in a system is considered to be the ability to regenerate a loss or injured resource. In the context of healthcare, there have been many events and needs that have coerced a response from HIS enactment for health care applications and warrant the condition for these abilities within the healthcare arena. Over the course of HIS undertaking for health care applications, there have been events such as the resurgence of pandemics like COVID-19 and the global health priorities for SDG 3 attainment that has imposed the need for sustainability and resilience within the healthcare arena (Adams *et al.* 2013; Jinabhai *et al.* 2021; Crooks *et al.* 2022; Soltysik-Piorunkiewicz and Morawiec 2022).

Sundry literature also divulged that there are many other additional transformational dares, such as deplorable infrastructure, lack of human resources, meagre service delivery, health centres inaccessibility and inadequate HIS associated with the delivery of health care in the healthcare arena (McAllister and McAllister 2013; Guidotti *et al.* 2016; Mutale *et al.* 2018; Nocera *et al.* 2018; Epizitone 2022). While there have been many attempts to address these phenomena, the need for these attempts to be robust and long-term is paramount to successful health care applications. Kpobi, Swartz and Ofori-Atta (2018) highlight the need to anticipate and plan for HIS' enactment and sustainability. Similarly, Adams *et al.* (2013) reveal the need for post-millennium developmental goals within the healthcare arena to be defined to enable innovations to anchor on existing attainments and creativity to tackle future health dares under the clarion call of universal health coverage priorities (Mills *et al.* 2019). Furthermore, the critical review literature divulges the paucity of studies that assess the sustainability and resilience of HIS for health care applications in contrast to the presence of many studies that target the improvement of HIS for health care applications (Adaba and Kebebew 2018; Bawack and Kamdjoug 2018; Alsharo, Alnsour and Alabdallah 2020; Alahmar, AlMousa and Benlamri 2022). Authors Adaba and Kebebew (2018) reported the need for studies on the HIS sustainability for health care applications indicating it to be an essential HIS optimisation and health care applications.

The resilience of the HIS system is considered to have tremendous implications on stakeholders' safety, health and well-being within the healthcare arena (Zhang and Lin 2010). Gardoni (2019) synthesises that frameworks need to include fundamental functions that enable the attainment of resilience and sustainability. The presence of many challenges in the health settings has alluded this need severally, necessitating their applications within the healthcare arena (Sari and Prayoga 2018; Clay-Williams and Braithwaite 2019). Employing these two unique capabilities within the healthcare system can successfully tackle HIS dares by providing a long-term solution. Hence the need for resilience and sustainable HIS for health care applications framework is paramount in the healthcare arena (Clay-Williams and Braithwaite 2019; Tilahun *et al.* 2021; Epizitone 2022).

2.16.2 Current challenges of health information systems from related work

The enactment of HIS has created and presented equal opportunities and dares within the healthcare arena (Askar, Ardakani and Majdzade 2017; Nyangena *et al.* 2021). It is well known that there has been enhanced economic and administrative efficiency of health care applications as well as enhanced patient care quality and interceptive health technologies. However, with the presence of these opportunities, there are several challenges encountered in the implementation and deployment of HIS in the healthcare arena (Sligo *et al.* 2017; Mozaffar *et al.* 2018; Price, Green and Suhomlinova 2019; Jabareen, Khader and Taweel 2020; Weber and Ho 2020; Negro-Calduch *et al.* 2021; Garcia, De la Vega and Mercado 2022). These challenges stem from several areas within the healthcare environment. A study by Tummers *et al.* (2021c) report a high dissatisfaction degree of HIS regardless of its high adoption rates.

Similarly, extant literature reveals a rife snag, shortcomings and failures associated with HIS enactment Negro (Askar, Ardakani and Majdzade 2017; Sligo *et al.* 2017; Mussi *et al.*

2018; Garcia, De la Vega and Mercado 2022). Correspondingly, Vaganova *et al.* (2017) signpost these challenges' areas and associations within the healthcare arena. Identifying the different needs of health practitioners, the extreme limitations on medical device and equipment purchases, the external ownership of innovative health products, time-consuming technological implementations and compatibilities issues as some of the challenges.

Tummers *et al.* (2021a) revealed that these HIS dares, such as fragmentation, are the reason for its encumbered understanding and characterisation. These studies aggregately highlight the need for solutions for the prevailing dares associated with HIS. Additionally, although these challenges paint a negative representation of HIS and its enactment in health care applications, it is important because it highlights practical starting points for the development of a resilient and sustainable HIS. Additionally, these challenges have been reported in sundry literature with the anticipation of inciting a resolution that targets health care applications optimisation in the healthcare arena. A stimulating response is the report of extant literature with proposed ameliorations. Steil *et al.* (2019) propose an inter and multidisciplinary collaboration between humans and machines in making hybrid health care application decisions.

Similarly, Crepaldi *et al.* (2018) suggest a nuanced and multidisciplinary evaluation for a favourable outcome of HIS objectives. At the same time, several scholars suggested the development of a strategic plan that synchronizes and points in the right direction communal exertions to a more integrated, worthwhile and sustainable HIS (Askar, Ardakani and Majdzade 2017; Awang Kalong and Yusof 2017; Bagayoko *et al.* 2020). Epizitone (2022) summarised these dares in line with a proposed the development of resilience and sustainable HIS for health care application framework. **Figure 2-3** present a summarised illustration of these challenges.

Challenges	Cited Sources
Application selection criteria	Dehnavieh *et al.* 2019
Communication Infrastructure	Dehnavieh et al. 2019; Najimudeen, Aldheleai and Ubaidullah 2021.
Data (completeness, ownership and security)	Kiberu et al. 2014; Karuri et al. 2014; Suresh and Singh 2014; Dehnavieh et al. 2019.
Finance (Funding Sources)	Manoj et al. 2013; Al-Nashy 2015; Bergum et al. 2015; Fusheini and Eyles 2016; Dehnavieh et al. 2019.
Lack of Training	Sheikh and Bakar 2011; Adaletey, Poppe and Braa 2013; Manoj et al. 2013; Karuri et al. 2014; Al-Nashy 2015; Kiwanuka, Kimaro and Senyoni 2015; Manya and Nielsen 2015; Nguyen 2015; Dehnavieh et al. 2019.
Political, cultural, social and structural infrastructure	Suresh and Singh 2014; Fusheini and Eyles 2016; Dehnavieh et al. 2019.
Pre-deployment (Pilot System).	Sheikh and Bakar 2011; Manoj et al. 2013; Al-Nashy 2015; Dehnavieh *et al.* 2019
Project Management	Sheikh and Bakar 2011; Manoj et al. 2013; Dehnavieh et al. 2019
Stakeholder coordination.	Dehnavieh *et al.* 2019
Top Management and leadership	Sheikh and Bakar 2011; Manya et al. 2012; Adaletey, Poppe and Braa 2013; Manoj et al. 2013; Karuri et al. 2014; Manya and Nielsen 2015; Dehnavieh et al. 2019.
Workforce capacity	Manoj *et al.* 2013; Karuri *et al.* 2014; Kiwanuka, Kimaro and Senyoni 2015; Dehnavieh *et al.* 2019.

Figure 2-3 HIS Challenges (Sources: Epizitone 2022)

2.16.3 Redesign of HIS: a socio-technical approach

The healthcare arena has been for many years engaged in endorsing technologies in the delivery of healthcare. Over time there has been a growing evolution of technological deployment within healthcare, with prominent concepts such as telemedicine, mHealth and eHealth taking centre stage (Cook *et al.* 2016; Hoque 2016; Finet *et al.* 2018; Maramba, Chatterjee and Newman 2019; Sharma and Prashar 2019; Ammenwerth *et al.* 2020; Grosjean, Bate and Mestre 2020; Jurkeviciute *et al.* 2020; Oberschmidt *et al.* 2022). Although this has contributed to the delivery of health care in a broader scope, there are still many concerns involved with the social component (Bygholm 2018; de Carvalho Junior and Bandiera-Paiva 2018; de Carvalho and Bandiera-Paiva 2020). These instances are also evidence of the alienation of HIS within the healthcare arena, which has resulted in the passive inference attributed to these systems. Extant literature questions the interaction of human and nonhuman intelligence within the healthcare arena (Steil *et al.* 2019). According to scholars, redesigning HIS requires a comprehensive overview of stakeholders' interactions with the system to ascertain their needs and preferences to incorporate into the design (Eslami, Firoozabadi and Homayounvala 2018). Citrin *et al.* (2018) state that "A key opportunity to address these challenges lies in two inter-related developments in global healthcare systems design: 1) the expanded scope of community healthcare workers in healthcare delivery systems; and 2) digital systems for longitudinal care".

Additionally, highlighting the indispensable need for recognition to be afforded to healthcare providers for an effective, agile and adaptive population-level data systems healthcare delivery. While the need for a sustainable and resilient HIS is urgently needed, it is paramount to address these flaws in the enactment of HIS (Zhang *et al.* 2020). To mitigate failures and challenges, a robust and resilient HIS must be redesigned to incorporate and engage key stakeholders (Beck *et al.* 2018; Mutale *et al.* 2018). Teixeira, de Pinho and Patricio (2019) mentioned the importance of stakeholders like end-user involvement in the designing of HIS. At the same time, a study by Martikainen, Kaipio and Laaveri (2020) confirms the essential disposition of stakeholders in the development of HIS for health care applications. While Beck *et al.* (2018) state that HIS feat requires all stakeholders' alliance and political will, highlighting that the presence of technologies is not the sole solution. Alsharo, Alnsour and Alabdallah (2020) argue that stakeholders' perception of HIS is an interruptive influence in health care applications that adversely affects its efficacy in the healthcare arena. Thus, this study proposes incorporating insight from patient data to enhance quality health care applications. The framework presented in this study capitalised on HIS data as a means to renew health care efforts and conquer emerging threats like lack of integration in the enactment of HIS and isolation of stakeholders in the healthcare arena.

2.16.4 Socio-technical theory

Technology deployment within healthcare has been purposeful for specific targets and objectives. Many of these deployments have been void of the social component that incorporates communication from stakeholders and decision-makers (Høstgaard, Bertelsen and Nøhr 2017; Hughes-Lartey *et al.* 2020; Ghaffari *et al.* 2021). Ghaffari *et al.* (2021) assert that the interaction of stakeholders with health information technology (HIT) such as HIS is important in the development of their competency. According to Panerai (2014), HIS deployment is beneficial in many ways and maintains a pervasive stance in the healthcare arena. There is no reservation that the HIS fosters a relationship between stakeholders such as patients and healthcare providers (de Quiros, Dawidowski and Figar 2017; Bertelsen, Petersen and Nøhr 2020; Faridah *et al.* 2020; Ayele *et al.* 2021; Jeyakumar *et al.* 2021). In actuality, studies have commended the role of good relationships in attracting, retaining and even heartening the incorporation of core stakeholders such as patients in decision making (Clay-Williams and Braithwaite 2019; Steil *et al.* 2019; Teixeira, de Pinho and Patricio 2019). Extant literature further associates good relationships with effective communication that subsequently enhances health and quality of life and enables the management of chronic diseases (de Quiros, Dawidowski and Figar 2017; Crepaldi *et al.* 2018). Additionally, Almunawar and Anshari (2012) content that for relationships to grow and develop, it must be managed and urges organizations to acknowledge changing needs and be alert. Despite these premises, the deprivation of stakeholders' incorporation with healthcare technologies remains evident in extant literature (Ifinedo 2018; Giussi Bordoni *et al.* 2019; Mejia Medina *et al.* 2019; Ghaffari *et al.* 2021).

HIS is a complex system that requires several aligning corporations where they are deployed (Eslami Andargoli *et al.* 2017; Palojoki *et al.* 2017; Hariyanto, Denison and Stillman 2018; Prodinger and Taylor 2018; Clay-Williams and Braithwaite 2019). Its survival relies on incorporating developed technological devices and key stakeholders (Palojoki *et al.* 2017). Key stakeholders, such as developers and end users, share a mutual responsibility for the success and failure of HIS. However, this can hardly be materialised in most settings as parties do not share the same realities and expectations (Mutale *et al.* 2018). Vaganova *et al.* (2017) report this difference and indicate that the developer's reality is limited to the technical possibilities, while stakeholders such as end-users are particularly concerned about costs, returns and health. These studies reveal the absence of key stakeholder involvement in the development process. Crepaldi *et al.* (2018) report the limited point of view of health care recipients in HIS. Although HIS has been marked in extant literature for its many benefits, the lack of health care recipients' views reveals the need for a HIS that is depended on the specialised requirements of the healthcare zone (Teixeira, de Pinho and Patricio 2019). Moreover, extant literature reveals the development of HIS as a complex socio-technical process imbued with an elevated degree of uncertainty (Vaganova *et al.* 2017; Rohani and Yusof 2022).

Additionally, HIS design and output have been marred with many failures due to the illustration of HIS as “data on computer” (Panerai 2014). In an attempt to tackle HIS design flaw, several studies have presented elucidations on the way forward. A study by Teixeira, de Pinho and Patricio (2019) theorise the use of a service design approach in the development of HIS that fosters stakeholders’ participation in co-creating solutions via the incorporation of a participatory, holistic, creative and visual slant on an iterative course of exploration, ideation, reflection, and implementation. Correspondingly, another study proposes an action-led HIS in contrast to the data-led one that infused mathematical and statistical scientific techniques to afford insights into scenarios within the healthcare arena (Panerai 2014). These studies endorsed the integration of developmental models into current HIS settings (Awang Kalong and Yusof 2017; Grenha Teixeira, Pinho and Patrício 2019).

A critical review of HIS and health care applications research reveal a pertinent need for the incorporation of stakeholders’ perspectives for the strengthening of HIS (Awang Kalong and Yusof 2017; Mutale *et al.* 2018; Alsharo, Alnsour and Alabdallah 2020; Ayele *et al.* 2021; Biru *et al.* 2022). Extant literature postulates HIS’s knowledge and practices among stakeholders such as doctors and staff to be truncated (Sadoughi et al. 2017). Thomas *et al.* (2022) indicate that many countries have different challenges specific to their context that influence the enactment of HIS; hence incorporating stakeholders’ perspectives is vital for reinforcing HIS capabilities. Similarly, Citrin *et al.* (2018) contend that the simultaneous technological and healthcare workforce advances present an avenue to tackle health care challenges. However, the presence of organisational concerns that are subjective and impede coordinated efforts toward theoretically-informed HIS and health care applications exertion (Cresswell and Sheikh 2013). Nevertheless, Cresswell and Sheikh (2013) state that HIS enactments in healthcare settings are fatefully imperative undertakings that need adequate research attention.

2.16.5 Health information system concepts trend

Over the last decades, there have been many trends and key concepts that have characterised the HIS for health care applications (Scheplitz 2021). Clay-Williams and Braithwaite (2019) reveal these trends and concepts to be lagging in the development of a resilient health care application. A critical look into HIS and health care applications related studies show that these trends have evolved gradually and still continue to evolve, indicating the relevance and need for these studies that seek to contribute to the advancement of HIS for health care applications (Epizitone 2022; Epizitone, Moyane and Agbehadji 2022). Many of the identified trends are biased toward enhancing and attaining sustainable and resilient HIS for healthcare applications. As a result, a need to ascertain their aggregate input to healthcare exists (Epizitone, Moyane and Agbehadji 2022). **Figure 2-4** illustrates the isolation of key concepts in a set of three identified concepts in extant literature. This gap highlights the need for design studies incorporating core and key concepts in the healthcare arena to attain sustainable and resilient HIS for enhancing health care applications.

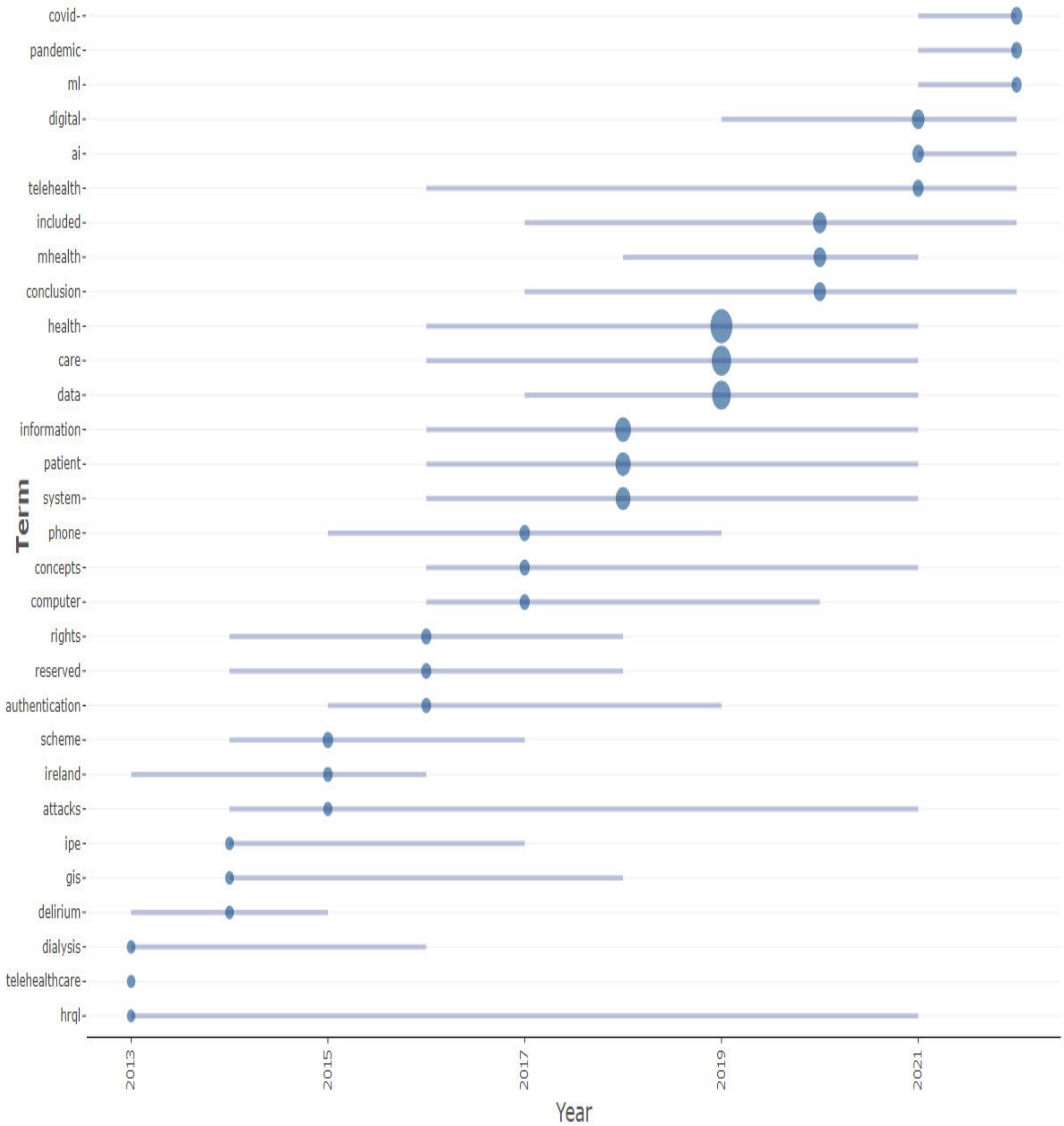

Figure 2-4: Trends in HIS and Health care applications studies

Source: Author creation.

Furthermore, Clay-Williams and Braithwaite (2019) study on resilient health care alludes the need for a new approach the regard system thinking to consider the everyday work variation in the enactment of HIS for resilient healthcare. Kumar *et al.* (2018) allege that the assimilation of system thinking keen on reinforcement HIS exertions will decrease HIS design-user reality fissure. According to these authors, despite the great potential of sustainability and enactment of complex health care services mediations, stakeholders must be incorporated for practical implementations (Braithwaite *et al.* 2017; Eslami Andargoli *et al.* 2017; Clay-Williams and Braithwaite 2019).

2.16.6 Study theoretical frameworks

The theoretical framework that has guided many IS studies within the healthcare arena has employed the use of the evidence base research and practice theory to afford elucidations on information system phenomena. Many of these have been centred on the deployment and benefits of HIS on healthcare applications creating a hiatus in the existing body of knowledge (Sahay, Nielsen and Latifov 2018; Dehnavieh *et al.* 2019; Sahay, Rashidian and Doctor 2020; Ostern *et al.* 2021; Epizitone 2022). These studies present many application of theoretical evidenced-based research that has resulted in the creation of a gap, as there are limited studies that delve into the design and action theory with the human component in view. In many research studies, the theoretical Framework (TF) often describes the blueprint that enables researchers to conduct their investigation. On the other hand, the conceptual framework (CF) builds on the TF to allow for incorporating the researcher's constructs in addressing the study inquest (Mensah *et al.* 2020; Lynch *et al.* 2021; Şimşek *et al.* 2022). Hence, this study employs the information system (IS) theory of design and action that explores and incorporates the socio-technical aspects to enable efficient ICT usage and designs in Healthcare (Gregor 2006; Adaba and Kebebew 2018; Grosjean, Bate and Mestre 2020; Grosjean *et al.* 2022).

These theories are preferred and supplement the evidence base theory (EBT) and diffusion of innovation theory (DIT) (de Oliveira *et al.* 2020). The DIT theory seeks to drive the adoption of innovative technology. In the context of HIS, implementation and adoption have already been grounded globally. However, the need for this system to be strengthened shifts the focus away from initial implementation and adoption to post-enactment (Biru *et al.* 2022). That emphasises the structural and process transformation for healthcare stakeholders anchoring on extant evidence to redesign existing HIS to be resilient and sustainable, resultantly improving health care applications.

This theory postulated that stakeholders and technology are equally valuable, and hence stakeholder perspectives should be incorporated into the design of ICT. It also disputes the foremost premise that HIS is solely a computer implementation (Panerai 2014). It adopts the credence that stakeholders can contribute to the development of resilience and sustainable HIS when included in the development (Faridah *et al.* 2020; Martikainen, Kaipio and Laaveri 2020; Sik, Aydinoglu and Son 2021). Faridah *et al.* (2020) allege there is a considerable value associated with proper coordination and adaptability of human resources in implementing HIS for health care applications. Therefore, using data science to present robust and sustainable HIS for health care applications is the main aim of this study set forth to contribute to the practical applications of HIS within the healthcare arena and subsequent enhancement of health care delivery. Extant literature posited that in order to attain favourable outcomes from health applications, scrutiny is needed that incorporates data-driven sciences and social judgement (Magdon-Ismail *et al.* 2019). However, many healthcare data sources can be classified into two categories: patient-oriented (clinical, administration, Financial and billing) and non-patient oriented, such as aggregate healthcare data (cost, statistics, procedures and diseases indexes, reports and scorecards). Regardless of the type of health data categories, many core stakeholders' actions are dependent on these data and the insights that can be obtained from it (Ahmadi 2017; Askar, Ardakani and Majdzade 2017; Flora, Margaret and Dan 2017; Yang *et al.* 2017b; Gesicho and Babic 2018; Stout *et al.* 2018; Hyppönen *et al.* 2019; Mazur *et al.* 2019;

Oza *et al.* 2019; de Carvalho and Bandiera-Paiva 2020; Bosch-Capblanch *et al.* 2021; Ng'etich, Voyi and Mutero 2021; Tappis *et al.* 2021; Boikos *et al.* 2022; Chanyalew *et al.* 2022; Ladas *et al.* 2022; Lal *et al.* 2022; Worku *et al.* 2022; Zuske *et al.* 2022). This study anchors on these data to resolve the passive engagement of the healthcare system, namely HIS, in delivering quality health care applications and demonstrating the socio-technical component value in implementing robust HIS. **Figure 2-5** illustrates the Venn diagram of the core theories employed in this study.

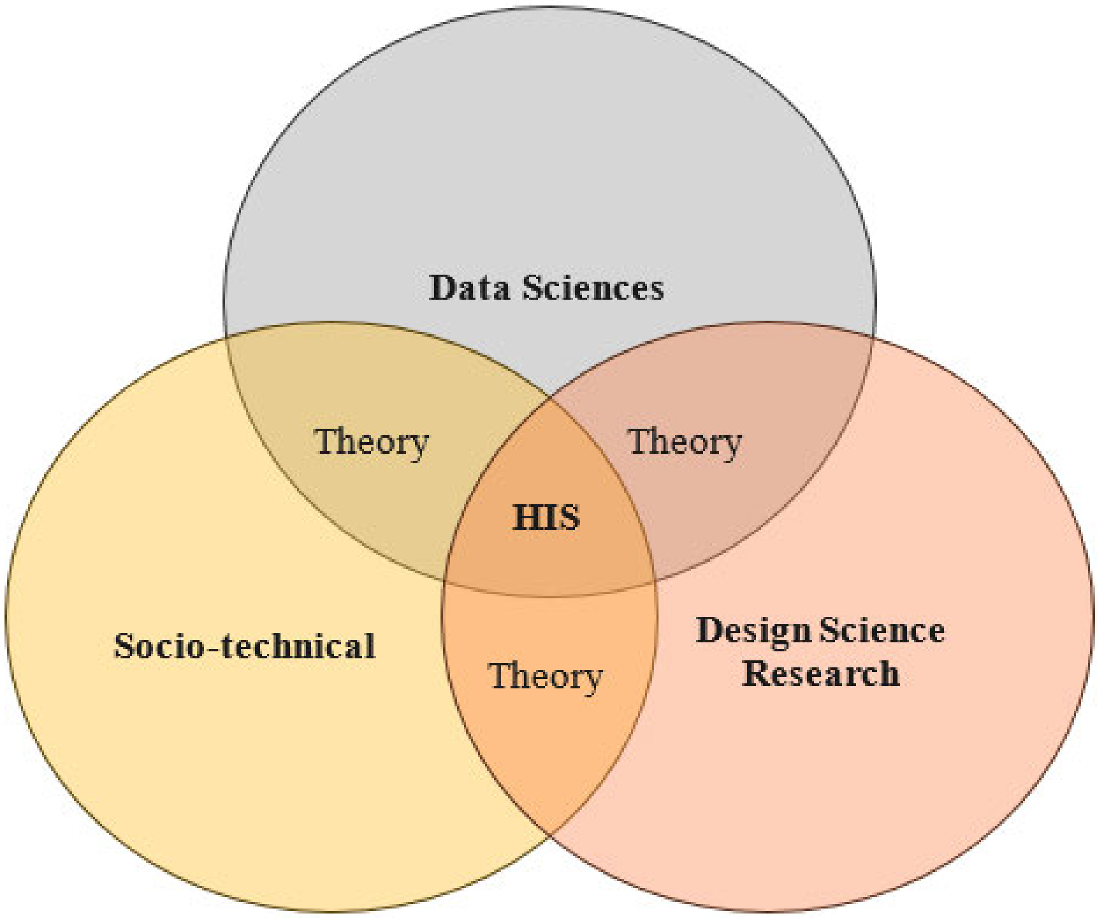

Figure 2-5 The underlying theories employed for the development of HIS

Source: Author creation.

2.16.7 Study conceptual frameworks

Although HIS is broad and has amassed myriad definitions that have been applied in varied contexts, extant Literature highlights the need to distillate its contributions to current and future health development and its enactment challenges (Panerai 2014). Considering that data is an essential and expensive resource in the Healthcare arena. Dissecting the data element to ascertain its role in attaining a sustainable and resilient HIS is crucial. The typical data processing cycle in an ideal HIS is seen to be tedious and requires isolated functions. Roth *et al.* (2018) case report on the scalable analytical platform enactment from the "business intelligent" system in the healthcare arena illustrates this cycle to be vital yet rely on external handles. Frameworks or models like the data management and analysis model are a unique advantage to attaining a resilient and sustainable HIS for health care applications (Joseph *et al.* 2022). All of which reveal the needed incorporation of the data constituent under the deployment of an adept.

Several studies present evidence of data constituents' significance in affording insight and edge in the HIS, which is paramount to its resilience and sustainability for enhancing health care applications. Hence, integrating data analysis under adept custody directly in the HIS for health care can afford a strengthened system that will be resilient and sustainable (Combi and Pozzi 2019). **Figure 2-6** shows the data management and analysis process in a healthcare space. The step detailed the critical phase entailed in managing and analysing health-related data within the healthcare arena to obtain insights. Like most Healthcare frameworks developed, the case of isolation and void of integration to implement the insight generated is predominant. However, the isolation of the data management process and analysis can be attributed to the lack of socio-technical incorporation at various phases of the process due to the nature and scope of HIS.

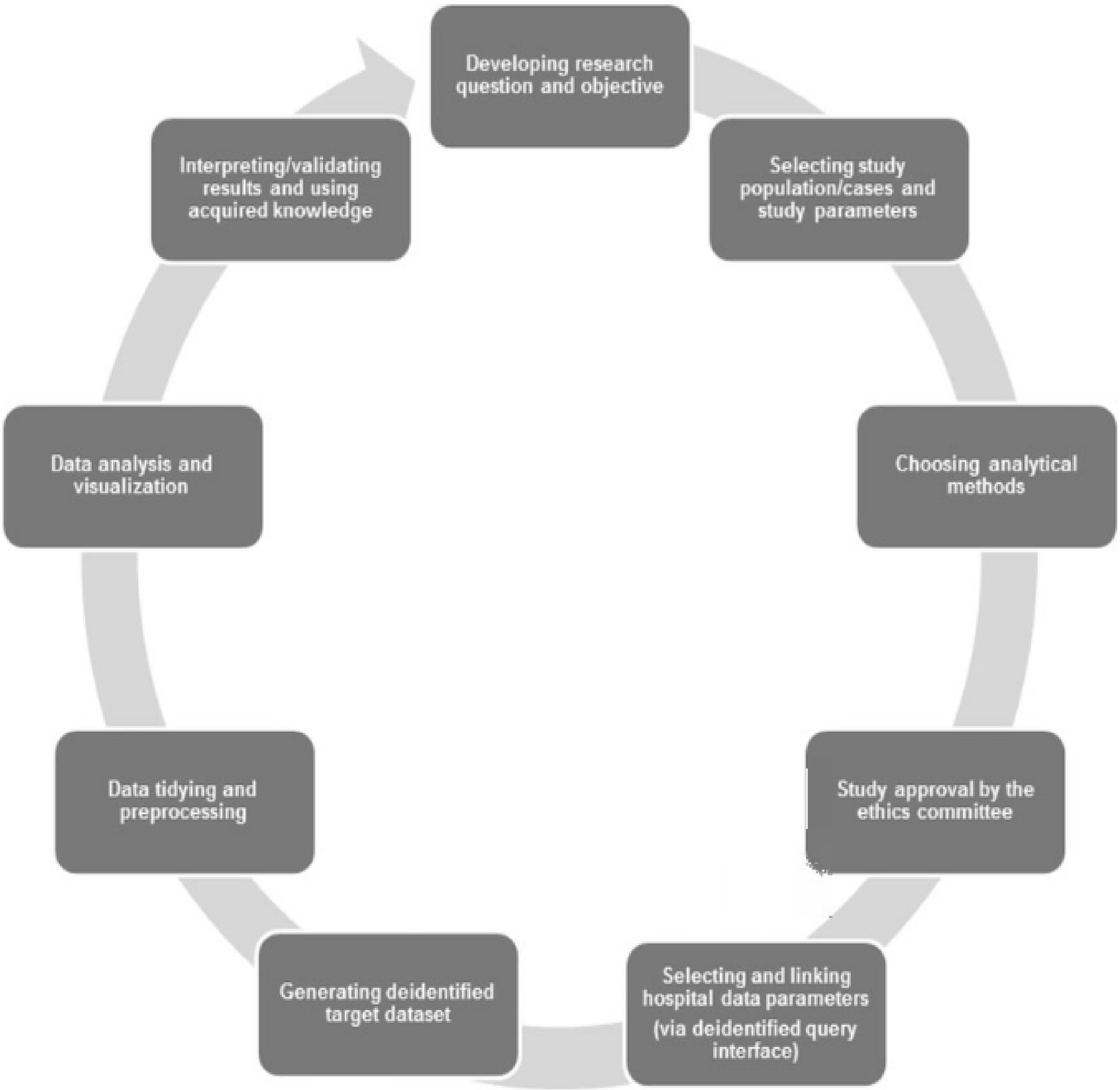

Figure 2-6 Data management and analysis process at the University Hospital Basel Source: Roth et al. (2018).

Nonetheless, many frameworks that are socio-technically focused have detailed successful enactment of health care services as they are tailored to enhance HIS. HIS frameworks such as "Patient-Reported Outcome Measure" (PROM) IS (Curtis and Brandow

2017; Prodinger and Taylor 2018), and health outcomes through mentoring, assessments (BHOMA) (Mutale *et al.* 2018) and “Patient-reported outcome (PRO) (Moloczij *et al.* 2018) are practical examples enacted. However, although all these frameworks remain isolated and dependent on specific constituents of HIS, they necessitate the need for an integrated data-driven framework that incorporates all components in the healthcare arena to afford quality health care applications is relevant.

Developing and implementing a data-driven paradigm for a resilient and sustainable HIS for health care applications would strengthen existing frameworks and enhance the potential of emerging technological applications for healthcare within the healthcare arena. This data-driven paradigm is also a critical undertaking needed for developing and strengthening the global health system (Rudd *et al.* 2019). However, extant literature reveals limited research on HIS benefits and influences on healthcare quality, especially in this regard (Ker, Wang and Hajli 2018). Highlighting the demand for more studies on HIS payoffs and influences on health care applications. Concomitantly efforts that target the appraisal of HIS enactment have been deliberated to be strategically advantageous in the attainment of robust health care applications (Noel, Taramasco and Marquez 2022). Jabareen, Khader and Taweel (2020) emphasise on supports that aid the need to develop strategies that anchor HIS in digitalisation. Thus, many facets of health care applications are set to benefit from the development and strengthening of HIS directly. Similarly, the enactment of data-driven applications, which propel the employment of HIS in the delivery of health care applications, will subsequently respond to and fulfil the sustainable development goals for health care for all (Mills, Lee and Rassekh 2019; Nsaghurwe *et al.* 2021).

2.17 Summary of the chapter

As the world advances, the population increases and many economic gradients are impacted. A sustainable and resilient HIS for quality health care applications within the healthcare arena is paramount. The need for real-time elucidations from HIS that transient between time and space is essential for stakeholders' health care. Hence the need for this study that pinpoints and constructs the development of sustainable and resilient HIS from a data-driven angle is necessary. The chapter draws from extant theories within the healthcare arena to present a conceptual context for developing a sustainable and resilient HIS for health care applications from the review literature. The first part of this chapter presents extant literature on HIS for healthcare. The latter part establishes the contextualise context that guides the subsequent chapters. The following chapter detail the methodology employed in the attainment of this study.

CHAPTER THREE: RESEARCH DESIGN

3.1 Introduction

This chapter presents the research methodology and maps out the research design and elements associated with this study. The research methodology articulated to traverse the aim of this study is grounded on the intersection of socio-technical theory, design sciences research, data sciences and study impetus, as well as the driving research question. The overarching question is: *How can knowledge generated from an analysed integrated information system be used to attain a resilient and sustainable integrated information system for Health Care applications?* To explore this main question, the following research objectives were further formulated for the study to be systematically addressed using a data-driven approach.

- Ascertain the knowledge, constraints, and perceptions of the Health Information Systems deliverables.
- Explore knowledge creation that addresses ill-defined problems in the Integrated Health Information System.
- Investigate the performance of Health information systems for health care applications.
- Structure an efficient and effective holistic model framework for a robust, resilient, and sustainable integrated Health Information System.
- Empirically validate data science techniques for achieving a resilient and sustainable HIS and evaluate the developed machine learning model with other models using well-known metrics.
- Enact the best deployment model for enhancing the healthcare information system.
- Provide theoretical and practical reflections from the study that may be used to implement a resilient and sustainable HIS.

3.2 An overview of the problem and purposes

The Healthcare arena has in place many systems to afford health care to its stakeholders. Over time technological deployment has proven to be of great benefit within the healthcare arena. Many advances have been attained for HIS deployments, such as improving healthcare and enabling evidence base decisions (Nwankwo and Sambo 2020; Delnord *et al.* 2021). The HIS is an integrated information with many interrelated components; people, processes and technology have been indispensable for a decade within the healthcare arena. Its employment for health care applications such as care, treatment and intervention has been commendable. However, there are many dares associated with the HIS, such as its lack of symmetry and feebleness that limits its potential to afford sound health care applications (Nøhr *et al.* 2019; Epizitone 2022). The health care system is posited to be complex and flout simplistic ameliorations. Regardless, new paradigms of knowledge are replacing outdated approaches associated with working, thinking and improving healthcare systems (Braithwaite *et al.* 2017). Hence, the core of this new shift is reliant on the approach "contextualisation" on a robust and scientific footing. Thus this study was synthesized in the data science and design science approaches to afford a resilient and sustainable HIS for healthcare applications. The study intends to leverage the power of data sciences, which can structure systems to attain a resilient and sustainable HIS for health care applications within the healthcare arena. Several methodological steps are taken in order to develop a resilient and sustainable HIS for health care applications. F**igure 3-1** illustrates the proposed "framework to develop a resilient and sustainable integrated information system for Health Care applications" using data orientated approach.

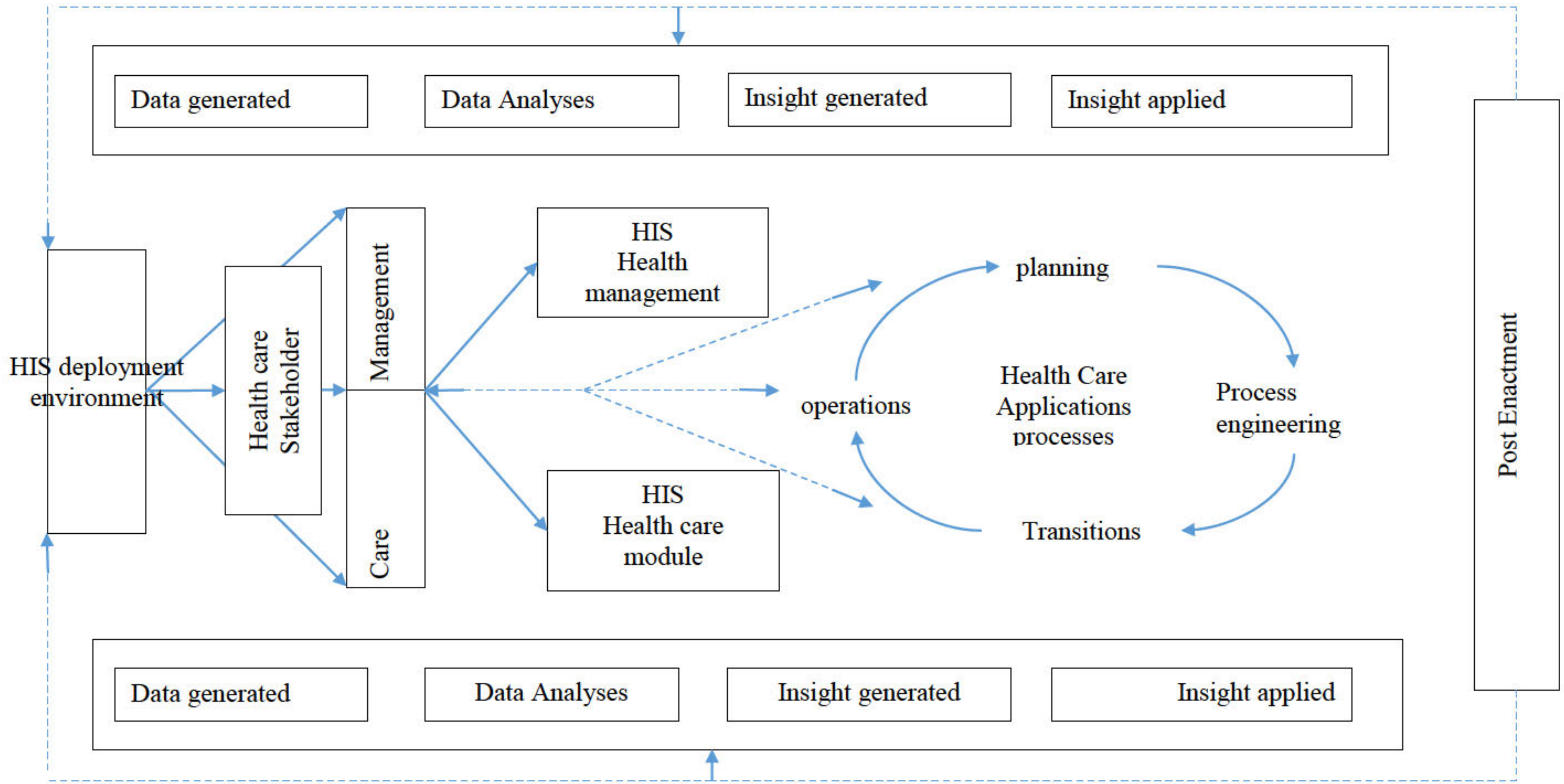

Figure 3-1 Propose framework to develop a data-driven resilient, and sustainable HIS for health care applications.

3.3 Research Methodology

This study adopts the design science research (DSR) approach, which gained popularity in the 1990s and is now employed in a wide range of fields, including healthcare (Hevner *et al.* 2010; Kao *et al.* 2016). It is a research methodology that enables explicit guidelines for iteration and evaluation in a research project (Peffers *et al.* 2007; Hevner *et al.* 2010; Wieringa 2014). This approach, over other approaches, presents an outcome-based research strategy that enables the development and fine-tuning of artefacts such as design, methods and models. Several fields have adopted and implemented the DSR paradigm (Hevner *et al.* 2010; Hevner, Chatterjee and Iivari 2010; Geerts 2011; Mwilu, Comyn-Wattiau and Prat 2016; Van Aken, Chandrasekaran and Halman 2016). In the IS domain, the implementation of DSR has been employed to solve real-life snags and rendered employable artefacts (Peffers *et al.* 2007; Hevner *et al.* 2010; Dresch *et al.* 2015; Kao *et al.* 2016). In the healthcare arena, it is asserted to have several opportunities (Hevner and Wickramasinghe 2018). Many sectors of the healthcare industries have already benefited from its uses to advance their services (Lapão, Da Silva and Gregório 2017; Beinke, Fitte and Teuteberg 2019; Teixeira, Patrício and Tuunanen 2019; Johnson, Burgess and Sethi 2020).

The research approach formulated to realise the aim of this research study falls within the footing of design sciences at the intersection of data sciences and information systems (Provost and Fawcett 2013; Baskerville, Kaul and Storey 2015; Lee, Thomas and Baskerville 2015; Kao *et al.* 2016; Reubens 2016; Kala *et al.* 2020; Katarahweire, Bainomugisha and Mughal 2020). Hevner and Chatterjee (2010) posited the DSR approach is exceptionally pertinent to information systems research in dealing with key issues that are central, albeit contentious, to the role of information technology artefacts. This method was defined in the extant literature as a pragmatic research paradigm that encourages the creation of ground-breaking artefacts to solve real-world problems.

Thus, the DSR is paramount to this study in that it affords practical objectives that aid the successful realisation of the study in the ensuing sequence, which commences with a problem awareness in the healthcare sector, followed by a proposed artefact that will be developed and evaluated at the end (Wieringa 2014; Baskerville *et al.* 2018). Hence, the DSR is employed to satisfy the driving question; “How can knowledge generated from an analyse integrated information system be used to attain a resilient and sustainable integrated information system for Health Care applications?” And the subsequent research questions.

3.4 Multiphase Research Design

Following the DSR, a multiphase method approach was used because it is apt for the study's main aim as it utilises different methods at different phases that afford problem awareness, suggestion, development and evaluation at the different phases (Geerts 2011; Youngs and Piggot-Irvine 2012; Provost and Fawcett 2013; Bell *et al.* 2014; Venable, Pries-Heje and Baskerville 2016; Baskerville *et al.* 2018; Epizitone and Olugbara 2020). By exploring the study objectives, a pragmatic observation was conducted in diverse phases, which resulted in the research questions being explored in different stages of the study with data sciences in view. These stages were based on health-related data. The unique data cases used in this study are based on system-generated data. The insights gained from it are intended to be deployed by practitioners in decision making (Sivarajah *et al.* 2017; Van der Voort *et al.* 2019; van der Voort *et al.* 2021). A research objective and related works associated with the goal were addressed at each phase. Through data sciences, the alignment of the study with the research's overall objective was explored, with a broad view of data science knowledge creation (Priestley and McGrath 2019). The case studies were from the integrated information system and the healthcare domain with the problem at different scopes and structures (van der Voort *et al.* 2021). In the healthcare domain, knowledge from the health system, such as health data, will be explored to uncover the pertinent insights applicable to the case study. **Table 3-1** illustrates the different phases and the methodological approach used. In the multiphase research design, the qualitative and quantitative methodologies were strategized to complement and validate each other in order to produce a high-quality research artefact output.

Table 3-1 Multiphase Research Design

<table>
<tr><th>Phases</th><th>Research Objectives (RQ)</th><th>Approach</th><th>Method</th></tr>
<tr><td rowspan="2">Phase 1</td><td>RO1</td><td rowspan="2">Qualitative</td><td rowspan="2">Systematic content Analysis resulted in a comprehensive and systematic literature review output.</td></tr>
<tr><td>RO2</td></tr>
<tr><td rowspan="2">Phase 2</td><td>RO3</td><td>Mixed method (Qualitative and Quantitative)</td><td rowspan="2">Data Science techniques are employed at this phase to uncover insights and generate knowledge that can create and add value to current HIS for healthcare applications. Techniques such as bibliometric and machine learning analysis are used to design artefacts that can be replicated using the pipeline demonstrated in this study.</td></tr>
<tr><td>RO4</td><td>Mixed method</td></tr>
<tr><td rowspan="2">Phase 3</td><td>RO5</td><td rowspan="2">Mixed method</td><td>Content review for contextualise problems and paradigm modelling that supports decision formulations using Machine learning and related human schemes to provide cognitive artefacts on HIS for enhanced healthcare.</td></tr>
<tr><td>RQ 6</td><td>The data model/framework is structured, and experiments are developed to demonstrate its implementations.</td></tr>
<tr><td>Phase 4</td><td>RO7</td><td>Qualitative</td><td>Study inferences from findings to afford recommendations, suggestions, implications and contributions.</td></tr>
</table>

The research phases, as depicted in Table 3-1, illustrated the methodology employed at the different stages of the study. The first phase qualitatively explores the first two research objectives via a comprehensive and systematic content analysis of the relevant literature survey related to the case and proceeds to phase two. A comprehensive and systematic literature review output was produced at this stage. The review presents findings that substantiate the need for HIS sustainability and resilience and was further supported with a bibliometric analysis that analysed a large volume of qualitative data on HIS. Then the selected materials that make up the dataset are then analysed in alignment with the healthcare systems' need to identify and create insightful structure and information. In phase two, an investigation into what kind of knowledge can be afforded was conducted in relation to objectives three and four using a mixed methodology.

The bibliometric analysis augmented the information regarding the healthcare systems. Following the data-driven track to develop a data-driven paradigm can be used to achieve a resilient and sustainable HIS. In the subsequent research phase, objectives five and six were explored to validate the proposed model empirically. Machine models are developed and are evaluated, and the machine's decisions capabilities compared to humans. Through data science techniques, identified problems from the extant literature were mapped to the health system data. Several experimental analysis was made in alignment with the study objectives. The inferences are provided for comparison from human decisions with cognitive artefacts. From this comprehensive exploration, a qualitative appraisal was rendered between machine and human choices, and the summary provides empirical validation of the developed data-driven model. The last phase, objective seven, provides a theoretical and practical reflection that can be used to implement a resilient and sustainable HIS for healthcare augmentation.

Thus adhering to the DSR and using data science techniques, identified problems from the extant literature were mapped to the health system data. All experimental analysis was conducted in alignment with the study objectives. The inference was used to compare human decisions with cognitive artefacts. The inquiry in phases 1 through 7 rendered a qualitative comparison between machine and human choices. Drawing from the initial phases and analysis, the proposed model was established to aid the attainment of a resilient and sustainable integrated information system. The transformed and analysed health dataset in the final stage illustrates the pragmatic enactment of data sciences techniques that could be used to strengthen the HIS. The yielded computational prototype may also be integrated into the existing healthcare system to augment healthcare and enhance the HIS. As a result, the findings from applying and deploying data science approaches were used to construct suggestions and ideas to support future strategy formation and initiatives in the healthcare system, following the quantitative and qualitative methodology.

3.5 Research strategy

This study research strategy stems from the need to develop a resilient and sustainable HIS for health care applications within the healthcare arena. The research elements employed in this study were selected in conjunction with the appropriate philosophy of science and the research paradigm dimension (Makombe 2017; Epizitone and Olugbara 2020). Extant literature reveals these paradigms, namely ontology, epistemology and axiology, to be vital to a researcher in the underlying the subsequent philosophy adopted for a study (Iofrida *et al.* 2018; Epizitone and Olugbara 2020). In line with the DSR, these underlying philosophies, namely ontology, epistemology and axiology, oversee that the adopted viewpoint permits a socio-technical driven stance within the context of the study, that the artefact is developed within the context to create and improve understanding. Thus the pragmatic philosophical stance was adopted over positivism, post-positivism and interpretivism because it argues that there are no predetermined frameworks or theories to shape knowledge or truth. Thus there is no strict restriction to a single system, reality or philosophy (Epizitone and Olugbara 2020).

Additionally, the pragmatism stance agrees that one or more positions can be adopted for a study. Thus it is the main premise of the mixed method that incorporates multiple contextualization to establish an unconventional state that is socio-technological empowered (Wahyuni 2012; Epizitone and Olugbara 2020). The hybrid method implemented in this study enabled the scholar to afford new knowledge emerging from the research question within the context of HIS and health care applications. Similarly, in conjunction with the pragmatic stance, the research nature adopted for this study was a combination of descriptive, explanatory and exploratory to afford valuable insight into the attainment of a resilient and sustainable HIS for health care applications (Kumar 2018; Nabee and Walters 2018; Epizitone and Olugbara 2020). Additionally, the abductive approach strategy, which combines the inductive and deductive was adopted on the premise that it permits a flexible movement between the inductive that anchors on the qualitative and deductive approach that anchors on the quantitative (Åsvoll 2014; Epizitone and Olugbara 2020). These combined slants afford a holistic view of HIS for health care applications and enable insights into the phenomena associated with these health systems constitutes.

Thus the methodological choice of this study consists of three paradigms, namely quantitative, qualitative and mixed methods (Johnson, Russo and Schoonenboom 2019; Epizitone and Olugbara 2020). The qualitative method is asserted in extant literature to be apt for studies that seek to obtain appropriate information on an intrinsically bounded phenomenon within that context. In contrast, the quantitative method affords measurement of studies variables using statistical analysis to twig and construe numerical input. Both qualitative and quantitative methods complement each other in this study that focuses on the development of a resilient and sustainable HIS for health care applications. In addition to these methods, a hybrid method that incorporates both ways is used to assemble both numerical and text input to provide a commendable finding to the research question. Thus, the potential of these research methods in line with the pragmatic philosophy and research paradigm is effected in the research phases to aid the augmentation of a "resilient and sustainable" HIS for health care applications which are highly needed in the healthcare arena.

3.6 Data and Material

The data sciences enactment in this study is based on health care data. A dataset that contains features that pertain to the healthcare system and applications were used in this study. Downloaded data from an online repository is used for the experiment in this thesis. Owing to the standard nature of the dataset benchmark, the preparation of data collection for the experiments was not taken into deliberation. Nonetheless, the attributes that delineate these data were deliberated. These included but were not limited to the data nature (binary or continuous), the number of features and the number of observations. The obtained data were pre-processed, and exploratory data analysis was done on the dataset to ascertain its features. The selected characteristics were then analysed, crossed validated, modelled and evaluated. The detailed appropriate measures are outlined in the upcoming chapters. The dataset obtained from the online repositories was open-source and represented material associated with health care.

The name of the dataset repository is the Mendeley dataset repository, which contains various datasets that can be used for experiments. It consists of the Electronic Health Record of 4412 individual laboratory report results obtained from a hospital based in Indonesia. More information on the dataset exploration is provided in Chapter 5. The rationale for using this dataset is based on the assumption that it represents a standard benchmark dataset for experimental research and serves as material from a HIS that is apt for this study. The study required the use of software and programming language for the data analysis experiment. The R and python programming languages were used as they afford a practical platform with several library packages apt for data sciences. The software packages have inherent capabilities to support the data analysis experiments fundamental to the attainment of this study's overarching objective.

3.7 Summary of the chapter

Framework development of HIS for health care applications is not a new agenda within the healthcare arena. However, many extant studies on HIS for health care applications reveal evidence of many dares encompassing the enactment of a resilient and sustainable integrated health information system. As a result, the design of this research project was geared toward adding to the existing body of gen on the topic, with the dual objectives of strengthening the existing HIS and optimising it into practice for various healthcare settings. The research methodology that traversed the main aim of this study at the intersection of design science research and data sciences in conjunction with a socio-technological concept to afford a resilient and sustainable HIS for health care applications was employed to attain these goals. The knowledge claim used in this study was based on the pragmatic stance that supports a mixed method deployment to address the study's objection. This chapter discusses in detail the methodological framework that was used for this study in line with the study's impetus. The subsequent chapters present a detailed elucidation of the data-driven resilient, and sustainable HIS for health care applications introduced in this chapter.

CHAPTER FOUR: A DATA-DRIVEN PARADIGM FOR RESILIENT AND SUSTAINABLE INTEGRATED HEALTH INFORMATION SYSTEMS FOR HEALTH CARE APPLICATIONS

4.1 Introduction

This chapter presents the data sciences technique impetus that underpins the development of a resilient and sustainable HIS for health care applications. The data-driven tract serves as the anchor for enabling the attainment of resilient and sustainable HIS that enhances health care application. Through the incorporation and application of data analytics insights. Many transformations, such as the fourth industrial revolution and the uncertainty of certain occurrences, such as pandemics, have driven the adoption and implementation of HIS in healthcare. Moreover, these HIS deployment for health care applications has been influenced by external and internal factors aligning with the global transformation. At the epic of these transformations is digitalisation, which has crept into every nook and cranny of the healthcare arena with massive data generation. The hallmark digitalised transformation within the healthcare arena has been characterised by the continuous growth of healthcare data which has been considered complex and dynamic (Negro-Calduch *et al.* 2021). Thus, the need to harness data-generated insight to develop a resilient and sustainable HIS for health care applications is pertinent (Anwar *et al.* 2018).

4.2 HIS implemented frameworks for health care applications

A critical review of the extant literature reveals that many benefits of HIS for health care applications are being compromised by the presence of factors such as inadequate resources, incompetent staff, data dissemination issues and investment concerns (Ahmadi 2017; Kpobi, Swartz and Ofori-Atta 2018; Samra, Li and Soh 2020). Therefore, in order to harness the HIS potential, many authors have presented frameworks for its enactment for healthcare (Braithwaite *et al.* 2017; Alsharo, Alnsour and Alabdallah 2020; Chaney *et al.* 2021; Dudley *et al.* 2022). However, extant literature identified the initial design of the information framework as one of the dares for HIS implementation, revealing the fault line to revolve around the ease of access and utilization of the relevant stakeholders (Mezarina *et al.* 2020). Several frameworks have been developed and reported in the discourse of HIS for healthcare applications, many of which have been technological and socially driven (Kalong and Yusof 2017; Joseph *et al.* 2022). A popular framework is the Technological Acceptance Model (TAM) employed in HIS to ascertain perception to drive its adoption (Hung and Jen 2012; Hoque 2016; Alsharo, Alnsour and Alabdallah 2020). The “Human, Organization, Process and Technology-fit” (HO(P)T-Fit) framework is another that builds on the foundational “Human, Organization, Process and Technology-fit” (HOT-Fit) designed to decrease HIS induced medical errors to enhance health safety (Yusof 2019). Other frameworks include the Information Success System Model -ISSM (Ebnehoseini *et al.* 2022), Task-Technology Fit -TTF (O'Connor, Andreev and O'Reilly 2020), Extended Technology Acceptance Model -TAM2 (Omar, Ellenius and Lindemalm 2017), Fit between Individuals, Task, and Technology -FITT and Unified Theory of Acceptance and Use of Technology - UTAUT (Ammenwerth, Iller and Mahler 2006; Bawack and Kamdjoug 2018; Kujala *et al.* 2020; van Bussel *et al.* 2022).

These have collectively been employed in the health arena to drive the enhancement and adoption of HIS for health care applications (Alsharo, Alnsour and Alabdallah 2020; Ebnehoseini *et al.* 2022).

Similarly, there have been conceptual and research frameworks along the same line (Andargoli *et al.* 2017; Mohamadali, Aziz and Zahari 2017; Mezarina *et al.* 2020; Ng'etich, Voyi and Mutero 2021; Dudley *et al.* 2022). A work by Helwig *et al.* (2020) accentuates the importance of HIS evaluation using an Eco health framework that highlights the stakeholders' worth. However, despite the development and implementation of these frameworks, HIS enactment still suffers major dares that limit its potential to benefit health care applications. As a result, there is evidence of a hiatus that needs to be filled in order to maximise the potential of HIS in the enhancement of health care applications. Furthermore, while there have been many technological focus frameworks in the current knowledge gen of HIS, there are limited data-centric frameworks. As a result, most HIS frameworks are utterly bereft of the data sciences perspective, which has enormous potential to leverage the contribution of modern-day data analytics. Furthermore, failing to provide cutting-edge solutions to many problems associated with HIS and health care applications. Thus, this study seeks to develop a data-driven framework for a resilient and sustainable HIS for health care applications as an attempt to curb some of the HIS dares within the healthcare arena.

4.3 A data-driven paradigm for resilient and sustainable HIS for health care applications

The impetus for a data-driven paradigm for resilient and sustainable HIS for health care applications is grounded on its evolutional capabilities that afford many promising things such as ease of access, intelligent decision making and seamless processes. Mohd Nor *et al.* (2019) assert future inference of data mining to healthcare development as a source of opportunities for enhancing health care applications. Several applications of data sciences in the healthcare arena have been alluded to afford insight from clinical narratives and unstructured data. Data sciences techniques such as dimensionality reduction, rule-based mining, natural language processing, machine learning and deep learning have been employed in many healthcare areas to enhance health care applications. These computational enhancement applications, such as machine learning, deep learning and artificial intelligence, have been deployed in many sectors where their input has afforded quality service delivery. In the healthcare arena, related work such as "natural language processing", "machine learning", and "deep learning" has been done (Yang *et al.* 2017a; Kasthurirathne *et al.* 2019; You *et al.* 2019; Chen and Hengjinda 2021; Digan *et al.* 2021; Jauk *et al.* 2021). However, there are challenges associated with healthcare data that have led to many computational applications shortfall. A study by Flora, Margaret and Dan (2017) identifies the incapability to qualify, scrutinize, and use data to plan and manage service delivery. Negro-Calduch *et al.* (2021) state that healthcare datasets nature poses various dares allied with processing, privacy, security, storage, analysis, data exchange and usability.

Notwithstanding, Chen *et al.* (2020) theorise that empirical testing and contextual analysis are essential components associated with data collection processes that can be used to develop frameworks for HIS (Chen *et al.* 2021). Thus, this study aims to create a resilient and sustainable HIS for health care applications via a data-driven paradigm. An overview of the data-driven paradigm for a resilient and sustainable HIS for health care applications is illustrated in **figure 4-1**.

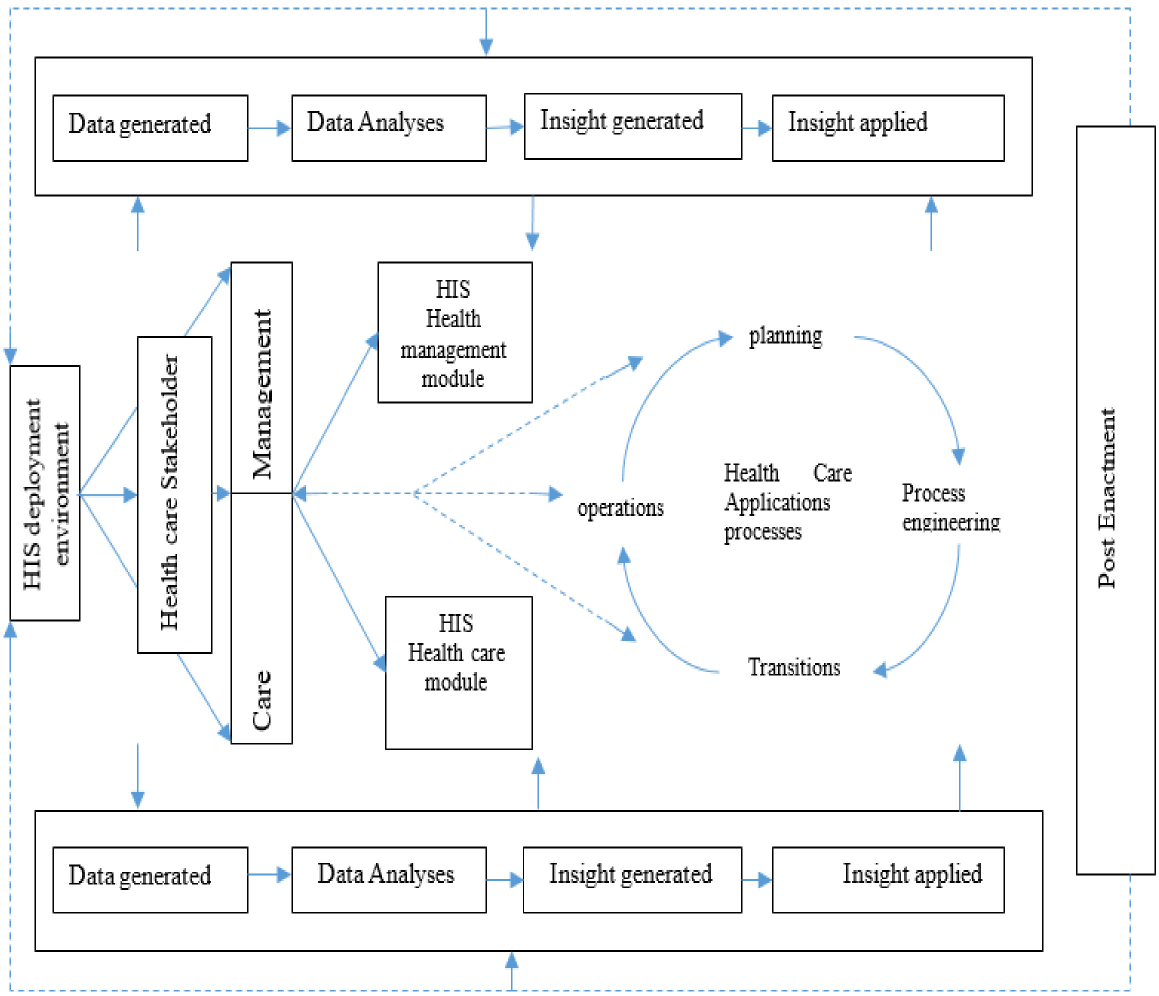

Figure 4-1 Data-driven paradigm for a resilient and sustainable HIS for health care applications, Source: Author.

Figure 4-1 illustrates a healthcare environment where the HIS is deployed. The deployed HIS is intended to serve healthcare stakeholders at different levels for care and management functions. These modules independently handle functions associated with care and management, such as diagnostics, admission, treatment, discharges and resource allocation. Both Modules directly interact with the health care application processes. These processes within the healthcare environment iterate across the four principal functions: planning, engineering, transition and operation. Every health care application provided by healthcare providers is first and foremost planned, engineered, transited and operated. In the planning phase, what needs to be done is defined. The process is modelled in the engineering phase before it gets to the transitions stage, where it is deployed into practical enactment. The next step is the operation stage, where actions are executed. Across the environment, data is generated that requires analysis. From the data analysed, insight is generated that, when applied, will transform and aid healthcare services. A post-enactment action is indicated to serve as a surveyor of the entire framework. This captures the socio-technical premise that posits that technology and human intervention are equally valuable to afford efficient and effective healthcare. The flow demonstrated how data transverses across the environment, indicating the action to be implemented to attain a resilient and sustainable HIS for health care applications.

4.4 Data sources

Contingent to the type of HIS instance, health data output emerges from the health care applications (Aziz 2017; Orellana, Estrada and Alfonso 2018). These data frequently have been regarded with contentions around many data-associated issues such as the size, access and exchanges (Moloczij *et al.* 2018; Braunack-Mayer *et al.* 2021). Azzopardi-Muscat *et al.* (2021) accentuate the need to strengthen data and information systems for an unobstructed interchange. These needs are anchored on the inability to leverage the vast availability of different health data emerging from HIS. Extant literature identified the lack of health data standardisation as a major barrier and the bases of an unprecedented global crisis affecting many nations (Azzopardi-Muscat *et al.* 2021; Braunack-Mayer *et al.* 2021). Several reasons involving the lack of data definition, calculation and formats have been associated with the delay in data relay between HIS and the different instances generating data. These, coupled with the dearth of integration, interoperability and trained personnel to manage and utilize these data within the health system, have necessitated the need for a data-driven paradigm for a resilient and sustainable HIS for health care applications within the healthcare arena (Moloczij *et al.* 2018; Gäbler, Lycett and Gall 2022). Thus, the study case data revolves around health care applications directly linked to HIS and healthcare stakeholders.

4.5 Data action and decisions

Data generated from health care applications within the healthcare arena are required to be timely, credible, reliable and actionable to enable decisions that are data-driven as well as to enable considerate monitoring and forecasting within the healthcare setting (Flora, Margaret and Dan 2017; Gesicho and Babic 2018; Azzopardi-Muscat *et al.* 2021; Gamal, Barakat and Rezk 2021; Gäbler, Lycett and Gall 2022). Within the healthcare space, Decision-making occurs in different sectors. For this decision to be made, data from different modules is targeted in the HIS environment. However, the absence of insight from data generated within this environment can hinder the effectiveness of decision making and their precision (Hyppönen *et al.* 2019). Gesicho and Babic (2018) reported data underuse in decision-making at various health system levels is prevalent. Thus, the needed actions that are data-driven are essential to critical decision making associated with health care applications and future health challenges (Ahmadi 2017; Azzopardi-Muscat *et al.* 2021; Braunack-Mayer *et al.* 2021; Delnord *et al.* 2021; Ng'etich, Voyi and Mutero 2021). Extant literature divulges that the foremost action for a data-driven decision is dependent on the mechanism established (Hyppönen *et al.* 2019; Chen *et al.* 2020; Azzopardi-Muscat *et al.* 2021; Braunack-Mayer *et al.* 2021). According to

Azzopardi-Muscat *et al.* (2021), the impetus of this mechanism is to facilitate data coordination, use and comparison in both national and international settings, which are asserted to foster effective coordination and centralization of diverse data sources. Thus, decision making employed this contraption to assimilate and dissimilate consistent and complete data (Yang *et al.* 2017a).

Furthermore, it is posited in extant literature that data's needs and related processes associated with its flow are required to be defined to enforce the rapid intervention needed for health care enhancement (Yang *et al.* 2017a; Jauk *et al.* 2021). **Figure 4-2** illustrates the pathway of effectors' decision making supported by HIS emerging from the data provided. The decision pathway espoused by Panerai (2014) demonstrates the foremost tract of data influences within the healthcare sector. It stems from data generated primarily from the determinants of health and flows through the HIS environment, necessitating the action that requires decisions making. However, it identified the PESTEL (political, environmental, social, technological, economic and legal) constraints that affect decision-making in the healthcare system. Health policy, resource allocation and health services are some effectors that are determined by the decision emanating from the data in the environment. The overall impact subsequently rests on the population, including but not limited to health levels, equity and satisfaction. The data still maintain a stronghold for both the effectors and the population with the environment.

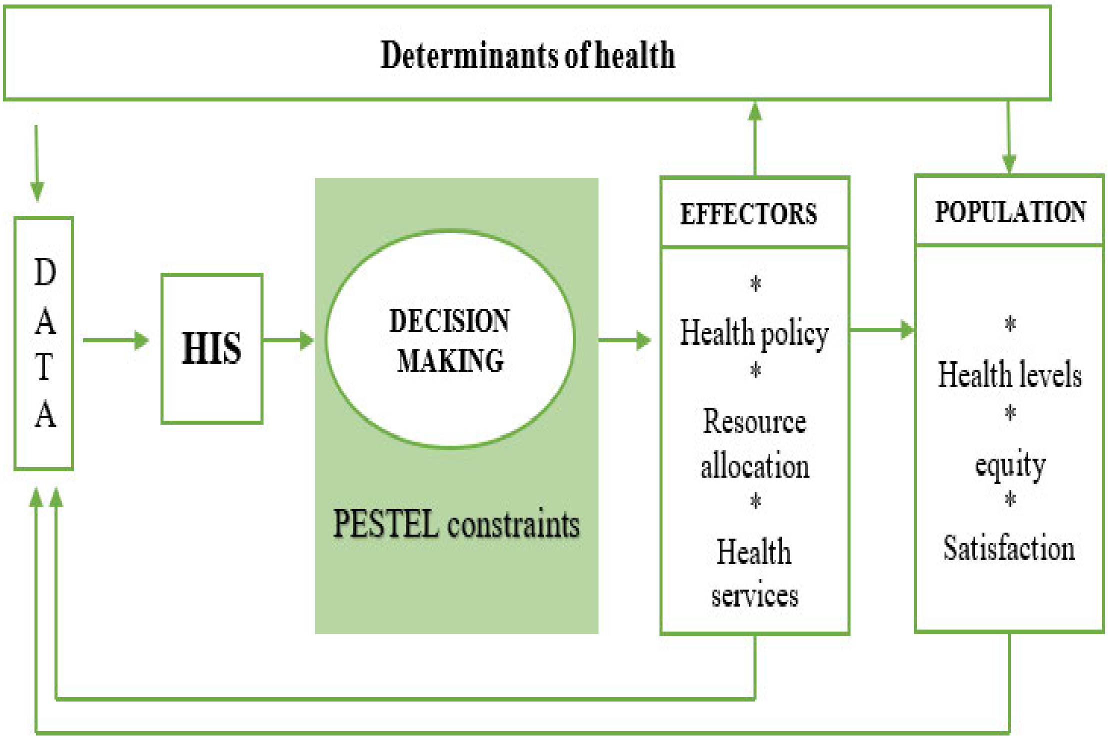

Figure 4-2 Effectors decision making pathway supported by HIS (Source; Panerai 2014)

4.6 Data science techniques

The emergence of data sciences in conjunction with statistics and sciences has been subsidized to deal with the plethora of data surges. It is heralded in extant literature to posit a multi-modal paradigm that incorporates knowledge production and scientific discovery (Priestley and McGrath 2019). It is also considered to have evolved as a function to curb many ill-defined qualms associated with data regardless of the discipline. Priestley and McGrath (2019) posit these applications to be the catalysts emerging from the fusion of statistics and computer science at their peripheries, fashioning an academic “heterosis” that retorts to the emergence of a novel problem set, for which the different silo discipline was ill-equipped to tackle. Thus data science is an umbrella of computerised applications that afford analytical insights where deployed. It is posited to afford descriptive, predictive and prescriptive analytics that delivers outcomes for precise and un-precise problems and challenges (Benis *et al.* 2018; Feldman *et al.* 2019; Medic *et al.* 2019). Specifically, providing insights into happenings to ascertain a well-defined outcome, predict future outcomes accurately and enable the best possible decisions and actions (Bozorgmehr *et al.* 2017; Martins *et al.* 2021; Neto *et al.* 2021). Thus within the healthcare arena, the employment of data science affords health analytics that entails a vast majoring of applications that enhance health care applications from prevention, diagnosis and streamlining operations (Tyagi and Singh 2018; Priestley and McGrath 2019; Martins *et al.* 2021). However, despite these impactful offerings and promises of data science capabilities, "datafication" within the healthcare setting is considered a source of data-centric dares and prospects (Priestley and McGrath 2019). Jeffery *et al.* (2018) associate meagre outcomes and verdicts with data impediments such as quality. Regardless, there are powerful applications of data science techniques in healthcare that have revolutionised healthcare applications (Tyagi and Singh 2018). Techniques spanning the pre-processing of data, exploratory data analysis to modelling data have proven indispensable for healthcare analytics that enhances health care applications. In a data-driven paradigm, these techniques are proposed to be incorporated into the HIS to render it sustainable and resilient in its pursuit of affording quality health care. Table 4-1 presents instances of different data science techniques employed in the healthcare arena for health care applications. The contributions of the state-of-the-art data techniques such as machine learning, natural language processing and deep learning is highlighted in this **Table (4-1)**. These techniques have been applied across the healthcare area to improve healthcare and enhanced processes.

Table 4-1 Data sciences techniques deployed in the health arena for health care applications.

Authors	Data Science Method/ Techniques	Healthcare area data
Tamm *et al.* (2022)	Natural language processing (NLP)	Clinical data on colorectal cancer
You *et al.* (2019)	Machine Learning (ML)	Patients with type 2 diabetes
Feldman *et al.* (2019)	NLP and ML	Identify disease activity from digital media reports
Martins *et al.* (2021)	Data Mining Techniques (DMTs) – ML	Cardiovascular Disease Prediction
Medic *et al.* (2019)	Deep Learning (DL), ML and NLP	Clinical Decision Support Systems in intensive care for the prognosis and identification of three disease states
Shimpi *et al.* (2020)	DL, ML	Periodontitis Decision Support Systems model
Neto *et al.* (2021)	ML	Prediction of Hospital Readmission of Diabetic Patients.

4.7 The serialisation of data science techniques within the health information system

There have been many applications of data science techniques within the healthcare arena to afford insights needed to transform health care delivery. Many of these applications have been applied to data emerging from HIS and experimented on outside its milieu. The need to incorporate data science techniques serialisation within the HIS affords a direct stream to implement insights from data and supports intelligent decisions. Implementing this will tackle many of the existing challenges confronting the healthcare arena. Benefits such as reduced time and intelligent decision support will be enacted within the healthcare arena for HIS and health care application. These will subsequently afford and enable ubiquitous HIS supports for the health care and health management modules as well as the health care applications. Across the different nodes within the HIS, the data analytics serialisation will convert the insights generated from the data analysis and channel to the appropriate area where they can be utilized to enhance health care applications.

4.8 Insights implementation and applications

The contribution of HIS data is paramount to the delivery of quality health care applications, and it has been alluded to be substantial in development within the healthcare arena (Tamm et al. 2022). The integration of data science techniques such as machine learning modelling and artificial intelligence that focuses on data is also considered to be paramount to the attainment of resilient and sustainable HIS for health care applications. Many accounts of insights generated from the application data science techniques have been successfully deployed to tackle health care application challenges. Although many computational systems designs are emerging with a keen anchor on data sciences, a lack of incorporation of generated insight in the computational pipeline is evident. Within the healthcare space, this is apparent with HIS. Thus a resilient and sustainable HIS for health care applications is envisioned to incorporate intensive data analysis and modelling for intelligent and ambient healthcare. Combining these capabilities afforded by health technologies to leverage the potentials of data analytics to provide practical evidence that can be used to initiate health care applications such as diagnosis and treatment as well as prevent and detect occurrences of health care events. Therefore, the generated insight emerging from health data can be deployed in all areas associated with and influenced by the data, thereby ameliorating health care applications using a data-driven paradigm (El Khatib et al. 2022).

4.9 Summary of the chapter

Several applications of data sciences in the healthcare arena have been alluded to afford insight from clinical narratives and unstructured data. Data sciences techniques that afford descriptive, predictive and prescriptive capabilities are highly significant in revolutionising health care applications. Although HIS has been transforming healthcare practices over the years, there have been significant concerns over its forte and capability to be harnessed. The enactment of a data-driven paradigm for resilient and sustainable HIS for health care applications is unparalleled in this digitalisation era (Mardani *et al.* 2020), as it affords an integrated footing for data analytics to support and assists health care delivery. These outlines serve as a robust, reproducible pipeline that can be employed to enhance health care applications within the HIS environment. Thus, in conclusion, the data-driven paradigm for a resilient and sustainable HIS converges the collaboration and support of technological advancement to leverage its abilities and capability to employ data insight for health care applications. This chapter discusses in detail the elements of a data-driven paradigm for resilient and sustainable HIS for health care applications. The ensuing chapters present the application of a data science technique on a health dataset. The background, analysis, results and discussion of the dataset explicitly characterized as healthcare data will also be presented.

CHAPTER FIVE: RESEARCH ANALYSIS, RESULTS AND DISCUSSION OF A HEALTH DATA

5.1 Introduction

The essence of this chapter is to demonstrate a practical data science technique, such as machine learning, that could be incorporated into HIS. The attainment of a "resilient and sustainable" HIS for healthcare necessitates the employment of technological advancement. Many technological advancement themes are embedded with potential as well as dares. Actions and steps that focus on optimising these potentials would enhance the capability of existing systems and leverage the associated dares. Thus this chapter, in alignment with the study objectives, presents a practical example of a data sciences technique applied to health data generated from a HIS environment that could be adopted as a reference point for future HIS implementations for healthcare applications. The chapter commences with related work done in the context and the present methodological step. The results and discussion are also presented with the summary.

5.2 Related work on integrated machine learning and data science approaches for health data

Technology advances have driven many healthcare applications, with many anchors on artificial intelligence and machine learning to modernised health care applications. Parallel to this is the plethora of data emanating from many arenas, such as healthcare, that has prompted many researchers to discover knowledge that can be translated to add value to existing systems.

Several healthcare datasets have already benefited from data science applications which serve as the impetus for further applications to be enacted. These computational applications have been employed as a knowledge strategy to uncover insights that can be used solidified systems and recolonize processes in many domains. Within the healthcare arena, data sciences techniques such as machine learning have proven to be indispensable. Extant literature asserts the substantial impact of artificial intelligence within the healthcare arena that has the potential to aid stakeholders with healthcare applications (Raza *et al.* 2022; Sajedul Alam *et al.* 2022). Sajedul Alam *et al.* (2022) assert the recent utilisation of these techniques aiding clinical publications, genetic information and diagnosis within the healthcare arena.

The deployment of these techniques is relevant to all stakeholders within the healthcare arena who can leverage its offerings to enhance health care applications. In the healthcare arena today, there is a need for urgent actions stemming from reliable data as well as its applications that is directly proportional to its deployment by healthcare' stakeholders (Averill *et al.* 2017; Aziz 2017; Colais *et al.* 2018; Craig *et al.* 2018; Tilahun *et al.* 2021). The stakeholders' reliance on a feed of real time and accurate data that is highly relevant for health care applications is paramount to healthiness (Askar, Ardakani and Majdzade 2017; Aziz 2017; Craig *et al.* 2018; Mills *et al.* 2019). Medical concerns, diagnosis, treatment courses and interventions are all depended on data, analysis and interpretation, which, if not appropriately done, could lead to significant loss at all fronts of the healthcare arena (Aziz 2017; Bozorgmehr *et al.* 2017; Anwar *et al.* 2018; Bargagli *et al.* 2019; Malik, Kazi and Hussain 2021; Fine *et al.* 2022). Lal *et al.* (2022) highlight the importance and essence of a robust health system in enabling early discovery and identification, swift treatment, and effective control of healthcare services. However, although the employment of artificial intelligence does not equal zero errors, it significantly enhances health care applications in many ways (Mohd Yusof *et al.* 2020;

Schreiner, Thurston and Willemsen-Dunlap 2020; Malik, Kazi and Hussain 2021). Literature reports attribute the potential of these computational applications to enhance health care applications (Colais *et al.* 2017; Sajedul Alam *et al.* 2022). According to several studies, technological advancement in the healthcare arena has uplifted many facets with many benefits such as ease of access to health care, ease of labour from already stress-out staffing issues and reduced mortality (Mazur *et al.* 2019; Dunstan *et al.* 2021; Raza *et al.* 2022; Sajedul Alam *et al.* 2022).

Additionally, these potentials have been posited in extant literature to be unharnessed as their development is not parallel to their adoptions and implementations within the healthcare arena where they are indeed needed (Jauk *et al.* 2021). Hence, many reports of declining health care and increased mortality are prevalent with the call for strengthening HIS (Jeffery *et al.* 2018; Rudd *et al.* 2019). However, this stance can also be attributed to the increasing reports of computer induce errors that have been aligned with many mortality cases (Palojoki *et al.* 2017; Yusof 2019; Mohd Yusof *et al.* 2020; Mohd. Yusof *et al.* 2020). Nevertheless, both phenomena stand to benefit significantly from the implementation of these enhanced automated interventions that not only afford medical support but additionally can be employed to save lives (Yang *et al.* 2017a; Kasthurirathne *et al.* 2019; You *et al.* 2019; Jauk *et al.* 2021; Raza *et al.* 2022; Sajedul Alam *et al.* 2022). Moreover, the foremost pressing phenomena that necessitate the need for data sciences analytics are the increase in the global population and the inadequacy of medical resources such as facilities, specialists and doctors (Sajedul Alam *et al.* 2022). This increase, coupled with other determinants, such as climate change, implies that without advanced computational applications, the outcome of these phenomena would be catastrophic. Indication of this can be perceived in the post-COVID-19 pandemic, where many deficiencies now exist due to the massive impact that resulted in the loss of health care providers and incapacitated facilities (Mardani *et al.* 2020; Feteira-Santos *et al.* 2022; Lal *et al.* 2022). In light of these phenomena, resolutions to meliorate these challenges and future challenges are critical. Hence, expanding on previous work to afford meliorations is the overarching impetus for this study that seeks to expand on prior related work to present a resolution that can be implemented.

Globally, healthcare issues are experienced by billions who turn to healthcare providers for solutions to ease and cure diverse ailments. In order to provide the much-needed intervention to avert mortality and other associated consequences such as disabilities and interruption of one's life, many healthcare providers employ supported services that afford insights into the human systems, such as laboratory tests from patients. The examinations serve the healthcare providers with inside that can lead to a diagnosis or even afford an intervention for severe cases as well as allocate the healthcare facility resources (Momany *et al.* 2017; Muriel Fernandez *et al.* 2017). Regularly the outcomes are categorised according to the degree of severity within a range of mild to extreme, which determines the course of treatment to be administered as well as the type of resources to be utilised (Jauk *et al.* 2021; Sajedul Alam *et al.* 2022). Moreover, being empowered with the knowledge of the degree of severity could lead to a decrease in mortality as well as a timely intervention that would subsequently enhance health and lead to healthiness (Momany *et al.* 2017; Kasthurirathne *et al.* 2019). However, hindrances and obstacles sabotage these healthcare objectives, such as delay and understaffing (Dunn *et al.* 2021). Extant literature reveals that many medical experts are currently overwhelmed and confronted with the need to make informed decisions that determine health outcomes, while other stakeholders, such as patients and dependents, are faced with a long waiting time that often results in devastating losses (Muriel Fernandez *et al.* 2017; You *et al.*

2019; Jauk *et al.* 2021). Thus, these decisions are paramount to diagnosing and treating and saving related costs in the healthcare space.

In light of these healthcare objectives, measures that target the augmentation and acceleration of essential treatment timeously to enhance health care applications are highly demanded. Hence the employment of data science is a relevant measure that seeks to augment health care applications and lead to healthiness. In recent years many disciplines have leveraged the potential of data sciences to decipher miscellaneous problems (Donoho 2017; Efron and Hastie 2021). In the healthcare arena, applications such as deep learning and machine learning have already proven to be valuable in the enhancement of healthcare applications (Yang *et al.* 2017a; Munoz *et al.* 2018; Kasthurirathne *et al.* 2019; You *et al.* 2019; Bacigalupo *et al.* 2021; Jauk *et al.* 2021; Raza *et al.* 2022; Sajedul Alam *et al.* 2022). The artificial intelligence application stemming from data sciences has captured the interest of many stakeholders in the way they deal with complex and even ill-defined phenomena (Colais *et al.* 2017; Munoz *et al.* 2018; Combi and Pozzi 2019).

Over the years, advances in these automated computational applications have driven many profitable experiences that have resolved many dares (Penfold *et al.* 2018). Their deployment for predictions, detections and classification have been used severally to add value to the plethora of massive data surges as well as revolutionise processes within many arenas like healthcare. Data modelling has necessitated health care application enhancement within the healthcare arena, where they have delivered significant health augmentation. The abilities and versatility of these applications have revolutionised healthcare in many ways. Whereby the cases of generalisation have been reduced to personalised enactment that has enabled the improvement of many healthcare functions and tasks. Within the healthcare arena, applications such as “deep learning” and “machine learning” have been used to afford insight to facilitate healthcare improvement. Raza *et al.* (2022) use an ensemble learning base model to predict maternity health in an attempt to save lives and mitigate the risk of health complications within that segment. A study by Sajedul Alam *et al.* (2022) used multiple approaches to classify patients' state of severity.

Similarly, a study by Jauk *et al.* (2021) illustrate the adoption of machine learning approaches in clinical settings to improve health care in the case of predicting delirium. Another study by Feldman *et al.* (2019) employs machine learning, natural language processing and human expertise to identify disease activity from digital media reports proficiently. You *et al.* (2019) employed machine learning to inform decision-makers by exploiting routine observational diabetes patient data. Correspondingly, Kasthurirathne *et al.* (2019) also use a machine-learning approach to automate screening for patients who need advanced care for depression. A prior study by Yang *et al.* (2017a) combine machine learning approaches with inference engines to render clinical diagnosis and treatment strategy meritoriously.

These studies highlight the potential contribution of data sciences techniques in health and safety improvement in the healthcare arena and underpin the current study’s implementation. This study employs integrated machine learning techniques such as the classical and ensemble classifier. The predominant technique used is ensemble learning, namely the random forests. These artificial intelligence applications are conducted with the vision to employ their offerings in healthcare. Particularly within HIS to learn from its data and uncover patterns that can be used to afford robust insights for enhancing health care applications. A developed model entails data exploration, pre-processing, model training, feature selection, model optimisation and parameterisation, prediction, and deployment. With the aid of the machine processing power unit like graphics, the ingested data enables the parallel processing of machine-designed models. The machine-designed model accuracy enables class distinction based on its predictor’s aptitude that can be deployed to aid healthcare delivery within the healthcare space.

5.3 Material and methods

5.3.1 Methodology

Different phases are required to develop the model to predict the kind of treatment based on the degree of severity of the patient’s condition. The phases that correspond with the techniques and method used to indicate the type of treatment mode are elucidated in this section and can be visualised in the flow diagram in **figure 5-1**. Figure 5-1 depicts all the actions and steps involved in the analysis, from the data acquisition to the healthcare applications delivery.

The **first phase** entailed the acquisition of the dataset from a HIS environment. The electronic health record (EHR) dataset from the HIS environment is acquired in this phase. The dataset is obtained from a repository that is openly accessible and available to the public. Mujiono Sadikin contributed the dataset, which was published on May 10, 2020, in Mendeley data version 1(Mujiono 2020). Originating from a healthcare arena, an Indonesia hospital, the dataset is structured and available for research. The dataset was aggregated using a HIS instance that recorded patients' laboratory results and contained prominent features that determine the type of treatment prediction.

The **second phase** involves the pre-processing and EHR exploratory data analysis (EHREDA) investigation of the data to ascertain insight into the features and determine and resolve any concerns relating to missing and unbalanced data. Descriptive statistics are conducted in this phase, and graphs and charts are employed to visualise the data.

The **third phase** involved the transformation of data that are in strings to binary for machine readability. The target feature and associated string variables are converted in this phase, and the data is then split into two portions in the ratio of 80% to 20%. The more significant portion is used for training the model, and the residual part is subsequently used for testing and evaluating the model.

The next phase, the fourth, involves building the model experiments, which are trained on the 70% sample and tested and evaluated using the 30% quota.

In the fifth Phase, several classified models are built, and the extracted features are used to train the models and the evaluation metrics; accuracy, classification reports, F1 score, ROC curve, precision and recall score are used.

In the sixth phase, the hyper parameter tuning is performed on the model with the best result. Based on the performance results, evaluation is done to finalise the experiment. The "scikit-learn" free software machine learning library for the Python programming language was used for model training and tuning (Pedregosa *et al.* 2011). The experiments are performed using a personal machine with the following specifications: 11th Gen Intel(R) Core(TM) i7-1165G7 @ 2.80GHz, 2803 MHz, 4 Core(s), 8 Logical Processor(s).

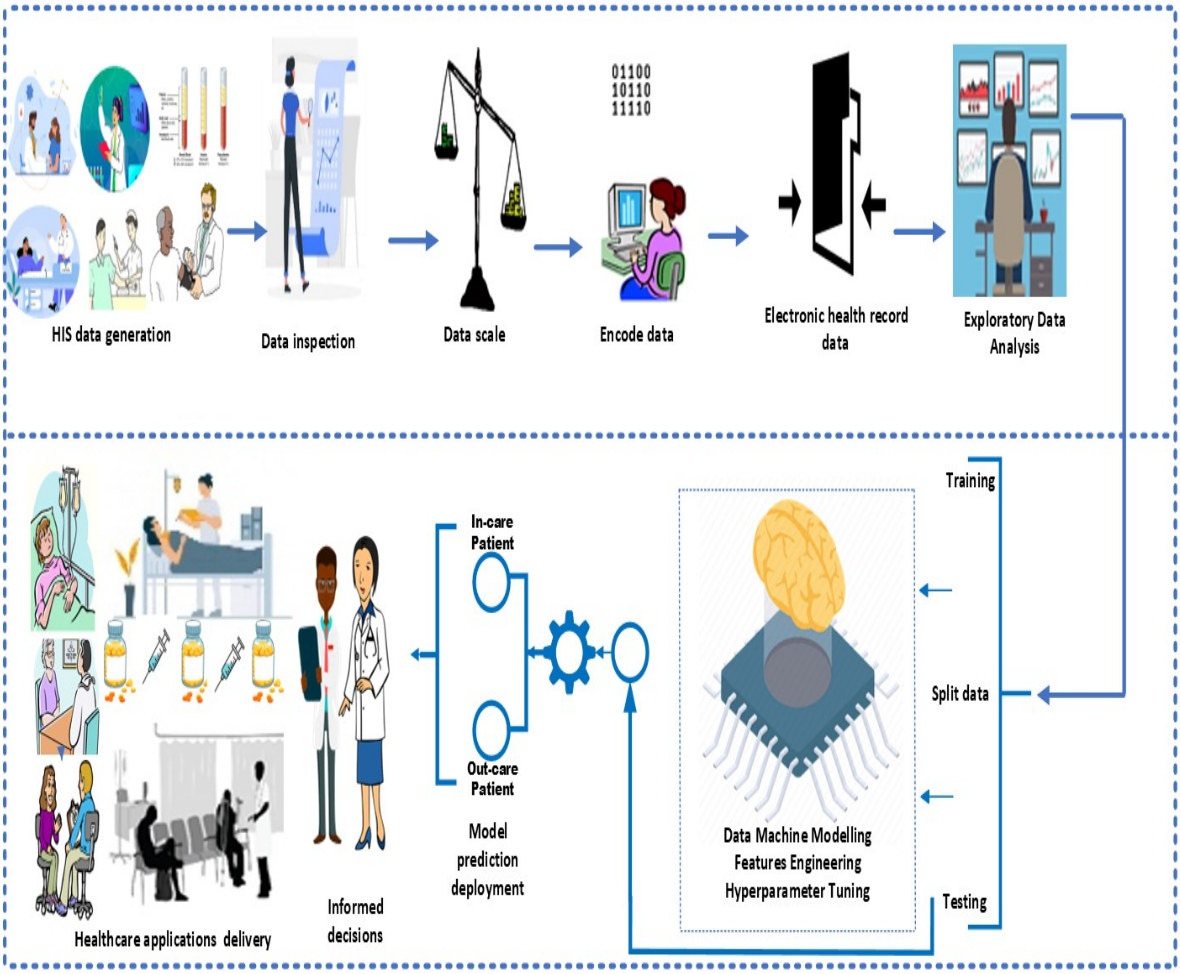

Figure 5-1 The Methodological presentation of the data sciences analysis

5.3.2 Electronic Health Record (EHR) datasets

In the healthcare environment, many data sources contribute to the influx of data. These include the "**electronic health record"** (EHR), "**electronic medical record" (EMR**), "**electronic patient record" (EPR),** and "**personal health record" (PHR).** These instances form the data sources that many health providers' especially physicians, nurses and other medical personnel, rely on to model treatment after diagnosis. Though, extant literature reveals that user interfaces of today's electronic health records (EHR) are not designed to their full potential, which may be associated with excessive cognitive workload and poor performance

(Mazur *et al.* 2019). These digitalised records constitute information pertaining to individuals' conditions, such as type of disease, prior treatments, and health care. The material employed in this study consists of the EHR of 4412 individual laboratory report results obtained from a hospital based in Indonesia. These data were employed to ascertain the course of treatment to be given based on the degree of severity a decision was taken to afford either "in" or "out" hospital treatment. The dataset has 11 features, namely Haematocrit, Haemoglobins, Erythrocyte, Leucocyte, Thrombocyte, MCH, MCHC, MCV, Age, Sex and Source as the target class. This dataset was downloaded from an open-source data repository with diverse datasets that can be experimented on and is publicly available (Mujiono 2020). The descriptive statistics and information of the EHR dataset with its features are illustrated in Tables 5-1 and 5-2.

The EHREDA also reveals the distribution of all the features associated with the target feature that contains a ratio of 59.6 to 40.4 of the treatment afforded. The "in-care patient" represents those with a high degree of severity and needing hospitalisation; they represented 40.4% of the data. The highest portion was 59.6%, while the "out care patient" with a lesser degree of severity. **Figure 5-2** illustrates this distribution using the orange colour to represent the in-care patients and blue colour for the out-care patients. For the final part of the experiment, the features "SEX" and "MCHC" were excluded due to their contribution. Regardless of the SEX, treatment needs to be provided, and MCHC is already accounted for in the dataset as it represents the mean of the MCV and MCH. Thus to prevent the issue of misrepresentation and maintain health equity, these considerations were regarded. Moreover, for the model to be deployable care need to be given to the metrics used when reporting the laboratory results.

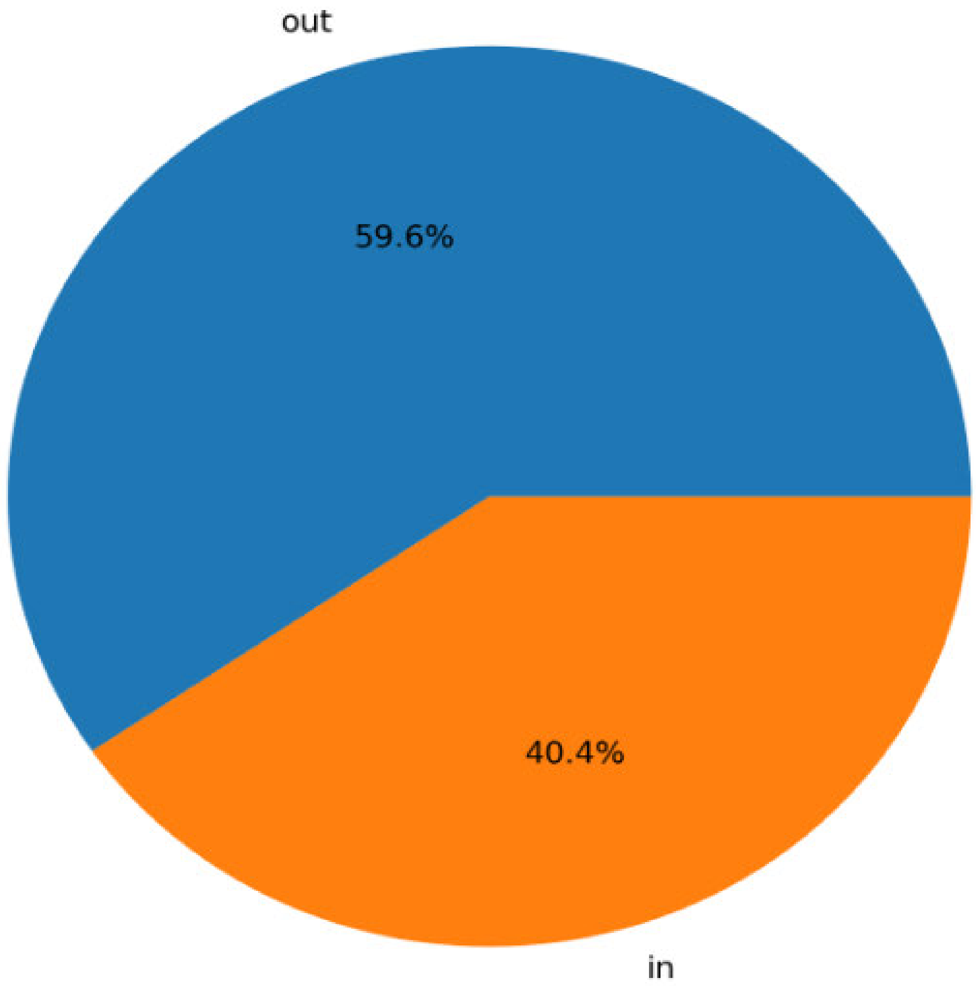

Figure 5-2 Type of Treatment care for the patients' ratio

Table 5-1 depicts the qualities and format of these features in the context of health, as well as their consequences for the type of treatment. The components measured during the test are referred to as features/attributes. The type of data is shown in the table, along with a sample of the possible values. Their description of the feature is also provided. The standard/normal levels represent the range of each recorded attribute. The resulting effects of levels above and below typical values are also shown in the table below.

Table 5-1 The EHR dataset features associated information.

Feature/Attribute	Data Type	Value Sample	Patient's laboratory test result	Standard Normal Levels		Consequences When low	Consequences When high
Haematocrit,	Continuous - float64	35.1	The percentage of red cells in the blood	Male - 41% - 50%	Female - 36% - 48%	Anaemia	Polycythaemia
Haemoglobins,	Continuous - float64	11.8	Enable the red cell to transport oxygen and carbon dioxide.	Male - 13.5 -17.5 gram/decilitre	Female - 12.0 -15.5 g/dl		
Erythrocyte,	Continuous - float64	4.65	Red blood cells that are the functional component accountable for the transportation of gases and nutrients throughout the human body	Male - 4.0 -5.9 x 10*12L	Female – 3.8 -5.2 x 10^{12}L	Low levels may indicate B12 or folate deficiency and signify internal bleeding, kidney disease or malnutrition.	High levels are associated with dehydration, heart disease and polycythaemia
Leucocyte,	Continuous - float64	6.3	Also known as leukocytes are white blood cells that are clear and colourless and associated with assisting the body in fighting germs,	4.5 -11.0 x 10^9/L		Risk of infections from diverse conditions	Hyperviscosity syndrome and impaired blood flow
Thrombocyte,	Continuous - float64	3.10	They are pieces of very large cells in the bone marrow called megakaryocytes that assist in forming blood clots to slow or stop bleeding and help heal a wound.	150000 – 450000 (platelets per microliter of blood).		Bone marrow problems such as leukaemia or lymphoma, plastic anaemia	Thrombocythemia Form a blood clot that can block blood flow.
MCH (Mean corpuscular haemoglobin)	Continuous - float64	25.4	Haemoglobin amount per red blood cell	27 – 31 pictograms/cell		Hypochromic anaemia	Hypochromic anaemia
MCHC (Mean corpuscular haemoglobin Concentration) MCHC = MCH/MCV	Continuous - float64	33.6	the amount relative to the size of the cell (Haemoglobin concentration) per red blood cell	32 – 36 grams/decilitre g/dl 320 – 360 gram per litre g/L		Hypochroma Reduce capacity to transport oxygen to the tissue	Hyperchroma
MCV (Mean corpuscular Volume)	Continuous - float64	75.5	Average red blood cell size	80 – 100 femtolitre		Microcytic anaemia	Macrocytic anaemia
Age	Continuous - float64	12	Ages of Patience				
Sex	Nominal-object	F/M	Genders of Patience; Male and Female				
Source	Nominal-object	In-Out	class target; IN, for “in care patient” and OUT, for “out care patient”				

5.3.3 EHR exploratory data analysis (EHREDA)

The EHREDA is employed rudimentary visualisation and descriptive statistics to uncover any patterns within the dataset and test as well as check for hypotheses and assumptions that may be present. The main dataset attributes and structure association analysis that aid the models' prediction aptitude is obtained using the EHREDA. **Table 5-2** presents the descriptive statistics result of the dataset constructed based on the count, mean, and standard deviation; (std. dev.), minimum; (min), first quartile 25%, median 50%, third 75%, and maximum; (max) values. The analysis authenticates the non-null count of each variable within the dataset containing 4412 instances. The minimum and maximum values are the lowest and highest limits for all features. The distribution of the datasets features from the first quartile 25th, second quartile 50th (median) and third quartile 75th. The original data type is shown for the variables in the datasets (Original Dtype), and to unify the data type, the feature was encoded to machine-readable format for those that were initially objects and int 64 to float64. For the age variable, the youngest patient is one year, and the oldest is ninety-nine years old. For the Haematocrit, Haemoglobins, Erythrocyte, Leucocyte, Thrombocyte, MCH, MCHC and MCV, their minimum and maximum values are illustrated in Table 5-2.

Table 5-2 EHR Descriptive statistics

#	Features/Attributes	Original Dtype	Dtype	count	mean	Std. dev	min	Q1-0.25	Q2-0.5	Q3-0.75	max
0	HAEMATOCRIT	float64	float64	4412	38.20	5.97	13.70	34.38	38.60	42.50	69.00
1	HAEMOGLOBINS	float64	float64	4412	12.74	2.08	3.80	11.40	12.90	14.20	18.90
2	ERYTHROCYTE	float64	float64	4412	4.54	0.78	1.48	4.04	4.57	5.05	7.86
3	LEUCOCYTE	float64	float64	4412	8.72	5.05	1.10	5.68	7.60	10.30	76.60
4	THROMBOCYTE	int64	float64	4412	257.52	113.97	8.00	188.00	256.00	321.00	1183.00
5	MCH	float64	float64	4412	28.23	2.67	14.90	27.20	28.70	29.80	40.80
6	MCHC	float64	float64	4412	33.34	1.23	26.00	32.70	33.40	34.10	39.00
7	MCV	float64	float64	4412	84.61	6.86	54.00	81.50	85.40	88.70	115.60
8	AGE	int64	float64	4412	46.63	21.73	1.00	29.00	47.00	64.00	99.00
9	SEX	object	float64	4412	0.52	0.50	0.00	0.00	1.00	1.00	1.00
10	SOURCE	object	float64	4412	0.40	0.49	0.00	0.00	0.00	1.00	1.00

Figure 5-3 illustrates the EHREDA visualisation of features associated with the target variable. The colour code in the figure represents the target variable's two classes: orange, the in-care patients, and blue, the out-care patient.

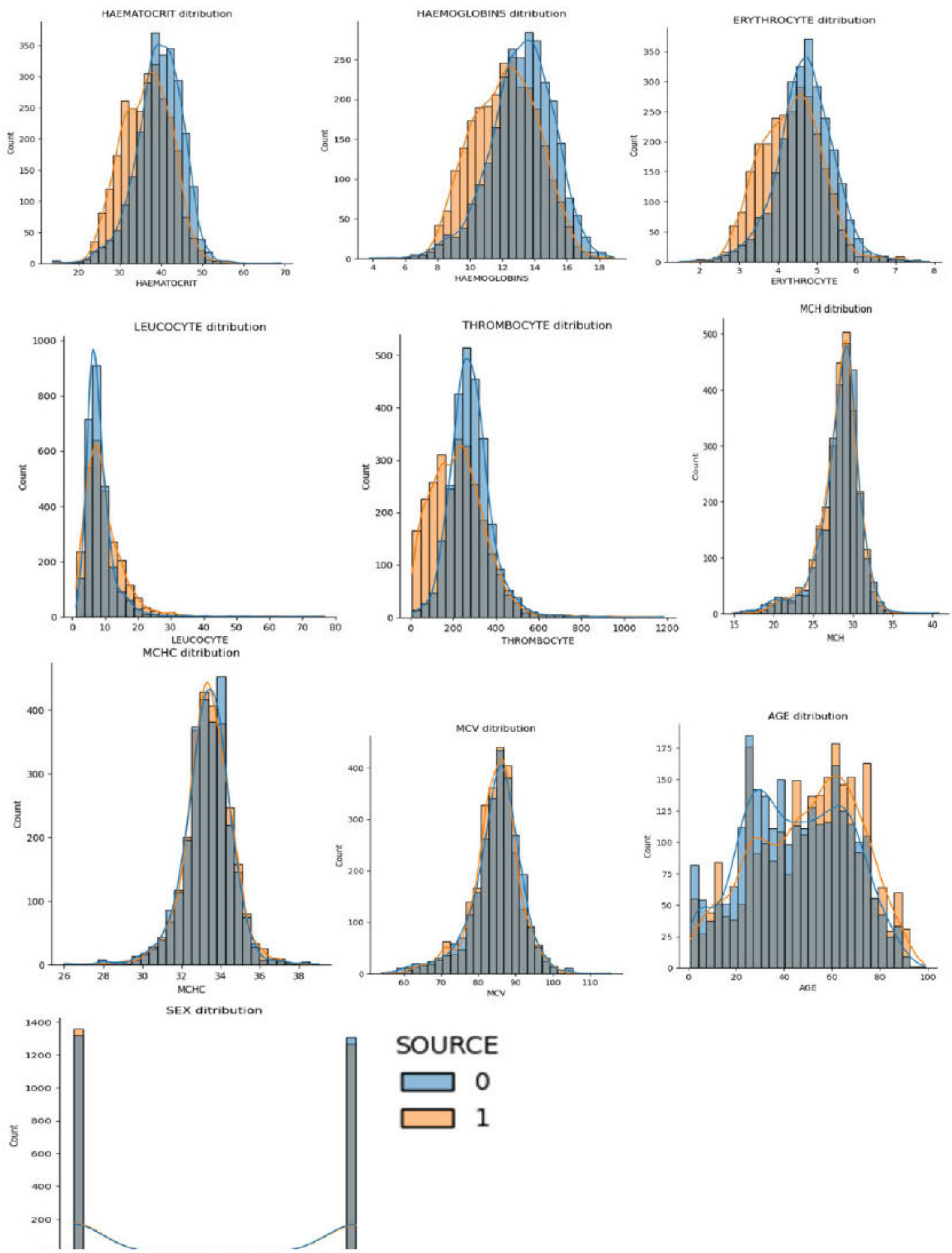

Figure 5-3 Features distribution to the target variable.

The EHR's correlation analysis that reveals the association of the variables in the dataset is shown in **Figure 5-4**. The results illustrate the degree of consequential ties and association among the variables, with the most robust present with positive statistics and the weakest in negative values. The analysis shows some negative correlation that is demonstrated by the darker tone in the values. The Erythrocyte negatively correlates with the following features: MCH, MCV and Age. While MCH, MCV and Age correspondingly negatively correlate with the Thrombocyte feature. Most features in the dataset exhibit a positive correlation, with the strongest exerted by the Haematocrit, Haemoglobin, Erythrocyte, MCH and MCV. These correlation results present a significant output necessary for modelling the EHR data. The features with high correlation hold a substantial contribution to the modelling.

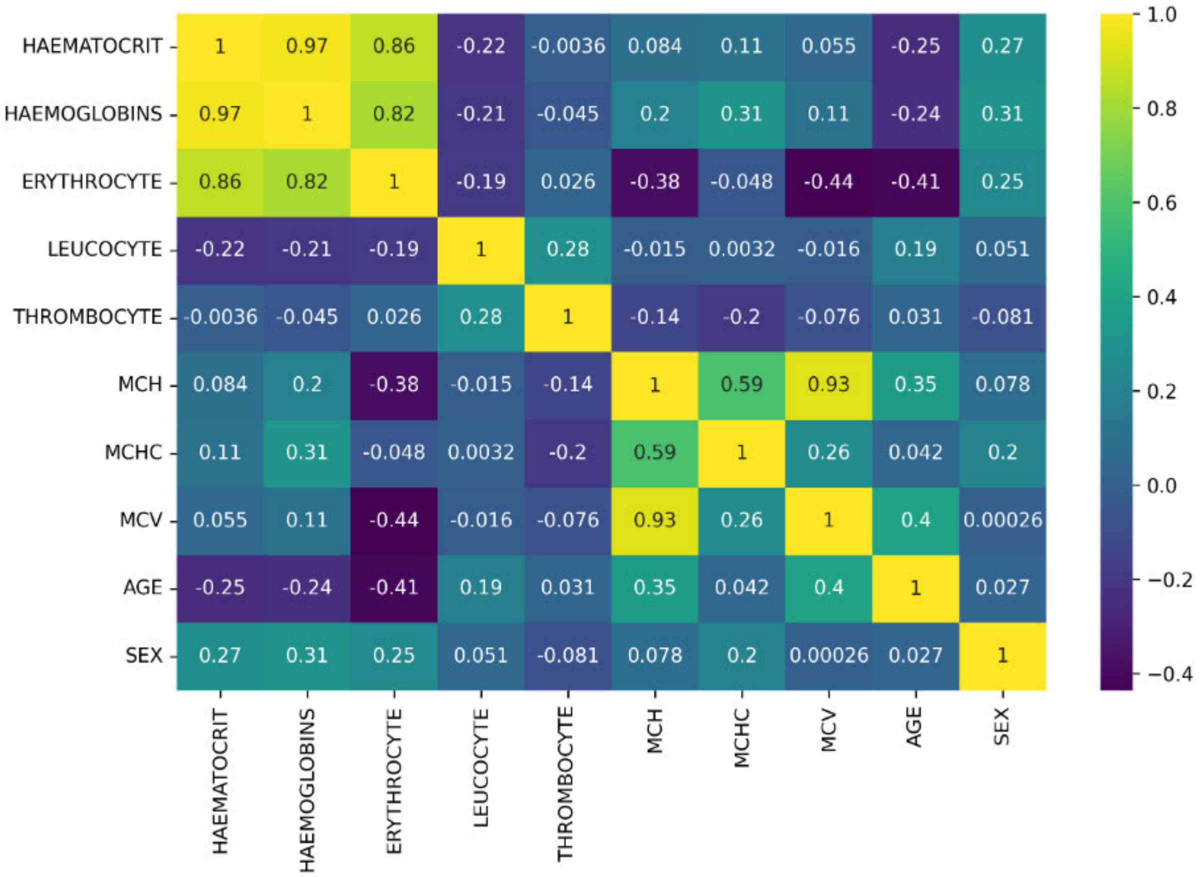

Figure 5-4 Statistical analysis of dataset feature for correlation.

The Haematocrit, Haemoglobins and Erythrocyte present the first most substantial correlation band at 82, 86 and 97 percentages. Haematocrit and Haemoglobins hold a 97% correlation. Haematocrit and Erythrocyte follow at 86%. Haemoglobins and Erythrocyte has an 82% correlation. The other features with high correlation are MCH and MCV (93), MCH AND MCHC (59), MCV and Age (40), MCV and age (35), Haemoglobins and Sex (31), Leucocyte and Thrombocyte (28), Haematocrit and Sex (27) and Erythrocyte and Sex (25). Due to the feature being required to determine the type of treatment, all were treated in the model. To ensures that the deployment and applications at practical levels are consistent and not compromised as a trade-off for higher accuracy and precision.

Additionally, the pair plot visualisation that presents the preeminent set of the dataset features is done during the EHREDA. This expounds on the associations in relation to all the components in a separate cluster, which is used to visualise the datasets and holistically identify the interrelationships. This is essential as it provides the outlook for the appropriate algorithms that best suit the dataset. The pair plot has been asserted in extant literature to be vital in the attainment of feature selection for the modelling of datasets (Raza *et al.* 2022; Sajedul Alam *et al.* 2022). **Figure 5-5** presents the pair plot analysis that maps the associated and interrelationship of the features with the target variable “Source” and demonstrates the contributions of the individual features for the two classes in the dataset. The pair plot shows a similar distribution of the Haemoglobin, and the Haematocrit is similar as well as Erythrocyte. Another equal distribution is also visible for MCH and MCV, confirming the correlations among these features.

Figure 5-5 Pair plot analysis for feature selections.

5.4 Result and discussion

The positioning of HIS within the healthcare system cannot be overlooked as it significantly contributes to many vital areas. HIS plays a significant part in the health organization and management of appointments, the admission of patients, the daily control of hospital beds, the planning and execution of surgical procedures, the maintenance of current information regarding patient discharges, and the registration of patient transfers either within or outside the hospital (Farrahi *et al.* 2019). Similarly, HISs' generated data facilitate these procedures within healthcare institutions and significantly contributes to stakeholders and health organisation administration. Insights generated from HISs' data could afford a massive value to all healthcare stakeholders that will revolutionise the healthcare processes. Thus, the analysis and results of "EHR" data are embedded with the potential to add value and enhance healthcare systems in many ways significantly.

Proceedings of the exploratory data analysis of the EHR dataset was pre-processed function that was used to transform the data type into a uniform format that will be accepted for the model experiment. The dataset's features, which included "SEX" and "SOURCE", were encoded into machine-readable forms of 0 and 1. Thus the featured sex encoded from nominal to binary, where "F" is (0), and "M" is (1) and similarly, for the target feature Source, 0 was specified as "out" and 1 for "in". The dataset was further experimented on after being scaled and normalized. A spot experiment included several machine learning basic and ensemble algorithms to ascertain the one that was apt for the dataset was done. Several models were built and compared. The Random Forest model and other ensemble learning models highly outperformed the other models in the experiment and were selected for further modelling. After additional processing and experimenting, all the features, including MCHC, which represents the mean of MCH and MVC and Sex, a feature with only two instances, were retained and included to improve the model's accuracy. The experiment uses a hybrid of supervised algorithms, and the best algorithms were further experimented on to select the one with the highest performance. The following performance metrics, “Accuracy”, “Precision”, “Recall”, “F1-Score”, ROC and AUC”, were employed to analyse their results. These performance metrics are defined in equations 5.2 to 5.6, and the whole meaning of the elements presented in the equation is shown in **Table 5-3**.

Table 5-3 Equations elements meaning

Equation elements	**Meaning**
TPR	True Positive Rate
TNR	True Negative Rate
FPR	False Positive Rate
FNR	False Negative Rate

The accuracy of the prediction indicates the measurement of the accurate predictions from the total prediction of the model (Li and Akagi 2019; Raza *et al.* 2022; Sajedul Alam *et al.* 2022). The equation is provided beneath:

$$\text{Accuracy} = \frac{\text{TPR} + \text{TNR}}{\text{TPR} + \text{FPR} + \text{TNR} + \text{FNR}} \tag{5.1}$$

The precision indicates the proportion of accurately foretold samples by the projected model to all expected positive data samples (Raza *et al.* 2022; Sajedul Alam *et al.* 2022). The precision formula for this metric is given beneath:

$$\text{Precision} = \frac{\text{TPR}}{\text{TPR} + \text{FPR}} \tag{5.2}$$

The recall presents the model's preciseness (Raza *et al.* 2022; Sajedul Alam *et al.* 2022). It is often regarded as sensitivity, which measures correctly classified positive instances. At the same time, the proportion of negative cases correctly classified is the specificity. This metric is calculated using the formula detailed below:

$$\text{Recall} = \frac{\text{TPR}}{\text{TPR} + \text{FNR}} \tag{5.3}$$

The F1 score epitomizes the "harmonic mean" of recall and precision(Raza *et al.* 2022; Sajedul Alam *et al.* 2022). It strikes the balance of recall and precision to incorporate both cases of the two classes with regard to their made-up positives and negatives.

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5.4}$$

The ROC "Receiver Operating Characteristic" curve represents the probability curve that shows the TPR compared to FPR at different threshold values (Raza *et al.* 2022). Along with the ROC, the AUC "Area Under the Curve" is also used to present the value of the bi-dimensional space under the curve. Higher values assert the superiority of the projected learning technique performance; thus, the ROC and AUC are robust comparative metrics for model comparison.

$$\text{ROC Curve} = \int_0^1 \text{TPR}(\text{FPR})\text{dFPR} \tag{5.5}$$

A fleeting description of these techniques is discussed below. They highlighted based on their strengths and adoption in dealing with real-life issues where they have been cited.

5.4.1 Logistic Regression (LR)

Logistic Regression (LR) is a commonly used classifier that provides an output value that is equivalent to the likelihood of belonging to a given class (Stoltzfus 2011; Gasso 2019). Thus in the EHR data, the LR inducer seeks out connections between the independent features and the target class based on their probability. The primary focus is on developing a likelihood function that ingests input features to present as output that classifies the identity of the class as per the target (Adeliyi *et al.* 2022; Sajedul Alam *et al.* 2022; Srimaneekarn *et al.* 2022). Extant literature asserts LR to be computationally economical, using fewer machine resources (Adeliyi *et al.* 2022; Mutanga, Naicker and Olugbara 2022). LR was one of the selected classifiers with high EHR model evaluation scores. The analysis result for the model can be seen in the **table 5-4**.

Table 5-4 Logistic Regression Model Report

Logistic Regression				
LR	**Precision**	**Recall**	**F1-Score**	**Support**
out - 0	0.71	0.85	0.77	526
in - 1	0.61	0.49	0.57	357
Accuracy			0.70	833
Macro average	0.70	0.67	0.67	833
Weighted average	0.70	0.70	0.69	833

5.4.2 K-Nearest Neighbour (KNN)

K-Nearest Neighbour (KNN) is another simple machine-learning technique that classifies features by assigning them to a class in the data target(Zhang 2016; Sajedul Alam *et* *al.* 2022). It is simple supervised learning that also ingests input data and provides an output classification depending on the predefined function set (Chumachenko *et al.* 2022; Lin, Lin and Gu 2022). Over other models, it could be applied to several problems but is restricted as its accuracy decreases as the number of iterations increases (Zhang 2016). KNN is commonly known as a lazy classifier because it does not perform any underlying function before its implementation on the training data (Sajedul Alam *et al.* 2022).

5.4.3 Support Vector Machines Classifier (SVC)

Support vector machines classifier (SVC) is a straightforward machine learning classifier that creates a hyperplane to detach and assemble features, with support vectors maximising the distance between them to make a more exact decision border (Adeliyi *et al.* 2022; Sajedul Alam *et al.* 2022). SVC is recognised for its ability to deal with linear and non-linear problems and provides precise decision boundaries between the features class. SVC has been deployed in several real-life cases, giving noticeable classification (Suthaharan and Suthaharan 2016; Pisner and Schnyer 2020; Hansrajh, Adeliyi and Wing 2021; Mqadi, Naicker and Adeliyi 2021; Lin, Lin and Gu 2022; Mutanga, Naicker and Olugbara 2022). SVC was also among the top classifiers for 'EHR' data modelling. **Table 5-5** details the evaluation report score.

Table 5-5 Support Vector Machines Classifier Model Report

Support Vector Machine Classifier				
SVC	**Precision**	**Recall**	**F1-Score**	**Support**
out - 0	0.73	0.83	0.78	526
in - 1	0.69	0.55	0.61	357
Accuracy			0.72	833
Macro average	0.71	0.69	0.70	833
Weighted average	0.72	0.72	0.71	833

5.4.4 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) exerts an optimal application in classifying binary classes from a linear combination of different features (Jolliffe, Morgan and Young 1996; Aladjem 1997; Sancho-Gomez *et al.* 2018; Gardner-Lubbe 2021). Its application has been deployed in real-life problems to discriminate different kinds of classes in a given context (Lv *et al.* 2017; He *et al.* 2018; Ahmad *et al.* 2021). Though, it is one fast and simple algorithm that surpasses others like the LR. It also has some limitations that limit its potential, such as its inadequacy to perform well with littler category features. Nonetheless, it also performed well on the selected dataset. **Table 5-6** details the model performance for LDA on the 'HER dataset.

Table 5-6 Linear Discriminant Analysis Model Report

Linear Discriminant Analysis				
LDA	**Precision**	**Recall**	**F1-Score**	**Support**
out - 0	0.71	0.86	0.78	526
in - 1	0.70	0.47	0.57	357
Accuracy			0.71	833
Macro average	0.70	0.67	0.67	833
Weighted average	0.70	0.71	0.69	833

5.4.5 Naïve Bayes (NB)

Naïve Bayes (NB) is another laid-back and fast classifier that works great with a multi-class forecast (Wickramasinghe and Kalutarage 2021; Sajedul Alam *et al.* 2022). It is established on the Bayes theorem that measures the class probability with the premise that features are independent (Adeliyi *et al.* 2022). Regardless of its reliance on assumptions, it is considered as an urbane classifier (Ijaz *et al.* 2021; Wickramasinghe and Kalutarage 2021). It has been recorded to have performed better over other classifiers like the SVC in specific contexts (Kang, Yoo and Han 2012). It is an algorithm that has been widely deployed to address real-life issues in different fields, including healthcare and marketing (Guzella and Caminhas 2009; Kang, Yoo and Han 2012; Maheswari and Pitchai 2019; Sanchez-Franco, Navarro-Garcia and Rondan-Cataluna 2019)

5.4.6 Decision Tree (DT)

Decision Tree (DT) is among the commonly used classifiers whose interpretation and elucidation are straightforward (Blower and Cross 2006; Geurts, Irrthum and Wehenkel 2009;

Jena and Dehuri 2020). It uses rules inferred during training to determine the predictions of the target class. DT structure consists of internal nodes that signify the features, branches that symbolise the rules and leaves that indicate the outcomes (Dortmans and Punter 2022; Raza *et al.* 2022). DT deployment has benefited Many real-life phenomena (Tweedie *et al.* 2013; Teles *et al.* 2020; Shan *et al.* 2022). In healthcare, it has been demonstrated to be apt for predictions of health-related issues (Maheswari and Pitchai 2019; Zane *et al.* 2019). However, there are issues of overfitting data when it comes to DT. Thus, caution is needed when executing the DT algorithm (Talekar and Agrawal 2020).

5.4.7 Neural Network (NN)

Neural Network (NN) is inspired by the human brain functions composed of many interconnected nodes, namely neurons, which process and compute operations (Sordo 2002; Saxena and Saad 2007; Rogova 2008; Bianchini and Scarselli 2014; Geiger 2021). This classifier relies on establishing layers, namely the input, hidden and output layers. Data is ingested at the input layers and acted upon at the hidden layers, which then relay the output to the output layer. Standard NN algorithm applications are Artificial Neural Networks (ANN) and Multi-Layer Perceptron (MLP) (Zhai *et al.* 2016). Many applications have been deployed to handle practical tasks (Rai, Trivedi and Shukla 2013; Tsangaratos and Benardos 2014). The advantages of NN are based on the fact that it can tackle non-linear and complex associations, which are reasons for their adoption, especially in the healthcare arena (Naraei, Abhari and Sadeghian 2016; Roy *et al.* 2018; Harjai and Khatri 2019; Krishna and Reddy 2019; Srivastava, Singh and Suri 2020). However, it is subject to overfitting and computationally costly (Zhai *et al.* 2016).

5.4.8 Bagging Classifier (BC)

The Bagging Classifier (BC) is an ensemble learning classifier that employs bootstrap aggregating to vote with equal weight the results from the aggregate of the individual prediction to make the final prediction (Kabari and Onwuka 2019). It is one of the typical ensemble learning Classifiers used (Adeliyi *et al.* 2022). It has been used in many areas to solve complex classification tasks (Zareapoor and Shamsolmoali 2015; Agarwal and Chowdary 2020; Yousaf *et al.* 2020). It has also been used in healthcare to provide a useful predictive model (Sandag 2020). It is also known to prevent overfitting and decrease variance, thus the reason for its endorsement in many fields like the healthcare arena (Ganie and Malik 2022). Accordingly, BC was among the best-performing classifier for the EHR modelling. It yielded good scores for the classification of the type of treatment to be provided (**Table 5-7**).

Table 5-7 Bagging Classifier Model Report

Bagging Classifier				
Bagging	**Precision**	**Recall**	**F1-Score**	**Support**
out - 0	0.77	0.84	0.80	526
in - 1	0.73	0.63	0.68	357
Accuracy			0.73	833
Macro average	0.75	0.74	0.74	833
Weighted average	0.75	0.76	0.75	833

5.4.9 Extra Trees Classifier (ETC)

Extra Trees Classifier (ETC) is also commonly used in classification problems. ETC is established on the DT to randomise the trees extremely (Bhati and Rai 2020; Kharwar and

Thakor 2022). Similar to DT and RF, it has several advantages over other DTs, such as minimising overfitting and over-learning of data by randomising specific data subsets and decisions (Sharaff and Gupta 2019). ETC is also inexpensive with computer resources. Although ETC is alleged to reduce variance and bias, it is prone to over fit large datasets and underperform when high correlation features are present.

Nevertheless, It is used in many areas to handle classification tasks (Maier *et al.* 2015; Kaur and Mittal 2020; Kumar, Singh and Dawra 2022; Ossai and Wickramasinghe 2022). ETC has also been widely used with other classifiers to deal with intricate issues (Peng *et al.* 2021; Rani, Kumar and Jain 2021; Sharma, Kumar and Jain 2022). Therefore, it provided an excellent classification of the type of treatment from the EHR modelling. **Table 5-8** presents the evaluation report for ETC on the HER dataset. It was one of the best classifiers close to the RF with a high AUC.

Table 5-8 Extra Trees Classifier Model Report

Extra Trees Classifier				
ETC	**Precision**	**Recall**	**F1-Score**	**Support**
out - 0	0.76	0.85	0.80	526
in - 1	0.73	0.61	0.67	357
Accuracy			0.75	833
Macro average	0.75	0.73	0.73	833
Weighted average	0.75	0.75	0.75	833

5.4.10 Gradient Boosting Classifier (GBC)

Gradient Boosting Classifier (GBC) is another commonly deployed ensemble learning classifier that gives enthralling results (Ferreira and Figueiredo 2012; Natekin and Knoll 2013;

Khan *et al.* 2022). GBC constructs a sequence of weak learners to render them more robust by optimising the weights of the instance grounded on the pitch of the loss function (Mayr *et al.* 2014). Other types of GBC comprise the XGBoost, CatBoost and LightGBM; these focus on augmenting algorithms' speed and accuracy(Postnikov, Esmedljaeva and Lavrova 2020; Asselman, Khaldi and Aammou 2021; Sajedul Alam *et al.* 2022). It has been recognised and deployed in many areas to solve problems that directly influence real life (Morid *et al.* 2017; Dhillon and Singh 2019; Akbar *et al.* 2020; Hancock and Khoshgoftaar 2021).

5.4.11 Ada Boosting Classifier (ABC)

Ada Boosting Classifier (ABC) is an adaptive boosting that relies on the boosting principle to enhance DT and other weak classifiers (Mayr *et al.* 2014). ABC is similar to GBC because it converts weak classifiers into more robust ones by prioritising misclassified instances from previous classifiers (Bahad and Saxena 2020; Khan *et al.* 2022). Some inherent deficiency of ABC is based on its sensitivity to outliers and overfitting with higher iteration(Mayr *et al.* 2014). However, ABC is considered one of the leading ensemble classifiers with many implementations (Dhillon and Singh 2019; Zheng *et al.* 2020; Alharbi and Almutiq 2022).

5.4.12 Random Forrest (RF)

Random Forrest (RF) is a supervised machine learning model heralded in extant literature to be robust in diverse solicitations. This machine-learning technique was proposed by Breiman et al. (1984) in 1984 and was later popularised (Breiman 2001). Random forest employs the statistical bagging approach established on a bootstrapped nature that attempts to aggregate all the trees in the forests to enhance the decision tree model (Verikas, Gelzinis and Bacauskiene 2011; Forkan, Khalil and Atiquzzaman 2017; Kaur, Kumar and Kumar 2019).

Over other models, the RF classifier can accurately fit nonlinear relationships and is robust to noise in the data (Fox *et al.* 2017). The technique employed decision trees to learn about the ingested data by creating a bitwise split at every node of either in or out output. The technique is optimised using the Gini purity that subjects it to a brute force approach to optimising every possible outcome. **Figure 5-6** depicts the enactment of the random forest technique where the decision tree and its node represent possible outcomes; the first tree shows how the binary split points and the middle tree represent a tree with just a 50% chance to be exactly like the tree on the right.

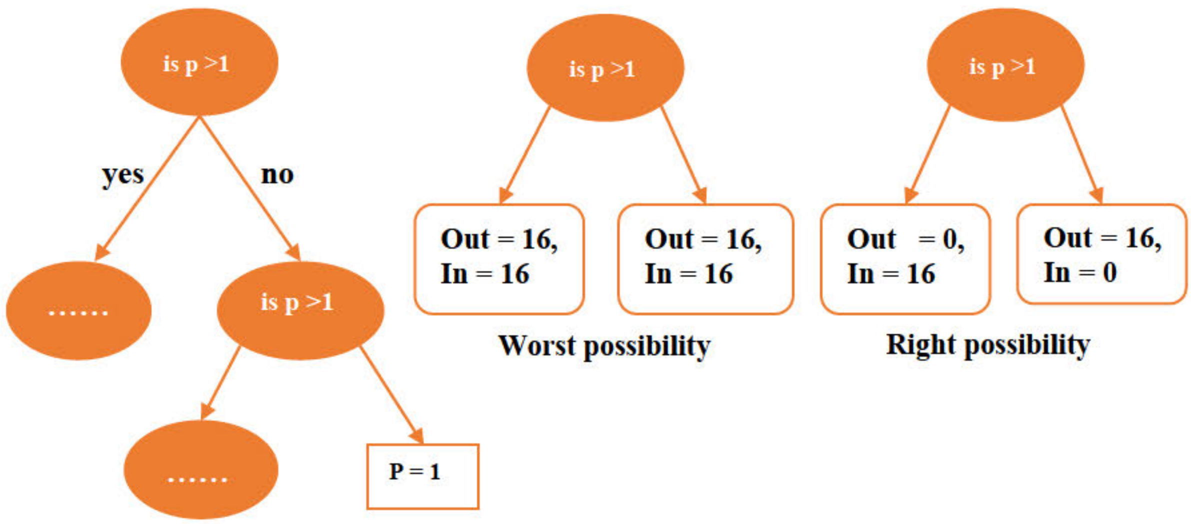

Figure 5-6 Random Forest decision tree illustration

In this study, we employed Bayesian optimization to improve the accuracy. For the final experiment, the hyper-parameters elected by Bayesian optimization included a "maximum" depth of 500, "maximum" features of 42 and the number of "estimators" equivalent to 300. These parameters ensure the trees' adherence in the forest to grow to the maximum depths, choosing the preeminent tree splits selected randomly at each node to be confined to the maximum number of features. Additionally, the Gini impurity coefficient metric, defined in equation 5.1 where "f" denotes the frequency label of "i" at a node and c denotes the distinct label, is also implemented for optimisation. Another metric employed is entropy, which is an alternative to the "gini" criteria. The model algorithm is implemented using the scikit-learn package in Python 3.0, and the measures are tuned and refined to overcome overfitting for the optimal outcome (Pedregosa *et al.* 2011; Biau 2012). The hyper parameter grid search and random search CV were included in the end to improve the results

$$\text{Gini impurity} = \sum_{i=1}^{c} f_i(1 - fi) \tag{5.6}$$

The evaluation metrics employed in this study include the following metrics to evaluate the model: accuracy, precision, recall, F1 score, and ROC curve accuracy score values.

The result of the machine learning model presented different accuracies for the models included in the experiments. Several experiments were done to determine which models performed well. These models included several machine learning and ensemble machine learning classifiers. The dataset splitting was initiated with an 80% to 20% ratio, followed by a 70% to 30% ratio to analyse the models' performances. Table 5-4 shows the results of the deployed model at the different split ratios. For the first experiment at the 80/20 ratio, the following model output was obtained with reference to the accuracy: Logistic Regression (70.89%), K-nearest Neighbour (68.97%), Support Vector Machine (69.99%), Linear Discriminant Analysis (70.55%), Naïve Bayes (68.63%), Decision Tree (65.69%), Multi-Layer Perceptron (74.08%), Random Forest (76.33%), Gradient Boosting (75.76%), Bagging (73.61%), Extra Tree (75.65%) and Ada boost (74.07%).

A slight difference was observed after applying the scaling to the data partitions. The following model output was obtained with reference to the accuracy: Logistic Regression (70.55%), K-nearest Neighbour (72.70%), Support Vector Machine (73.61%), Linear Discriminant Analysis (70.55%), Naïve Bayes (68.62%), Decision Tree (65.45%), Multi-Layer Perceptron (74.17%), Random Forest (76.21%), Gradient Boosting (75.65%), Bagging (74.52%), Extra Tree (76.44%) and Ada boost (74.24%). ETC, KNN, SVC, and BG benefited from the data scaling to improve their accuracy and assert that the applied scaling can alter the results of the models.

The ensemble learning classifier performed well more than the other simple classifiers. In the initial experiment, the Random forest model outperformed the other models with the highest accuracy of 76.1% and 76.33% in all the categories. For the simple classifiers, the second best model was Logistic Regression (LR) with 70.89%, and the third was Linear discriminant analysis (LDA) with 70.55%. For the ensemble learning category, the RF classifier maintained the top performance with an accuracy of 76.33%. Gradient boosting (GB) and Extra tree classifier (ETC) scored 75.76% and 75.65%, respectively. The Ada boost and Bagging scored 74.07% and 73.61%, respectively. **Table 5-9** presents the results of all the experiments conducted in this study. From the experiments, the overall model with the highest score was the RF, with a maximum of 77.01%. The other ensemble learners followed the RF to demonstrate highly accurate results.

Table 5-9 Experiments Results of the classifier

Machine Learning Classifiers Model Scores						
Machine Learning Classifier	**Exp. Phase 1 Split80/20**	**Exp. Phase 1 Split 80/20 Standard Scaled**	**Exp. Phase 2 Split 70/30**	**Exp. Phase 2 Split 70/30 Standard Scaled**	**Exp. Phase final –Split 80/20**	**Exp. Phase final –Split 70/30**
Random Forest	76.1	76.21	76.13	75.98		
Logistic Regression	70.89	70.55	71.98	71.52	70.44	71.68
Linear Discriminant Analysis	70.55	70.55	70.32	70.31	70.55	70.31
Support Vector Machine	69.99	73.61	70.54	74.92	71.91	72.25
K nearest Neighbour	68.97	72.71	68.96	73.41		
Naïve Bayes	68.63	68.63	68.73	69.73		
Decision Tree	66.93	65.47	66.54	66.61		
Multi-Layer Perceptron	74.18	74.75	74.77	74.41		
Ensemble Learning Classifier						
Random Forest	76.33	76.21	75.83	75.98	75.98	77.01
Gradient Boosting	75.76	75.65	76.06	76.06		
Extra Tree	75.65	76.44	74.70	75.76	75.38	75.20
Ada boost Classifier	74.07	74.29	74.24	74.54		
Bagging Classifier	73.61	74.52	73.64	73.11	75.54	75.20

For the subsequent experiment with all the features retained, the following outputs were obtained for LR (71.98%), KNN (68.96%), SVC (70.54%), LDA (70.32%), NB (68.96%), DT (66.54%), RF (76.13%), GB Classifier (76.06%), ETC (74.70%) and Bagging (74.24%). The splitting ratio was set at 70% to 30% to prevent the models' overfitting. At scale, the was a significant improvement by most of the models, especially the standard learners like SVC (74.92) and KNN (73.41). The RF classifier remained the highest in all the rounds of the experiment. A subsequent investigation was conducted to extract the classification report. It was found that the RF maintained the highest accuracy of 77.01% and 77.24% with the randomised search cv hyper parameter. The other ensemble learning classifier, Bagging, ETC, had 75.56% and 76.22%, respectively. The SVC, LDA, and LR models scored 72.25%, 70.78% and 70.67%, respectively. In the category, the SVC was the highest. The bar plot of the accuracy score for the different partitions is presented below. **Figures 5-7** illustrate the accuracy of the models at the 70% to 30% partition.

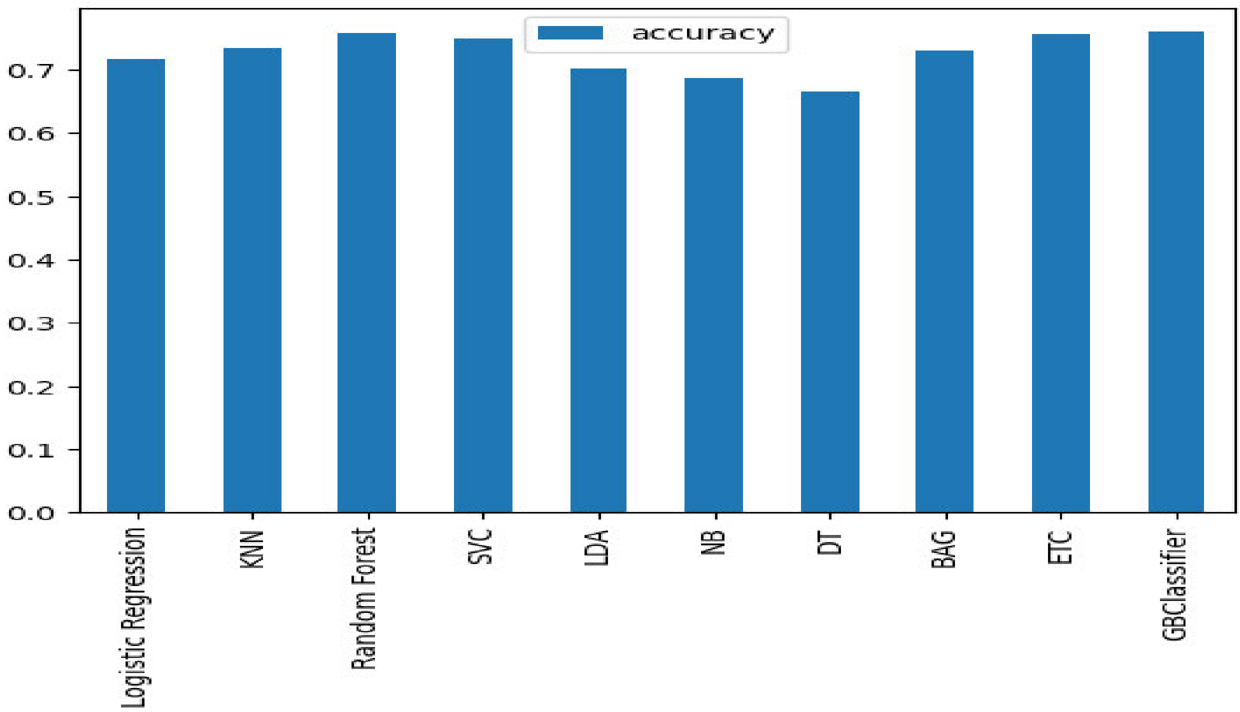

Figure 5-7 An illustration of the model scores 70:30 partition.

Figure **5-8** illustrates a bar plot of the model scores for the 80% to 20% partitions with a slight increase in the accuracy toward the 80 range for the greater partition.

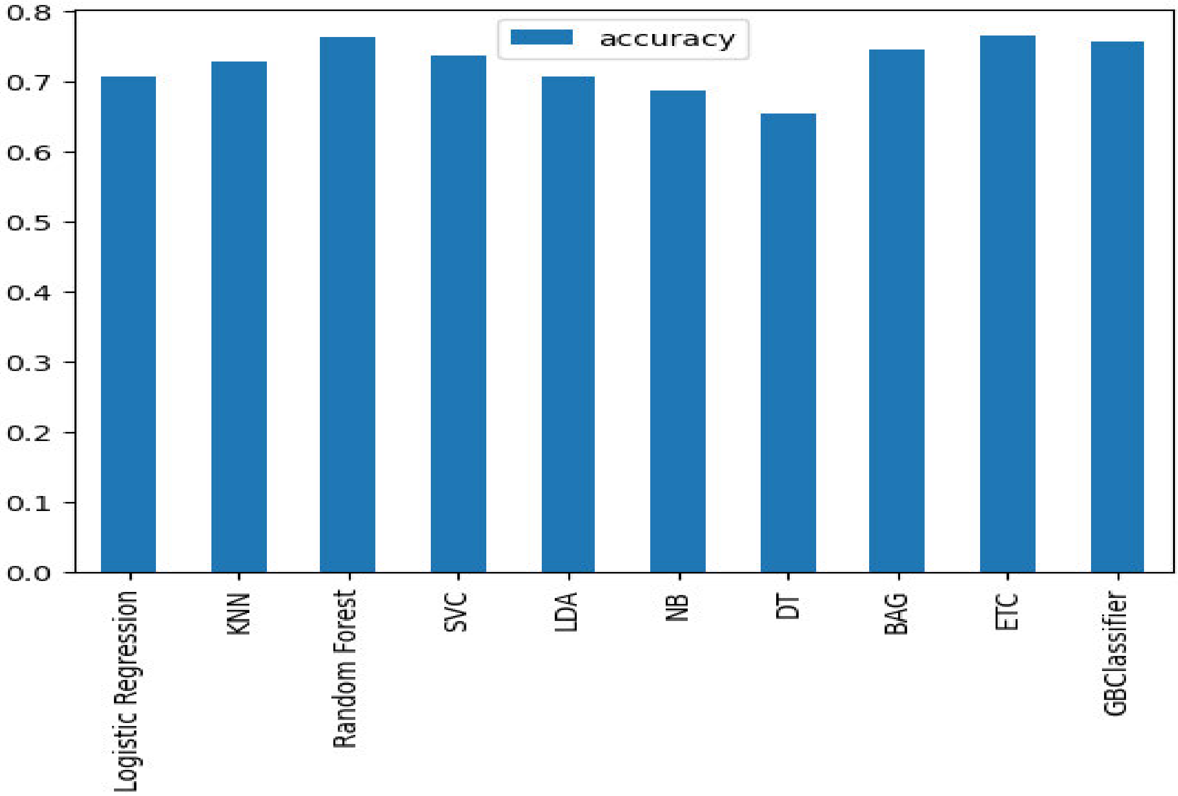

Figure 5-8 An illustration of the model scores at the 80:20 partition

The final experiment's results accentuate the classifiers with high performances from the start of the investigation and incorporate features pertinent to the patient's laboratory result within the healthcare context. The experiment yielded a higher accuracy of 77.01% for the Random Forest model, 75.98% for the gradient boosting classifier and 75.38% for the extra tree classifier. The Support Vector, Linear Discriminant Analysis and Logistic Regression score an accuracy of 72.25%, 70.78% and 70.67%, respectively. The features used in the final investigation included Haematocrit, Haemoglobins, Erythrocyte, Leucocyte, Thrombocyte, MCHC, MCH, MCV and Age. The results demonstrate the classification report of the patient laboratory data. The out-care patient category scored (0), which is the prevalent class, has a 78% precision score, 85% recall score, and 81% F1 score with the RF classifier.

Given that the prevalence class was the out-care patients, the F1 score was distributed accordingly. The in-patient category (1) has a 74% precision score, 66% recall score, and 70 % F1 score with the RF classifier. **Table 5-10** presents the detailed performance score for the random forest model and all the models deployed at the final stage of the experiment. The weighted average percentages for the model were as follows 77 for RF, 72 for SVC, 71 for LDA, 70 for LR, 76 for Bagging and 75 for ETC.

Table 5-10 Model results

RF				
RF	**Precision**	**Recall**	**F1-Score**	**Support**
out - 0	0.78	0.85	0.81	526
in - 1	0.74	0.66	0.70	357
Accuracy			0.77	833
Macro average	0.76	0.75	0.76	833
Weighted average	0.77	0.77	0.77	833
SVC				
SVC	**Precision**	**Recall**	**F1-Score**	**Support**
out - 0	0.73	0.83	0.78	526
in - 1	0.69	0.55	0.61	357
Accuracy			0.72	833
Macro average	0.71	0.69	0.70	833
Weighted average	0.72	0.72	0.71	833
LDA				
LDA	**Precision**	**Recall**	**F1-Score**	**Support**
out - 0	0.71	0.86	0.78	526
in - 1	0.70	0.47	0.57	357
Accuracy			0.71	833
Macro average	0.70	0.67	0.67	833
Weighted average	0.70	0.71	0.69	833
LR				
LR	**Precision**	**Recall**	**F1-Score**	**Support**
out - 0	0.71	0.85	0.77	526
in - 1	0.61	0.49	0.57	357

Accuracy			0.70	833
Macro average	0.70	0.67	0.67	833
Weighted average	0.70	0.70	0.69	833
BC				
Bagging	**Precision**	**Recall**	**F1-Score**	**Support**
out - 0	0.77	0.84	0.80	526
in - 1	0.73	0.63	0.68	357
Accuracy			0.73	833
Macro average	0.75	0.74	0.74	833
Weighted average	0.75	0.76	0.75	833
ETC				
ETC	**Precision**	**Recall**	**F1-Score**	**Support**
out - 0	0.76	0.85	0.80	526
in - 1	0.73	0.61	0.67	357
Accuracy			0.75	833
Macro average	0.75	0.73	0.73	833
Weighted average	0.75	0.75	0.75	833

Figure 5-9 presents the confusion matrixes of the experimented models. The RF model obtained the highest prediction, followed by the other ensemble learning model, ETC and Bagging. The confusion matrix for the RF model can be seen in figure 5-9; from the visualisation, it is evidence that the model successfully produced a high amount of correct predictions, a total of 680 from 883 accurate predictions was made. A prior study on the same data reported 666 correct predictions from a total of 883 total predictions (Sajedul Alam *et al.* 2022). Over the 883 samples, the BC was second with a total of 667 correct predictions. 664 accurate forecast was obtained for the bagging classifier. 635 accurate forecast was obtained for the SVC, 623 for LDA and 622 for SVC.

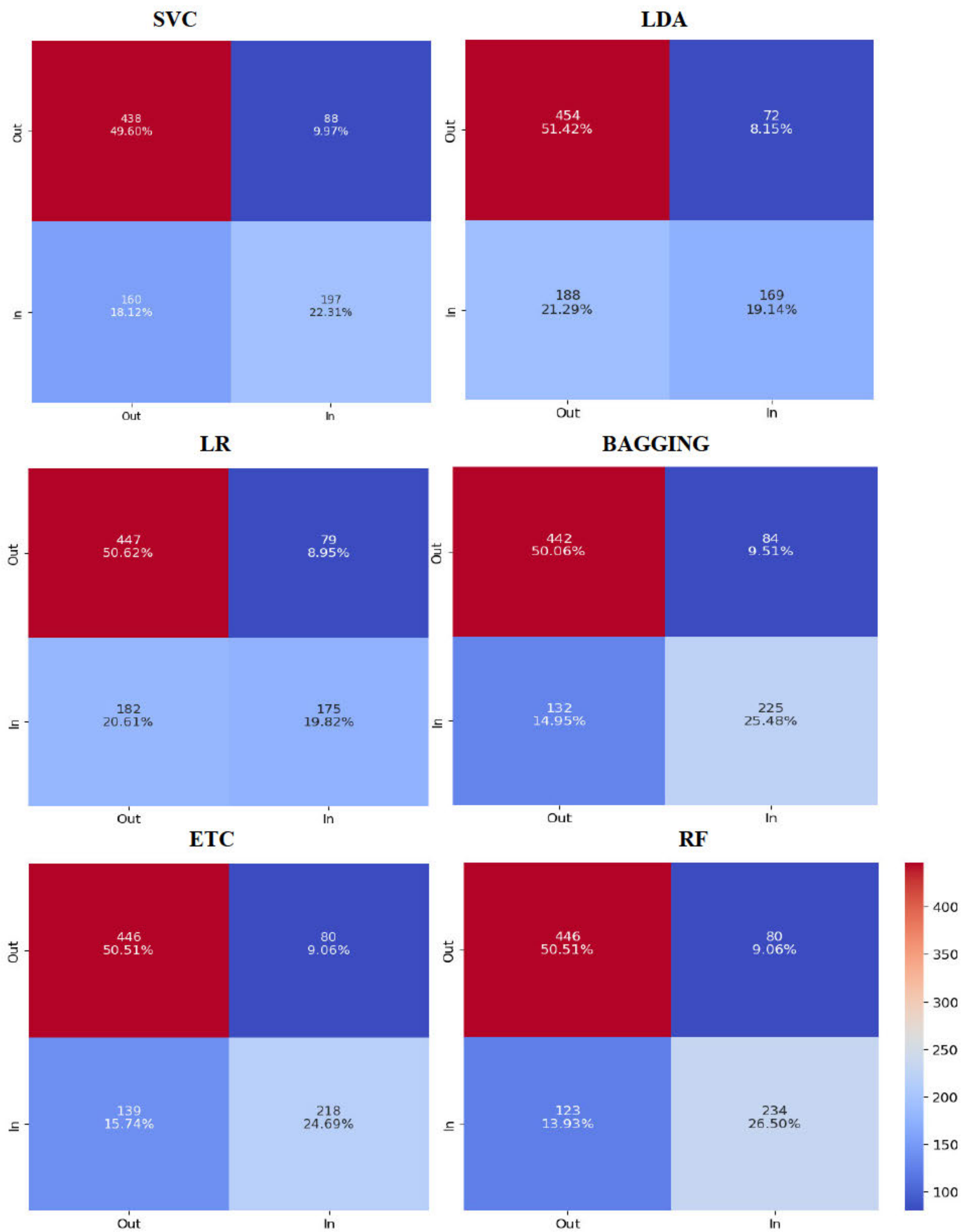

Figure 5-9 Confusion Matrix

The ROC and AUC also measure the performance of the predictions for both target features. The AUC normal range is between 0.5 and 1. A lesser value that is below or equal to 0.5 implies that the classifier value is irrelevant. At the same time, a higher value between 0.7 and 0.8 is a good indication that reflects the classifiers' worth. The sensitivity measure on the curve reflects the proportion of the out-care patient, which was correctly classified. A higher value is attainable, with this being the positive and prevalent instance. At the same time, the specificity measure on the curve reflects the proportion of the in-care patient, which was correctly classified. A higher value related to its distribution was also attainable, with this being the negative and rare instance within the dataset. **Table 5-11** reports the AUC for the analysis of the two data partitions experimented on.

Table 5-11 AUC for the deployed models

Model AUC						
Data Partition	**SVC**	**LDA**	**LR**	**BC**	**ETC**	**RF**
70/30	76.64	76.00	76.09	80.16	80.84	80.85
80/20	75.41	75.21	75.22	80.58	81.24	81.08

The ROC curve in **Figures 5-10** and **5-11** reflects the higher prediction score that substantiates and validates the RF classifier model with an AUC of 80.85% and 81.08 at the 80%:20% to 70%:30% partition. The ETC had the highest AUC at the 80/20 partition, at 81.24%, followed by an 80.84% at the 70/30 partition, asserting the likelihood of the classifier as well as the quality regardless of the classification threshold. The BC was the third with AUC of 80.58 and 80.16. The other model produced lesser values below the 80 points, with their performance augmented at the 70:30 ratio SVC (76.64), LDA (76.00), and LR (76.09). Contrary to the standard learners' the ensemble learners had a higher AUC at the 80:20 ratios.

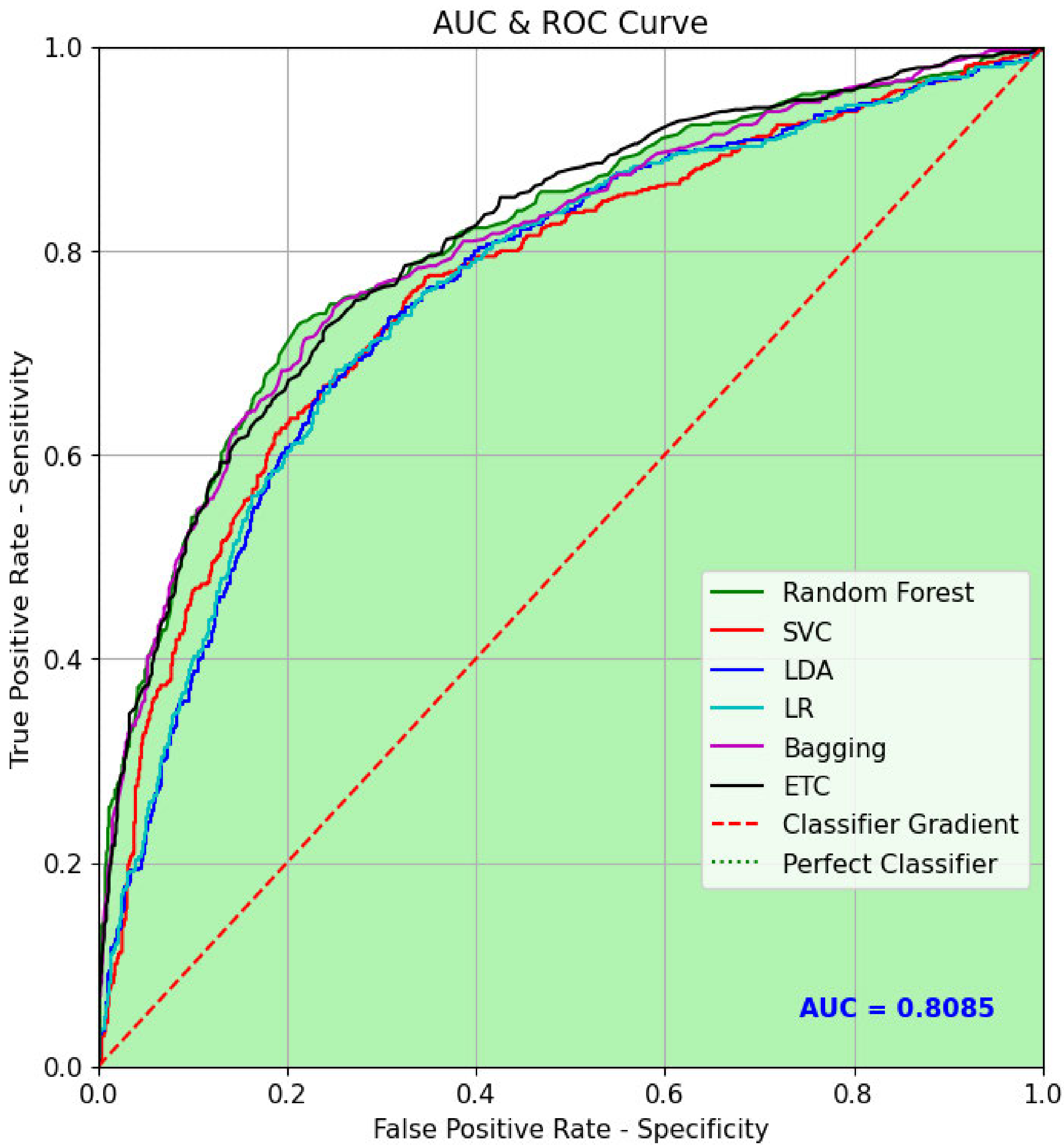

Figure 5-10 Curve for all models at 80/20 partition

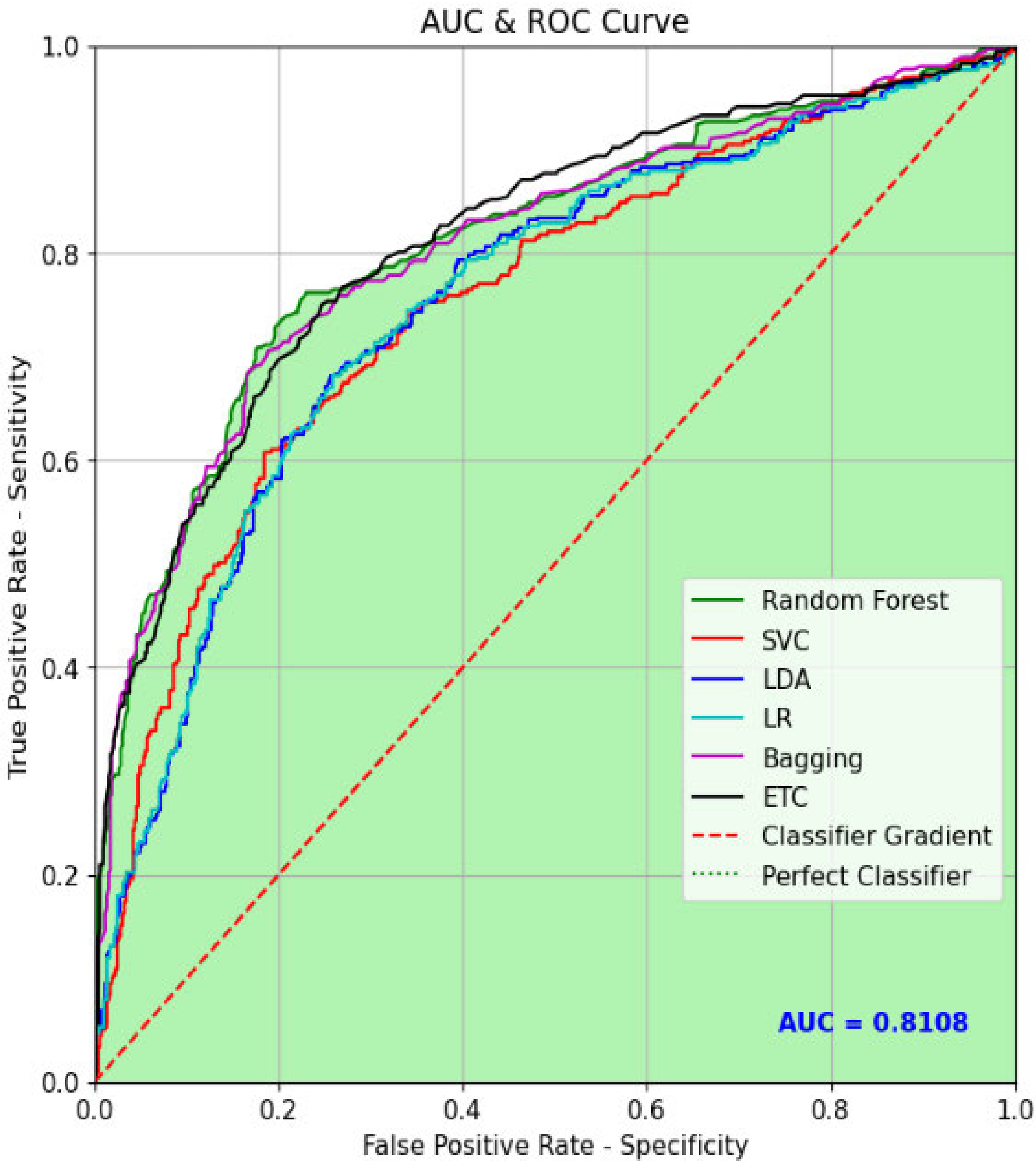

Figure 5-11 ROC Curve for all models at 70/30 partition

This finding, compared to a prior study, presents a high prediction. It improved the results of previous work done by Sajedul Alam *et al.* (2022), by increasing the number of correct predictions from 666 to 680 over a total of 883 using the lightGBM classifier. This study's results increased the accurate forecast from 658 to 680 for random forest classifiers in contrast to prior studies and the overall accuracy to 77.01%. **Table 5-12** presents the performance analysis of this study with prior existing approaches presented in extant literature.

Table 5-12 Performance analysis with existing approaches

Reference	**Year**	**Framework tool**	**Proposed Techniques—Multiple ML**	**Accuracy**	**Correct prediction (883)**
Sajedul Alam *et al.* (2022)	2022	Python	Random Forest	76	658
Author	2023	Python	Random forest	77	680

In this study, the RF model is presented for predicting the patient's mode of treatment based on the laboratory result. Based on the model's performance and the selected features, the model is apt to indicate the mode of treatment of patients when their laboratory results are known. Empirically, the performance of the prediction likelihood is seen to be superior when the features MCHC and sex are excluded. The selected features presented a high likelihood of prediction. The experiments were performed using all the features and a set seed of 42 at the 70:30 ratio of the data. Better results were obtained with selected features in contrast with all the features. The RF results demonstrate that 77.01% accuracy can be obtained with this model using the selected features.

Additionally, from the EHREDA, the Haematocrit, Haemoglobins, Erythrocyte, Leucocyte, Thrombocyte, MCH, MCV and Age are found to be the key features that contribute to the degree of severity of the patient’s health condition as well as the mode of treatment to be administered. These features are used by practitioners to determine the prognosis of the patient. In the RF model, Thrombocyte was the most significant with a score of 0.21728, followed by Leucocyte and Haematocrit with 0.12141 and 0.1143. The Erythrocyte score was 0.10204; the Age score was 0.09867; the MCV score was 0.08665; the Haemoglobins score was 0.08546; the MCH score was 0.07818; the MCHC score was 0.07754 and Sex was the bottom with a score of 0.01847. **Figure 5.12** illustrate the distribution of the features scores in a bar chat.

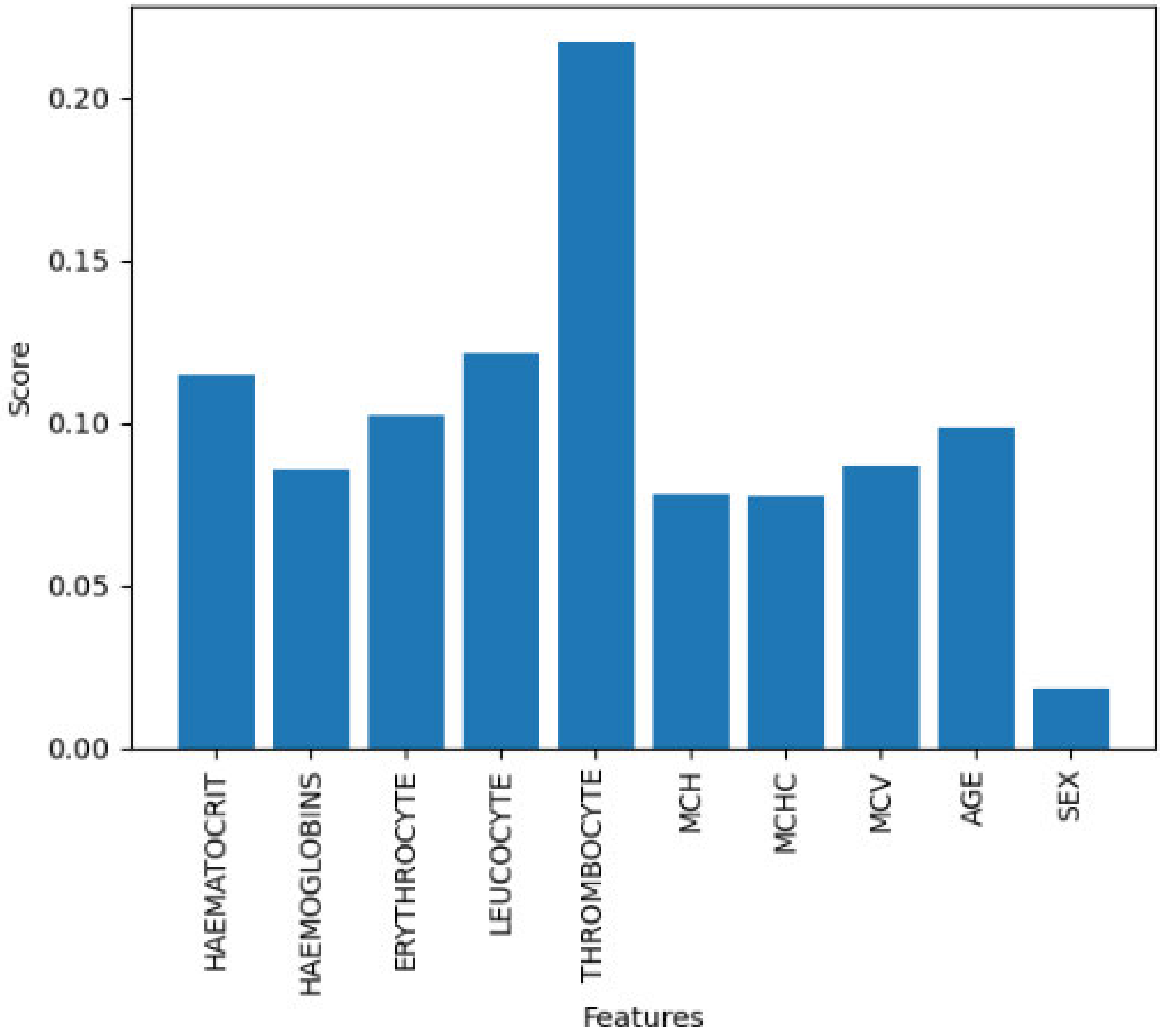

Figure 5-12 RF features significant

Figure 5-12 illustrates a practical use of data sciences techniques such as the RF model, which can be incorporated with selected features within the HIS setting to determine the appropriate health care applications and allocate resources within the healthcare arena. Assimilating these kinds of applications within the existing HIS environment will go a long way towards the achievement of quality healthcare and a robust HIS. These will enhance the quality of health care, be suitable positions within the healthcare arena, and tackle most of the current dares associated with the existing health care system.

Figure 5-13 enact the application of the best-fit machine learning model from the experiment that demonstrates how it can be employed. This commences with individuals who fall ill (patients) and visit healthcare facilities like hospitals and centres (healthcare facilities). At healthcare facilities, healthcare checks and tests are conducted by specialists who include but are not limited to doctors, nurses and laboratory technicians. The reports generated from the healthcare checks and tests are forms of health data (HIS data) that play a critical role in the decision phase. At this phase, the data analysis techniques, which could be ML, DL and NLP, are then deployed, and the best model (best learning model) is used to predict the type of treatment, which the healthcare provider enforces the treatment type after validating the output.

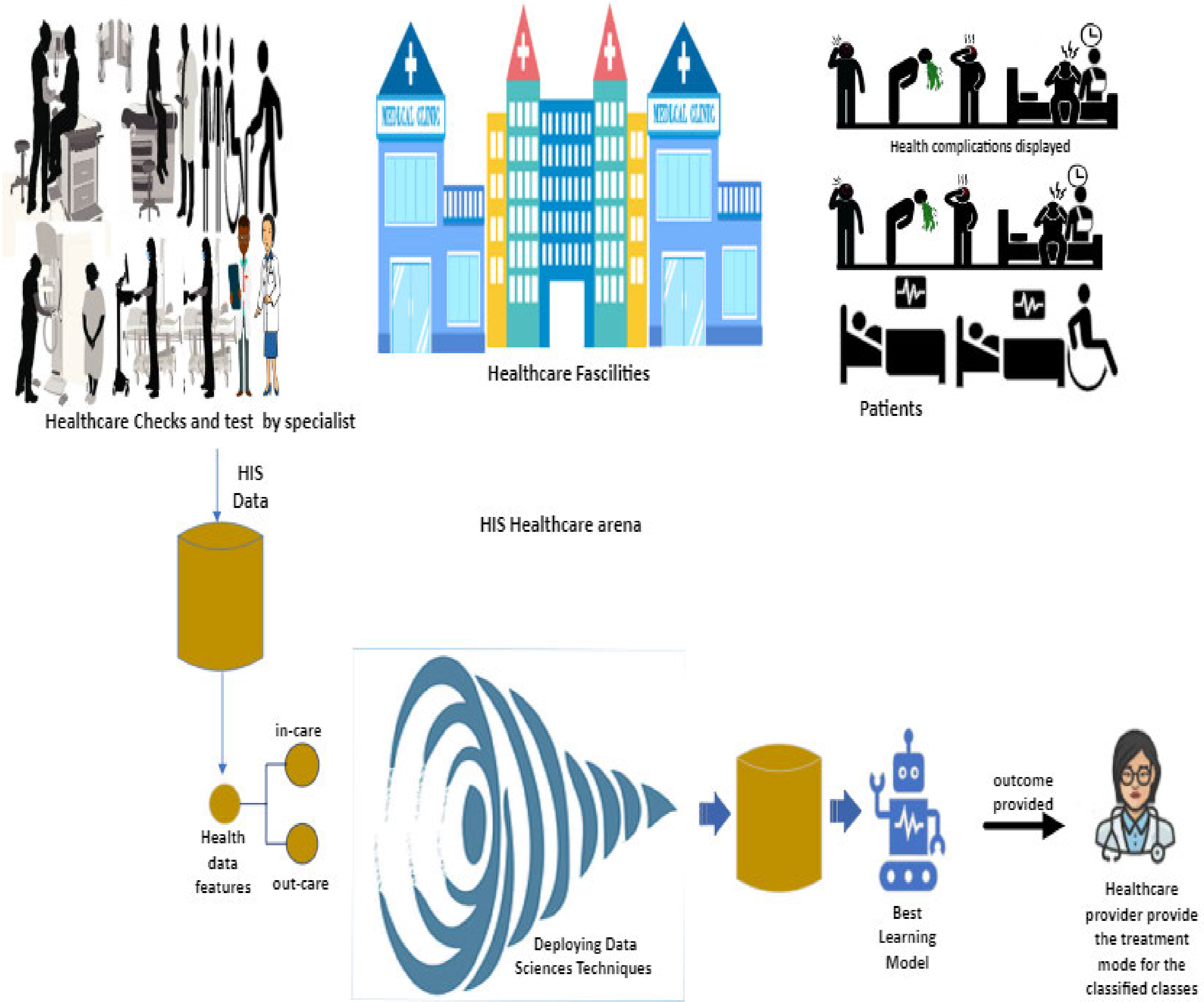

Figure 5-13 Health Data ML Modelling Prediction

The laboratory test result is highly relevant in ascertaining the severity of a patient's health condition. Prompt actions are necessary for emergency interventions that model health care applications to enhance the patient's well-being and appropriately apportion resources. This study reveals that these measures can be feasible and timely in averting health complications that are tantamount to mortality (Mayer *et al.* 2017; Martins *et al.* 2022). Thus, incorporating data sciences techniques in the existing HIS is highly relevant to enhance and fortify its offerings within the healthcare arena. Therefore, a data-driven paradigm is a core enabler in the attainment of a resilient and sustainable HIS that is indispensable and parallel to the enhancement of health care applications. These insights are believed to be beneficial to healthcare stakeholders such as nurses and doctors, professionals, and organisations to predict the type of health care to afford and subsequently alleviate possible outcomes and avert mortality associated with such conditions.

5.5 Summary of the chapter

Many healthcare studies have observed the availability of data sciences techniques to predict, detect, classify, and cluster outcomes to afford valuable services for the present and future. Although there have been many extant works on data sciences in healthcare, their direction has been accentuated by their capabilities. Little or no focus on their incorporation within the existing healthcare system has been expressed. Especially in alignment with the attainment of a sustainable and resilient integrated system such as the HIS for health care applications. The data analysis results in this chapter offer insights for health care offerings that include but are not limited to identifying determinants for diseases, the association between determinants and machine learning applications. A data science technique for predicting, detecting and classifying health-related predicaments can enable efficient health care applications for stakeholders who are directly and indirectly concerned. Incorporating these insights from data analytics of healthcare data affords a framework that can result in a sustainable and resilient HIS for healthcare applications. Hence, this chapter discusses in detail the elements of a data-driven paradigm for resilient and sustainable HIS for health care applications implementation. In line with the study's primary objective, the result presented in this chapter established the core element in the development of resilient and sustainable HIS, an integrated information system employed for health care applications. This chapter details the background, analysis, results and discussion of a dataset explicitly characterized as health care data to demonstrate a practical data sciences technique that could be integrated into the existing HIS environment. Adopting and implementing data sciences techniques like those shown in this chapter ensure the sustainability and resilience of HIS and its healthcare offering. The ensuing chapters present the contributions to knowledge and practical operation of healthcare services delivery afforded by this study.

CHAPTER SIX: RESEARCH THEORETICAL AND PRACTICAL CONTRIBUTIONS OF THIS STUDY

6.1 Introduction

Several studies highlight challenges within the healthcare arena, such as increased patients and workload as the determinants that necessitate the need for ameliorations (Alahmar, AlMousa and Benlamri 2022; Epizitone 2022; Garcia, De la Vega and Mercado 2022). These phenomena are the bases for the demand for a resilient and sustainable HIS. To partake in affording amelioration that will help shape the health care system and HIS. This chapter proffered this study's theoretical and practical contributions to the attainment of resilient and sustainable HIS for health care applications. The chapter commences by presenting the theoretical contributions amalgamation from the literature. Then it progresses to the practical contribution that validates the purpose of this study to afford insight that enables the transfiguration of existing HIS employed for health care applications. These contributions align with the need and call for existing HIS to be strengthened and optimised for health care delivery to afford knowledge that can structure and mitigate dares associated with these systems within the healthcare arena when endorsed.

6.2 Theoretical contributions

6.2.1 Health information systems and health care applications

In this study, the HIS was explored along with health care applications, and several theoretical contributions were identified concerning information systems within the healthcare arena. These contributions intersect the core concepts within the health information system environment. From this study, the case of HIS for health care applications was afforded an empirical account and a theoretical discourse on the potential function of HIS in the augmentation of health care applications. These concepts have been extensively discussed and comprehended within the healthcare and information system field. A systematic literature review and bibliometric analysis were published in the healthcare journal and a critical review research in the International Journal of Advanced Computer Science and Applications (Epizitone 2022; Epizitone, Moyane and Agbehadji 2022; Epizitone, Moyane and Agbehadji 2023). In many ways, 'HIS' research is vital for health care applications within the global arena. However, to my knowledge, little research has been done on how 'HIS' can be optimised and leveraged to unify health care applications within global settings. As aforementioned in the rationale of this study in chapter one, I contend that limited studies accentuate the optimisation of 'HIS' for health care applications. The gap necessitates the agenda of this study that underscores the optimisation of 'HIS' for enhancing health care applications within the healthcare arena. This agenda was further capitalised on the data-driven track to augment HIS and healthcare. Therefore, this study efficaciously bridges these two core constituents within the healthcare and information system research; *to identify the potential of resilient and sustainable 'HIS' in enhancing health care applications globally.*

6.2.2 Scalability of health information system for health care applications

The scope of advances in the healthcare arena and the scalability of HIS for healthcare applications are predominately evident in many nations. The ability of the system to change its size and scale in order to provide a variety of capabilities is referred to as the scalability of HIS. Existing research documents a surge in HIS use in the healthcare industry due to its capacity to help integrate and merge vast digital health information (Paul *et al.* 2015; Alahmar, AlMousa and Benlamri 2022). According to the extant research report HIS, progress has been stifled due to low reliance and diverted emphasis on health innovations. Negro-Calduch *et al.* (2021) associate HIS enactment dare to be associated with its scalability. Even though existing literature proclaims 'HIS' to be critical to stakeholder engagement in decision-making and planning for health care applications (Paul *et al.* 2015; Hurtado-Salgado *et al.* 2018; Murad 2018; Steil *et al.* 2019). This study theorises that it is critical to assess HIS scalability in order to capitalize on opportunities in settings *deployed for health care applications*.

6.2.3 Sustainability and resilience capabilities of Health Information Systems for health care applications

The concepts of sustainability and resilience of systems have been heralded in extant literature to afford diverse dimensions of well-being. Gardoni (2019) stated that the presence of sustainability and resilience within system avail opportunities to current and future generations with minimal disruption and afford and address certain considerations. Although the definition of these concepts varies across industries, in the context of healthcare, the demand for a response from HIS enactment for health care applications has been provoked by many events and needs in the healthcare arena. The resurgence of pandemics, namely COVID-19, the global health priorities SDG 3 and WHO priorities have imposed the need for sustainability and resilience within the healthcare arena (Clay-Williams and Braithwaite 2019; Mardani *et al.* 2020; Epizitone 2022; Lal *et al.* 2022). Adaba and Kebebew (2018) accentuate the HIS sustainability for health care applications highlighting the vital essence of HIS optimisation for health care applications.

Furthermore, Gardoni (2019) synthesize the need for frameworks to include fundament functions that enable the attainment of resilience and sustainability. The primary grounding of a resilient and sustainable capability is capitalised on the 'HIS' optimisation and the need for strategic resolution. Thus, this study highlights *the need for resilience and sustainable HIS for health care applications framework paramount position in the healthcare arena, asserting that the adoption and implementation of the resilience and sustainable capabilities of HIS can afford long-term ameliorations.*

6.2.4 The social-technical Theory in the discourse of Health Information Systems for health care applications

A pressing agenda uncovered from a critical review of the literature on HIS and health care applications research is the pertinent need to incorporate and leverage stakeholder's perspective to strengthen HIS (Mutale *et al.* 2018; Alsharo, Alnsour and Alabdallah 2020). Extant literature indicated the HIS's knowledge and practices among stakeholders such as doctors and staff are limited (Sadoughi et al. 2017). According to some authors, many countries encounter distinct dares relative to their context that influences HIS enactment; thus, incorporating stakeholders' perspectives is crucial for buttressing HIS capabilities (Thomas *et al.* 2022). Citrin *et al.* (2018) argue that the concurrent technological and healthcare workforce advancements present an avenue to tackle health care dares. However, organisational concerns that are subjective in nature impede coordinated efforts toward theoretically informed HIS and exertion in health care applications (Cresswell and Sheikh 2013).

Nevertheless, Cresswell and Sheikh (2013) state that HIS enactments in healthcare settings are fatefully imperative undertakings that need adequate research attention substantiating the incorporation of the socio-technical theory. This study captures vividly *the equal role of the stakeholders and technology in the successful implementation of HIS for health care applications. And it relates the concepts of social–technical theory to the sustainability and resilience of HIS for health care applications.*

6.2.5 Framework for health information systems for health care applications

This study proposed a data-driven paradigm for the attainment of resilient and sustainable HIS for health care applications. As outlined in section 4.3, there are a number of different frameworks in existence for HIS for health care applications. These technological, conceptual and research frameworks have been employed within the healthcare arena for the augmentation of healthcare (Andargoli *et al.* 2017; Bawack and Kamdjoug 2018; Alsharo, Alnsour and Alabdallah 2020; Mezarina *et al.* 2020; Dudley *et al.* 2022; Epizitone 2022; van Bussel *et al.* 2022). However, extant literature features the initial design of information framework among the list of dares for HIS enactment, associating their faultiness with the ease of access and utilisation of the relevant stakeholders (Mezarina *et al.* 2020). Furthermore, the development and implementation of these frameworks have afforded minimal remedy for HIS dares and, as such, limits the potential to benefit health care applications.

Moreover, despite many technological focus frameworks in the current knowledge gen of HIS being present, there are limited data-centric frameworks to my knowledge. Thus, the advancement of digitalisation and the importance of sustainable and resilient HIS for quality health care applications within the healthcare arena remain pertinent (Sahay, Nielsen and Latifov 2018; Dehnavieh *et al.* 2019; Sahay, Rashidian and Doctor 2020; Zotov *et al.* 2020; Ostern *et al.* 2021). This study lures extant theories within the healthcare arena to present a conceptual context for the development of a sustainable and resilient HIS for health care applications from the data track. To *propose the enactment of a data-driven paradigm for a resilient and sustainable health information systems for health care applications.*

6.2.6 Resilient and sustainable health information systems for health care applications data-driven paradigm

The adoption of HIS has been employed globally for its transformative effects on health care practices. The increase in these adoption has equally driven the call for these systems to be strengthened. Thus, the enactment of a data-driven paradigm for resilient and sustainable HIS for health care applications is unparalleled in this digitalisation era, as it affords an integrated footing for data analytics to support and assist healthcare delivery. The conception of this study proposed a framework for developing a resilient and sustainable integrated information system for Health Care applications. In order to enhance the knowledge of HIS's implementation through the novel integration of data science and machine learning techniques in the traction of Design Science Research (DSR). It was envisaged that the realisation of the objectives of this study would contribute toward the attainment of a strengthened HIS, and the artefact developed by this study will be used to create and drive initiatives that strengthen the healthcare capabilities and effective utilisation by stakeholders. Thus the findings of this study present many opportunities to harness the potential of HIS for health care applications via a robust, reproducible pipeline that can be employed to enhance health care applications within the HIS environment. Theoretically contributing to the fortification of HIS through *the development and enactment of a resilient and sustainable HIS for health care applications that is unparalleled in this digitalisation era and endowment of an integrated footing for data analytics to support and assists health care delivery. In so doing, the synthesised concept elevates HIS theoretically and pragmatically from the theorised synthesis of this study.*

6.3 Practical contributions

This study presents the practical contributions to bodies, practices and stakeholders within the health care arena in the form of practical advice based on my research and findings. In the context of this study, this refers to stakeholders within the healthcare arena that are directly and indirectly involved in the execution of health care applications globally. However, my research study has concentrated on Health information systems, health care and health data. Many organisations, healthcare practices, practitioners, and educators, can benefit from these contributions.

6.3.1 Consideration concomitant to the strengthening of Health Information Systems

There have been many reports of the need to strengthen the HIS as its direct association with health care application have many consequences, such as the shortfalls of evidence base decision making as well as 'HIS' induced mortality (Farnham *et al.* 2020; Saigi-Rubio *et al.* 2021). A strengthened HIS' benefits and prospects are extremely important to the enhancement of healthcare service delivery as well as the allocation of resources (Colais *et al.* 2018). Contrary to the notion that technology has wielded negative outcomes on its stakeholders, with many seeing it as disruptive, it has the capabilities to revolutionise the healthcare arena (Nadri *et al.* 2017; Benbrahim, Hachimi and Amine 2018; Moghaddasi *et al.* 2018; Rudd *et al.* 2019). HIS enactment affords numerous opportunities to enhance healthcare and service delivery within the health system. The first contribution of this study corresponds with the state of HIS in countries and their approach to it. To leverage the impact of weakening HIS and work on strengthening it, some considerations need to be taken into account. Thus healthcare stakeholders need to consider establishing the following:

- *Consider reviewing existing HIS to identify its weaknesses and consider employing insights from data analytics to leverage the flaw without compromising on the health care delivery.*
- *Consider implications of the socio-technical stance of HIS within the entire organisation/practices.*
- *Considered the need for humans and technology to share value and responsibilities equally.*

6.3.2 Consideration concomitant to establishing a resilient and sustainable Health Information System for health care applications

From the discourse on HIS, it is evident that numerous challenges are associated with HIS for health care applications within the healthcare arena. Among them is the proliferation of health data, which is considered problematic regarding quality and wholeness. Moreover, several reports highlight the dithering fragmentation of HIS within the local, national and global settings (Braa and Sahay 2012; Sahay, Nielsen and Latifov 2018; Sahay, Rashidian and Doctor 2020). These phenomena impact and limit the potential of HIS for health care applications. The development and deployment of HIS carries an imperial role in the development and strengthening global health system (Rudd *et al.* 2019). This preposition served as an impetus for the need for scientific cutting-edge design research intensive methods to generate pertinent, astute and valuable strategic solutions to critical problems facing the HIS enactment and application globally. To support efforts that target the appraisal of HIS enactment are deliberated to be strategically advantageous in the attainment of augmented health care applications (Noel, Taramasco and Marquez 2022).

Furthermore, in alignment with these reports that emphasise and advocate for support, this study adds to the established foundation to aid the need to develop strategies that anchor HIS in digitalisation (Jabareen, Khader and Taweel 2020). Couple with the benefits that many facets of health care applications stand to gain from HIS development and strengthening. The enactment of data-driven applications which propel the employment of HIS in the delivery of health care applications will subsequently respond to and fulfil the sustainable development goals for all (Mills, Lee and Rassekh 2019; Nsaghurwe *et al.* 2021). Therefore, this study recommends the enactment of the developed data-driven resilient and sustainable Health

Information System for health care applications presented in this research globally. Hence, practitioners at all levels, local, national and international, who are involved with HIS should institute the following considerations for an augmented health care application:

- *Leverage the potential of data sciences to mine health data through prevailing techniques afforded.*
- *Ensure that there is flexibility to model amelioration within the contexts of its set-up.*
- *Implement the proposed framework locally, nationally and globally to benefit from it and to enhance health care applications capabilities.*
- *Evaluate the performance and adopt practical measures to anticipate future occurrences from the present lessons and insights.*

6.4 Summary of the chapter

This chapter details the study's contributions to the body of gen of healthcare in the associated areas, namely HIS, health care applications and data. The chapter presents ample evidence of this study's theoretical and practical contributions that are bestowed with the potential to shape the healthcare arena. The combination of these contributions gives a concrete piece of knowledge that is needed and essential for attaining a resilient and sustainable HIS for health care applications. The next chapter focuses on the research summary and conclusion to consolidate the empirical findings of this study in a nutshell. The responses to the research objectives and questions are presented along with the inferences, future research application direction of this study and conclusion.

CHAPTER SEVEN: RESEARCH SUMMARY, RECOMMENDATION AND CONCLUSION

7.1 Introduction

In conclusion, this chapter completes this study by presenting the summary, implications, and recommendations. Closely aligned with the study objectives and research questions in chapter one, the responses and summary are provided. The answers to the research questions and the proposed data-driven paradigm for enacting a resilient and sustainable integrated information system for health care applications are conferred in this chapter, as well as conceivable recommendations for improvement on the presented framework.

7.2 Summary of contribution

Research on sustainable and resilient HIS for health care applications has been driven by many transformation challenges. These phenomena have led to the conclusion that healthcare needs to fortify and enhance these systems to afford quality care to stakeholders. Although throughout extant literature, attention has been drawn to the challenges confronting these systems within the healthcare arena more than to their resolutions. There are intrinsic characteristics of HIS that remains untapped. Globally, HIS is considered to be very instrumental in supporting the realisation of WHO healthcare's objectives as well as the SDG 3 goal that focuses on quality health for all (Sarmiento-Suárez *et al.* 2022). This emphasizes HIS dispositions in extant literature. Asserting HIS to be an indispensable tool that underpins the priorities of health and well-being attainment, global standardisation, service delivery synchronisation, accountability and governance fortification (Bernardi 2017; Scott and Gilson 2017). However, with the advancement of technology and the unpredictable occurrence of disease or pandemics, this magnificent portrait has been blurred, calling into question many stakeholders' reliance who fail to benefit from its implementation. Equally, the sustainability and resilience of HIS in supporting health care applications amidst the influx of data have also been an area of concern that has awakened the need to rectify existing flaws. Thus, these premises serve as the impetus for this study research agenda that aims to present a data-driven paradigm for a resilient and sustainable integrated health information systems for health care applications.

The research agenda of this study, driven by the overarching aim to scrutinise HIS challenges in association with health care applications, converges the data track toward developing an effective framework that enhances health care applications and strengthens HIS within the healthcare arena. The study’s objectives presented in this research's inauguration have been realised to satisfy the main question, “How can knowledge generated from an analyse integrated information system be used to attain a resilient and sustainable integrated information system for Health Care applications? As a result, these objectives are summarised in detail below, along with their respective questions and responses.

7.2.1 To ascertain knowledge, constraints and perceptions on the Health Information Systems deliverables

The first objective set forth in this study was driven by the research question: *What are the knowledge, constraints and perceptions on the Health Information Systems deliverables?* To satisfy this objective and respond to the driving question. This research study sets off by laying the background of HIS for health care application from its inception to its current enactment with reference to the challenges confronting it on the global platform in chapters 1 and 2. The potentials and dares associated with HIS for health care applications were uncovered in the different facets of HIS enactment within the healthcare arena from the developing to developed nations. The knowledge constraints and perceptions associated with HIS were covered in detail in Chapter 2, emphasising the importance of involving humans and technology equally in affording much-needed resilience and sustainable ameliorations.

Further elucidation was afforded on the indispensable role of quality data for health care applications mediated by HIS. The study also presented insight into the positioning of information systems and knowledge management within the healthcare arena. The evolution of the HIS was also demonstrated to highlight critical advances made in the development of the HIS for health care applications. Essential attributes of HIS in association with health care applications were also explained. HIS' implementation and design were also presented in detail. Thus the response to research question one was satisfied and addressed in the latter part of chapter one. The study background and motivation discussion was presented first in chapter one and then in earlier part of chapter two, which delves deeper into extant literature to substantiate the knowledge, constraints, and perception of HIS deliverables. Thus addressing and satisfying the first research question and objectives.

7.2.2 To explore knowledge creation that addresses ill-defined problems in the integrated information system

To address objective three. The question; *How can knowledge creation be employed to address ill-defined problems in the integrated information system? W*as asked, and the detailed response was presented in chapter two. The chapter identified and analysed the significant ill-defined difficulties in HIS. These included data quality associated with several determinants such as data heterogeneity, sources, security and privacy. Another consists of the complex and ill-defined HIS interoperability that is attributable to the presence of diverse HIS complex generating data. The usability, scalability, design and the internet were also recognized and discussed. These ill-defined problems in HIS necessitated the incorporation of a multidisciplinary perspective that identified healthcare stakeholders, technology and other actors in the field. As a result, the provided socio-technical paradigm validates and emphasizes equal human and technological involvement in solution development for HIS dares.

Furthermore, the study established that dealing with HIS' ill-defined requires an iterative and systematic strategy, for which the DSR and data sciences were adopted. Chapter 2, sections 2.5 to 2.16, presented a more detailed grasp of the difficulties and their corresponding explanations. This knowledge was integrated into the study context, resulting in an understanding that may be utilized as ill-defined HIS challenges persist, and an iterative approach is required. A systematic literature review was conducted and published in the healthcare journal to substantiate this systematic and iterative approach.

7.2.3 To investigate the performance of Health information systems for health care applications

The third research question that guided the objective mentioned above is: What is the performance of the health information systems and health care applications within the healthcare domain? In order to answer this question, further probing conducted to this extent presented commendable knowledge and insights into HIS, an integrated information system's current disposition for health care applications. The study reveals that data generated from HIS has an integral role in shaping its capabilities for health care applications while concurrently addressing many HIS phenomena. In chapter two, this study draws from extant theories within the healthcare arena to present knowledge and insight that pinpoint and construct the development of sustainable and resilient HIS from a data-driven angle in chapter three. The proposed framework to develop a data-driven resilient, sustainable HIS for health care applications shown in Figure 3-1 was developed, expanding the knowledge in Chapter 2. In chapter three, a research methodology that traversed the main aim of this study at the intersection of design science research and data sciences in conjunction with a socio-technological concept to afford a resilient and sustainable HIS for health care applications is presented. Additionally, in the course of this study, the performance of HIS and health care applications was revealed from the analysis of the extant body of gen on healthcare using bibliometric analysis. A journal publication to this effect was published in the healthcare special issue of MDPI, a Web of Science and Scopus index journal.

7.2.4 To structure an efficient and effective holistic model framework for a robust, resilient and sustainable integrated information system for health care applications

The fourth objective of this study was focused on developing a data-driven paradigm for achieving a resilient and sustainable HIS. The driving question: *What framework can be used to achieve a robust, resilient, and sustainable integrated Health Information System?* It was answered in chapter 4 of this thesis. The proposed model in Chapter 3 was expounded to demonstrate the positioning of the data-driven paradigm in the healthcare environment where HIS is deployed. This chapter proffered a detailed elucidation of the data-driven "resilient and sustainable HIS" for health care applications. The chapter highlighted data sciences' descriptive, predictive and prescriptive capabilities in revolutionising health care applications. This premise relied on the nebulous stances of the HIS, whose benefits have been blurred out due to challenges that obscure its capabilities to afford quality health care applications. Thus, chapter four presents an overview of the existing HIS framework with the proposed data-driven paradigm for its sustainability and resilience. It discusses data sources, actions and decisions and data sciences techniques within the healthcare arena. Additionally, it highlights data sciences techniques that could be deployed in the health arena for health care applications to attain HIS sustainability and resilience (figure 4-1). And illustrate the need for its serialisation within the healthcare system. The implementation and application of generated insights from data sciences were also presented to complete the paradigm.

7.2.5 To empirically validate data science techniques for achieving a resilient and sustainable HIS and evaluate the developed machine learning model with other models using well-known metrics

For the fifth objective of this study, the accompanying research question was: *How can data science techniques empirically validate HIS resilience and sustainability, and how can the developed machine learning model be evaluated relative to different models using well-known metrics*? The data-driven paradigm presented and discussed in chapter four is a framework that can be used to attain a "resilient and sustainable" integrated information system for health care applications. To validate this response, chapter five demonstrated the enactment of this framework on a HIS generated data, namely, the electronic health record of patients' laboratory tests. This chapter accentuates a data science application of a health data to predict the degree of severity of patients' conditions that can be used to determine the appropriate health care applications as well as allocation of resources within the healthcare arena.

The study employed state-of-the-art classical and ensemble machine learning models. The testing and training datasets were assessed to ascertain their performance for each model. The developed models were evaluated using well-known machine-learning metrics that indicated their accuracy, precision, recall and F1 scores. The evaluation of the models' performance enables the model's parameter tuning to enhance their effectiveness. Chapter 5.12 presented the findings and highlighted their application in transforming the health care application. Applying these techniques demonstrates how a data science technique could revolutionise the utilisation of HIS to enhance the healthcare system. Thus, the practical enactment of an effective holistic model framework that incorporates data sciences to achieve a robust, resilient and sustainable integrated system such as the HIS for health care applications was asserted. The data-driven paradigm is set to be presented at the US conference promoting development in Africa.

7.2.6 To enact the best deployment model for enhancing the healthcare information system

The sixth objective was to answer the following question: How can the best model be deployed to achieve a resilient and sustainable integrated information system for health care applications? In Chapter 5, the developed machine-learning models were compared, and the best model was selected for deployment. The random forest model was the best model among all the other models. A web interface was developed for the deployment of the model. The interface can be integrated into an existing HIS to support healthcare providers with automating decision-making and also enhance healthcare efficiency and effectiveness. Deploying and implementing this model in the real world would necessitate perpetual monitoring to refine, maintain, update and retrain it to maintain its effectiveness and efficiency.

Figure 7-1 presents the model interface. This computational prototype is a demonstration of the model's predictions with random numbers can also be seen below, where the model returned a decision indicating the severity of the patient's condition. Integrating this model into existing HIS would tackle several issues concomitant with healthcare inefficiencies, such as long delays, resource allocation and even mortality. **Figures 7-2** and **7-3** illustrate the two types of decisions the model provides based on the input report of the laboratory test. These target decisions are based on the degree of severity of the patient's health. The first decision demonstrated in Figure 7-2 indicates the severity of the patient's health to be less critical and reveals the type of treatment to be home-based. The subsequent decision signposts the severity of the patient's health to be highly critical and indicates the type of treatment to be hospital-based. In this case, the dictation of the mode of treatment could also influence the distribution of resources in the healthcare arena and save ample time for prompt intervention that subsequently enhances both the healthcare and its integrated information systems.

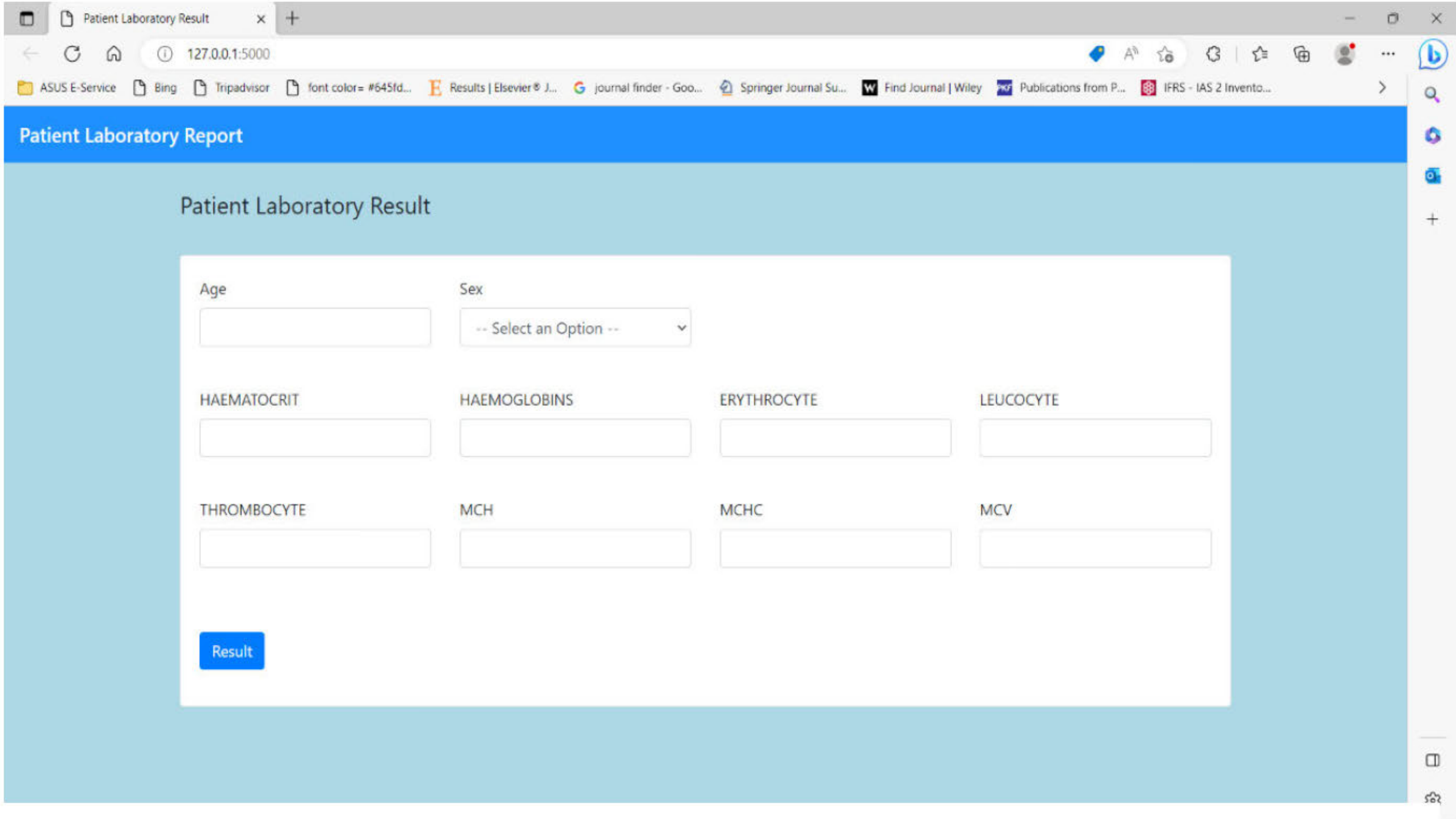

Figure 7-1 Model Application interface

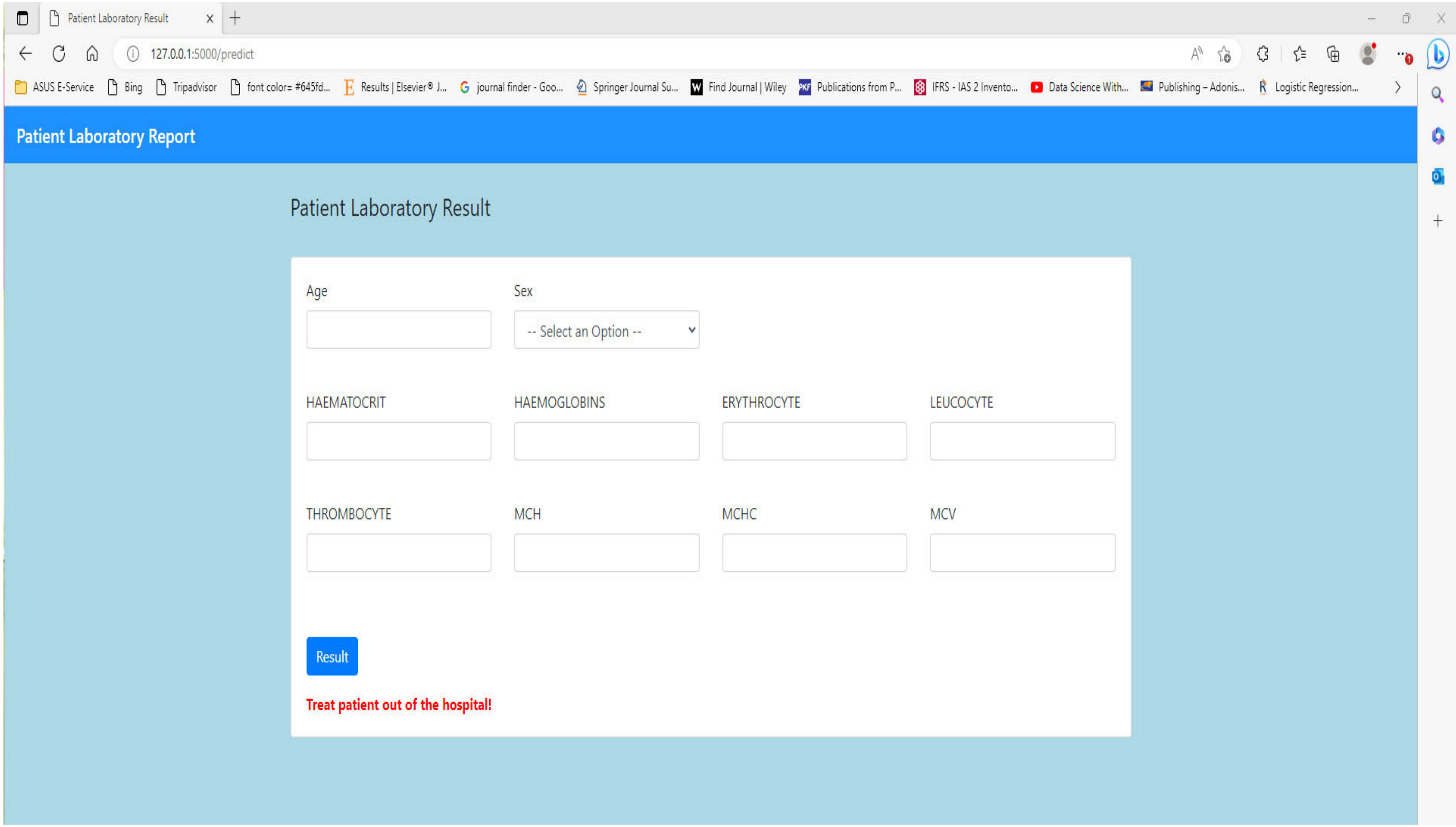

Figure 7-2 The target decision is "treat patient out of the hospital!"

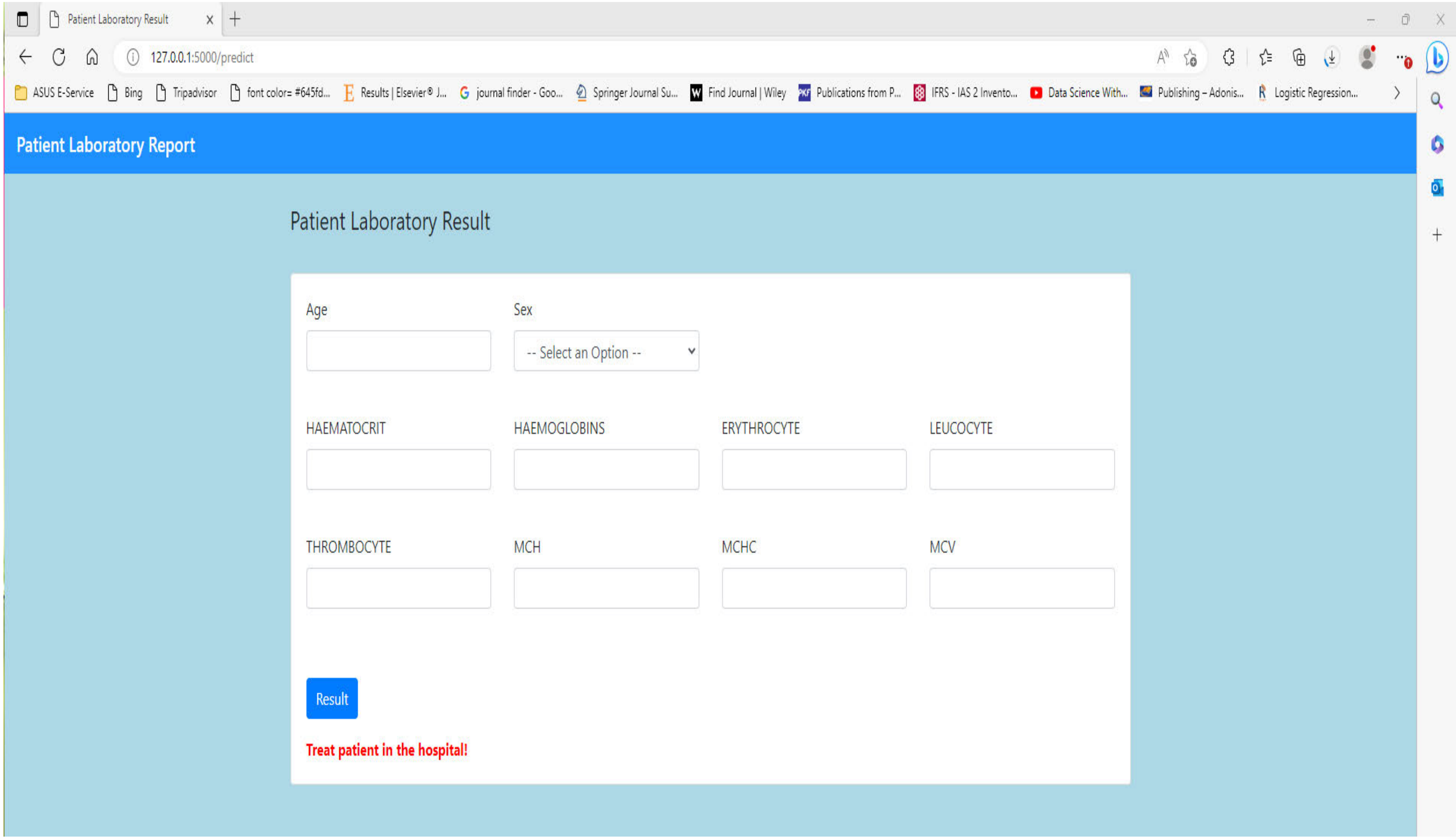

Figure 7-3 The target decision is "treat patient in the hospital!"

7.2.7 To provide theoretical and practical reflections from the study that may be used to implement a resilient and sustainable HIS

Finally, this study's last objective was to answer the question: *How can the study's findings be used to implement a resilient and sustainable* HIS? To accomplish this, chapter six offered practical and theoretical contributions, construed from the research reflections, to answer this question. They served as recommendations and suggestions tailored to the stakeholders' needs. These recommendations and guidance have been detailed in chapter six and presented in this chapter, which affords the final reflection of this study. Chapter six highlights the theoretical and practical contributions towards attaining a resilient and sustainable integrated information system for health care applications. The synthesized contributions serve as reference points that, upon adoption, can augment both HIS and health care applications. The findings in this study present theoretical constructs for scholars to expound on the advancement of technological ameliorations within healthcare and healthcare-related research. The results are practical artefacts for stakeholders' utilisation and serve organisations with the base for future healthcare initiative drives. Additionally, from this study, executive and strategical action can be taken to accentuate the implementation of a resilient and sustainable HIS for health care applications enhancement that urgently needed today.

7.3 An overview of knowledge generated from an analysed integrated IS for HIS resilience and sustainability

The deployment of HIS is instrumental in realising many sustainable development goals related to health and digitalisation. Sustainable development goals three and nine of the United Nations development programme (UNDP) highlight critical needs for which the knowledge generated from this study could serve as a practical amelioration. Specifically, goal 3, which focuses on good health and well-being, indicates uneven progress and off-track trigger. Goal 9, which focuses on industry, innovation and infrastructure, identified technological progress as a crucial component in achieving abiding solutions to economic and environmental challenges. These goals demand long-lasting solutions that solve their respective issues and serve as a foundation for their realisation by 2030. This study aligns with this strategy to afford theoretical and practical amelioration. The knowledge generated from this study can be utilised in various ways to benefit the global population. The findings and contribution could be employed in decision-making processes, monitoring and evaluation performances, affiliation management, collaborations and knowledge sharing, strategy development, product optimisations and predictive and forecasting analytics.

Given that knowledge generation from integrated information systems such as HIS is not an isolated function, the principal theory emphasized in this study is the socio-technological stance. With technology and humans giving equal attention, achieving these goals would be a reality. The proposed methodological framework presented and enacted in this work is a novel data-driven approach to sustainability and resilience inspired by the data influx, technological advances and the need for abiding solutions to global transformation. The solution developed solves complex and ill-defined problems with the HIS.

Systematically and iteratively deploying this multidisciplinary strategic output would benefit many stakeholders, such as healthcare, policy, technology, environmental and scholars. It is imperative to note that although transformations of any sort can be confined, measures that distinctive enable the identification of challenges can offer appending solutions. Thus, using the developed data-driven paradigm for achieving a resilient and sustainable HIS for healthcare applications could present applaudable benefits to the global society by promoting good health and well-being, supporting industries development, driving technological innovations and reinforcing and developing robust smartly enabled infrastructures.

7.4 Inference

From the work in this study, we uncovered that data science could afford valuable insight into the attainment of a "resilient and sustainable" HIS for health care applications that stakeholders by themselves are limited. Although this is not an absolute resolution to many of the challenges confronting the health systems globally. It is, however, an inimitable offering that affords ameliorations to enhance healthcare. Thus incorporating the data-driven paradigm within any HIS setting will afford tangible and beneficial outcomes that validate the input from data sciences as an important constituent within the health care system. The reproducible pipeline of the data sciences technique employed in this study infers that this application can be reused within practical settings considering the realistic setting context. Therefore, to support the attainment of a "resilient and sustainable" HIS for health care applications, it is necessary to consider the offerings from data sciences as well as the practical setting context.

Moreover, considering the contribution of data sciences in a parallel set-up with system thinking in place is advantageous for the knowledge created in this study to be incorporated within the healthcare arena. Doing so will enable the augmentation of HIS technological advancement and assert the possibility of the extension of this work and that data can be used to create knowledge for humans and humanoids through insight generated from it. Although this may not be the prime elucidation in the field, it is a rational, unswerving effort towards addressing many phenomena confronting technological advancement within the healthcare space.

Furthermore, this novel approach presented in this study anchors on data sciences applications such as machine learning and artificial intelligence. On its own is limited and cannot be standalone within the health care systems. The need for stakeholders' active involvement is demanded within the deployment of this paradigm. There are several implications of the enactment of artificial intelligence. While it may create value and reshape systems, it also poses perils from diverse angles within the same systems. Thus, in this study, the emphasis was on the knowledge-creation capabilities of data sciences. Our discussion accentuates the value creation and its implementation with emphasis on stakeholders' active involvement in the enactment, as certain cognitive abilities within healthcare practices are complex and not completely grasped. This premise infers that data on itself can not only be used to scheme HIS capabilities but also be used for scheming itself. Therefore, it is evident that there are confinements to this extent to which designs created by data using data sciences techniques are subjective. These reinforce the notion that the definition of any problem is a human task, not a machine problem.

Academically, the study implications present vast fissures in the areas of HIS implementation, healthcare, health care applications and data investigation. These fissures can be subjugated yonder by academics and practitioners to enhance understanding of what makes a resilient and sustainable HIS for health care applications via the data track to enact long-lasting strategic initiatives. These inferences, therefore, serve as a feasible segment for forthcoming research.

7.5 Future research

Several future research and work directions emanating from this study are significantly relevant to healthcare and HIS development. These future works are anchored on core agendas and practical objectives associated with sustainable development implementations and healthcare applications. There are health care application segments that are lagging in adopting and optimising HIS for healthcare coverage. These segments require future research and work that takes into consideration their context to implement practical and robust enactment of HIS. Thus few of such future research work that delves into healthcare-related agendas would be to:

Implement pilot projects incorporating data-driving paradigm into existing HIS.

Investigates the data-driven paradigm dares that hinder the enactment of a HIS for healthcare service delivery.

Investigating the transferability and generalisation of data insight implementation

Examine the service planning and management tools to uncover the HIS contributions to health development.

Investigating healthcare and climate change with mediating role of HIS within this dispensation.

Lastly, another scope of research for the future is the impact of data sciences on the quality of healthcare to enable proactive measures that combat eminent and uncertain challenges.

7.6 Conclusion

Technological advancement globally has presented many blessings and perils. Every technological development contains a parallel advantage and disadvantage. In the healthcare arena, HIS has been deployed as a core constituent within the healthcare system. Similar to its technology counterpart, it has offered significant opportunities and threats. There have been several measures to mitigate this downside and harness the potential of HIS within the healthcare arena. Thus, this study adds to the existing body on gen on HIS, health care application and data sciences. The findings serve as a vital tool for mitigating challenges confronting these areas. Thus, the foremost objective of this study was to employ data to attain a resilient and sustainable HIS for health care applications. Guided by this objective, this study fulfilled its purpose. The findings reveal insight from extant literature that supported the intersection of design science research and data sciences in conjunction with a socio-technological concept to afford a resilient and sustainable HIS for health care applications. The findings also acknowledge the existing HIS frameworks and present the data-driven paradigm for sustainability and resilience and discourse data sources, actions and decisions within the context of the healthcare arena. Furthermore, this study demonstrated the practical enactment of the effective holistic model framework that incorporates data sciences to attain a robust, resilient and sustainable integrated system such as the HIS for health care applications. To provide healthcare stakeholders with a unique offering to enhance healthcare and future research angle that focuses on the model's implementation.

REFERENCES

Abbasi, R., Khajouei, R. and Mirzaee, M. 2019. Evaluating the demographic and clinical minimum data sets of Iranian National Electronic Health Record. *Bmc Health Services Research*, 19: 10.

AbouZahr, C. and Boerma, T. 2005. Health information systems: the foundations of public health. *Bulletin of the World Health Organization*, 83: 578-583.

Adaba, G. B. and Kebebew, Y. 2018. Improving a health information system for real-time data entries: An action research project using socio-technical systems theory. *Informatics for Health & Social Care*, 43 (2): 159-171.

Adams, A. M., Ahmed, T., El Arifeen, S., Evans, T. G., Huda, T., Reichenbach, L., Ahmed, F., Ahmed, S., Ahmed, S. M., Azad, K., Bhuiya, A., Mahmood, S. S., Cash, R. A., Chen, L. C., Chowdhury, M. E., Chowdhury, A. M. R., Christou, A., Halder, S. R., Husain, M., Islam, M. S., Islam, K. S., Huq, S., Hussain, Z., Mahmud, S., Mallick, F. H., May, M. A., Osman, F. A., Peters, D. H., Perry, H., Rabbani, A., Rahman, M. A., Rahman, M., Rasheed, S., F Rashid, S., Al-Sabir, A. and Standing, H. 2013. Innovation for universal health coverage in Bangladesh: A call to action. *The Lancet*, 382 (9910): 2104-2111.

Adeliyi, T. T., Oyewusi, L., Epizitone, A. and Oyewusi, D. 2022. Analysing Factors Influencing Women Unemployment Using a Random Forest Model. *Hong Kong Journal of Social Sciences*,.

Agarwal, S. and Chowdary, C. R. 2020. A-Stacking and A-Bagging: Adaptive versions of ensemble learning algorithms for spoof fingerprint detection. *Expert Systems with Applications*, 146: 113160.

Ahmad, Z., Rai, A., Hasan, M. J., Kim, C. H. and Kim, J. M. 2021. A Novel Framework for Centrifugal Pump Fault Diagnosis by Selecting Fault Characteristic Coefficients of Walsh Transform and Cosine Linear Discriminant Analysis. *Ieee Access*, 9: 150128-150141.

Ahmadi, M. 2017. Dimensions and Assessment Methods of Data Quality in Health Information Systems. *Acta Medica Mediterranea*, 33 (2): 313-320.

Ahmadi, M., Khorrami, F., Dehnad, A., Golchin, M. H., Azad, M. and Rahimi, S. 2018. A Survey of Managers' Access to Key Performance Indicators via HIS: The Case of Iranian Teaching Hospitals. *Stud Health Technol Inform*, 248: 233-238.

Ajami, S. and Arab-Chadegani, R. 2013. Barriers to implement Electronic Health Records (EHRs). *Materia socio-medica*, 25 (3): 213-215.

Akbar, N. A., Sunyoto, A., Arief, M. R. and Caesarendra, W. 2020. Improvement of decision tree classifier accuracy for healthcare insurance fraud prediction by using Extreme Gradient Boosting algorithm. In: Proceedings of *2020 International conference on informatics, multimedia, cyber and information system (ICIMCIS)*. IEEE, 110-114.

Al-Marsy, A., Chaudhary, P. and Rodger, J. A. 2021. A Model for Examining Challenges and Opportunities in Use of Cloud Computing for Health Information Systems. *Applied System Innovation*, 4 (1).

Al-Shorbaji, N., Househ, M., Taweel, A., Alanizi, A., Mohammed, B. O., Abaza, H., Bawadi, H., Rasuly, H., Alyafei, K. and Fernandez-Luque, L. 2018. Middle east and North African health informatics association (MENAHIA): building sustainable collaboration. *Yearbook of medical informatics*, 27 (01): 286-291.

Aladjem, M. 1997. Linear discriminant analysis for two classes via removal of classification structure. *Ieee Transactions on Pattern Analysis and Machine Intelligence*, 19 (2): 187-192.

Alahmar, A., AlMousa, M. and Benlamri, R. 2022. Automated clinical pathway standardization using SNOMED CT- based semantic relatedness. *Digital Health*, 8: 17.

Alahmar, A., Crupi, M. E. and Benlamri, R. 2020. Ontological framework for standardizing and digitizing clinical pathways in healthcare information systems. *Comput Methods Programs Biomed*, 196: 105559.

Alharbi, M. T. and Almutiq, M. M. 2022. Prediction of Dental Implants Using Machine Learning Algorithms. *Journal of Healthcare Engineering*, 2022.

Almunawar, M. N. and Anshari, M. 2012. Health information systems (HIS): Concept and technology. *arXiv preprint arXiv:1203.3923*, Article ID.

Alsharo, M., Alnsour, Y. and Alabdallah, M. 2020. How habit affects continuous use: evidence from Jordan's national health information system. *Informatics for Health & Social Care*, 45 (1): 43-56.

Ammenwerth, E., Duftschmid, G., Al-Hamdan, Z., Bawadi, H., Cheung, N. T., Cho, K. H., Goldfarb, G., Gulkesen, K. H., Harel, N., Kimura, M., Kirca, O., Kondoh, H., Koch, S., Lewy, H., Mize, D., Palojoki, S., Park, H. A., Pearce, C., de Quiros, F. G. B., Saranto, K., Seidel, C., Vimarlund, V., Were, M. C., Westbrook, J., Wong, C. P., Haux, R. and Lehmann, C. U. 2020. International Comparison of Six Basic eHealth Indicators Across 14 Countries: An eHealth Benchmarking Study. *Methods of Information in Medicine*, 59: e46-e63.

Ammenwerth, E., Iller, C. and Mahler, C. 2006. IT-adoption and the interaction of task, technology and individuals: a fit framework and a case study. *BMC medical informatics and decision making*, 6: 1-13.

Ammenwerth, E., Knaup, P., Winter, A., Bauer, A. W., Bott, O. J., Gietzelt, M., Haarbrandt, B., Hackl, W. O., Hellrung, N., Hubner-Bloder, G., Jahn, F., Jaspers, M. W., Kutscha, U., Machan, C., Oppermann, B., Pilz, J., Schwartze, J., Seidel, C., Slot, J. E., Smers, S., Spitalewsky, K., Steckel, N., Strubing, A., van der Haak, M., Haux, R. and ter Burg, W. J. 2017. On Teaching International Courses on Health Information Systems Lessons Learned during 16 Years of Frank - van Swieten Lectures on Strategic Information Management in Health Information Systems. *Methods of Information in Medicine*, 56: E39-E48.

Andargoli, A. E., Scheepers, H., Rajendran, D. and Sohal, A. 2017. Health information systems evaluation frameworks: A systematic review. *International Journal of Medical Informatics*, 97: 195-209.

Anshari, M. and Almunawar, M. N. 2015. Tracking Future Path of Consumers' Empowerment in E-Health. *International Journal of E-Health and Medical Communications (IJEHMC)*, 6 (3): 63-76.

Anwar, J., Torvaldsen, S., Sheikh, M. and Taylor, R. 2018. Under-estimation of maternal and perinatal mortality revealed by an enhanced surveillance system: enumerating all births and deaths in Pakistan. *BMC Public Health*, 18 (1): 428.

Askar, A., Ardakani, M. and Majdzade, R. 2017. Bridging gaps in health information systems: a case study from Somaliland, Somalia. *Eastern Mediterranean Health Journal*, 23 (11): 764-773.

Asselman, A., Khaldi, M. and Aammou, S. 2021. Enhancing the prediction of student performance based on the machine learning XGBoost algorithm. *Interactive Learning Environments*, Article ID: 1-20.

Åsvoll, H. 2014. Abduction, deduction and induction: can these concepts be used for an understanding of methodological processes in interpretative case studies? *International Journal of Qualitative Studies in Education*, 27 (3): 289-307.

Aung, E. and Whittaker, M. 2013. Preparing routine health information systems for immediate health responses to disasters. *Health Policy and Planning*, 28 (5): 495-507.

Averill, R. F., Hughes, J. S., Fuller, R. L. and Goldfield, N. I. 2017. Quality Improvement Initiatives Need Rigorous Evaluation: The Case of Pressure Ulcers. *Am J Med Qual*, 32 (5): 552-555.

Awang Kalong, N. and Yusof, M. 2017. Waste in health information systems: a systematic review. *Int J Health Care Qual Assur*, 30 (4): 341-357.

Ayabakan, S., Bardhan, I., Zheng, Z. and Kirksey, K. 2017. The Impact of Health Information Sharing on Duplicate Testing. *MIS Quarterly*, 41 (4).

Ayele, W., Biruk, E., Habtamu, T., Tayer, G., Sisay, A. and Getachew, D. 2021. Implementation of Human Development Model Impact on Data Quality and Information Use in Addis Ababa, Ethiopia. *Ethiopian Journal of Health Development*, 35: 50-58.

Ayeni, F., Omogbadegun, Z., Omoregbe, N., Misra, S. and Garg, L. 2018. Overcoming barriers to healthcare access and delivery. *EAI Endorsed Transactions on Pervasive Health and Technology*, 4 (15): e2-e2.

Aziz, H. A. 2017. A review of the role of public health informatics in healthcare. *J Taibah Univ Med Sci*, 12 (1): 78-81.

Azzopardi-Muscat, N., Kluge, H. H. P., Asma, S. and Novillo-Ortiz, D. 2021. A call to strengthen data in response to COVID-19 and beyond. *Journal of the American Medical Informatics Association*, 28 (3): 638-639.

Bacigalupo, I., Lombardo, F., Bargagli, A. M., Cascini, S., Agabiti, N., Davoli, M., Scalmana, S., Di Palma, A., Greco, A., Rinaldi, M., Imperiale, D., Secreto, P., Golini, N., Gnavi, R., Biagini, C., Gualdani, E., Francesconi, P., Magliocchetti, N., Di Fiandra, T. and Vanacore, N. 2021. Validation of AN algorithm based on data of the health information systems (HIS) for the identification of dementia cases. *Journal of the Neurological Sciences*, 429: 115-115.

Bagayoko, C. O., Tchuente, J., Traoré, D., Moukoumbi Lipenguet, G., Ondzigue Mbenga, R., Koumamba, A. P., Ondjani, M. C., Ndjeli, O. L. and Gagnon, M. P. 2020. Implementation of a national electronic health information system in Gabon: a survey of healthcare providers' perceptions. *BMC Med Inform Decis Mak*, 20 (1): 202.

Bahad, P. and Saxena, P. 2020. Study of adaboost and gradient boosting algorithms for predictive analytics. In: Proceedings of *International Conference on Intelligent Computing and Smart Communication 2019: Proceedings of ICSC 2019*. Springer, 235-244.

Bargagli, A. M., Cascini, S., Agabiti, N., Kirchmayer, U., Marino, C. and Davoli, M. 2019. Determinants Of Antipsychotic Drugs Prescription Among Community-Living Older Adults With Dementia: A Population-Based Study Using Health Information Systems In The Lazio Region, Italy. *Clin Interv Aging*, 14: 2071-2083.

Baskerville, R., Baiyere, A., Gregor, S., Hevner, A. and Rossi, M. 2018. Design science research contributions: Finding a balance between artifact and theory. *Journal of the Association for Information Systems*, 19 (5): 3.

Baskerville, R. L., Kaul, M. and Storey, V. C. 2015. Genres of inquiry in design-science research. *Mis Quarterly*, 39 (3): 541-564.

Bawack, R. E. and Kamdjoug, J. R. K. 2018. Adequacy of UTAUT in clinician adoption of health information systems in developing countries: The case of Cameroon. *International Journal of Medical Informatics*, 109: 15-22.

Beck, E. J., Shields, J. M., Tanna, G., Henning, G., de Vega, I., Andrews, G., Boucher, P., Benting, L., Garcia-Calleja, J. M., Cutler, J., Ewing, W., Kijsanayotin, B., Kujinga, T., Mahy, M., Makofane, K., Marsh, K., Nacheeva, C., Rangana, N., Vega, M. F. R., Sabin, K., Varetska, O., Macharia Wanyee, S., Watiti, S., Williams, B., Zhao, J., Nunez, C., Ghys, P. and Low-Beer, D. 2018. Developing and implementing national health identifiers in resource limited countries: why, what, who, when and how? *Glob Health Action*, 11 (1): 1440782.

Beinke, J. H., Fitte, C. and Teuteberg, F. 2019. Towards a stakeholder-oriented blockchain-based architecture for electronic health records: design science research study. *Journal of medical Internet research*, 21 (10): e13585.

Bell, J. J., Rossi, T., Bauer, J. D. and Capra, S. 2014. Developing and evaluating interventions that are applicable and relevant to inpatients and those who care for them; a multiphase, pragmatic action research approach. *BMC medical research methodology*, 14 (1): 1-10.

Benbrahim, H., Hachimi, H. and Amine, A. 2018. Moroccan Electronic Health Record System. In: Proceedings of *Proceedings of the International Conference on Industrial Engineering and Operations Management Paris, France*. 1-8.

Benis, A., Harel, N., Barak Barkan, R., Srulovici, E. and Key, C. 2018. Patterns of Patients' Interactions With a Health Care Organization and Their Impacts on Health Quality Measurements: Protocol for a Retrospective Cohort Study. *JMIR Res Protoc*, 7 (11): e10734.

Bernardi, R. 2017. Health Information Systems and Accountability in Kenya: A Structuration Theory Perspective. *Journal of the Association for Information Systems*, 18 (12): 931-958.

Bernardi, R., Constantinides, P. and Nandhakumar, J. 2017. Challenging Dominant Frames in Policies for IS Innovation in Healthcare through Rhetorical Strategies. *Journal of the Association for Information Systems*, 18 (2): 81-112.

Berrueta, M., Bardach, A., Ciaponni, A., Xiong, X., Stergachis, A., Zaraa, S. and Buekens, P. 2020. Maternal and neonatal data collection systems in low- and middle-income countries: scoping review protocol. *Gates Open Res*, 4: 18.

Bertelsen, P., Petersen, L. S. and Nøhr, C. 2020. Does Health-IT Improve People Centered Care? *Studies in health technology and informatics*, 270: 956-960.

Bhati, B. S. and Rai, C. 2020. Ensemble based approach for intrusion detection using extra tree classifier. In: Proceedings of *Intelligent Computing in Engineering: Select Proceedings of RICE 2019*. Springer, 213-220.

Bhattacharya, A. A., Umar, N., Audu, A., Felix, H., Allen, E., Schellenberg, J. R. and Marchant, T. 2019. Quality of routine facility data for monitoring priority maternal and newborn indicators in DHIS2: a case study from Gombe state, Nigeria. *PloS one*, 14 (1): e0211265.

Bianchini, M. and Scarselli, F. 2014. On the complexity of neural network classifiers: A comparison between shallow and deep architectures. *IEEE transactions on neural networks and learning systems*, 25 (8): 1553-1565.

Biau, G. 2012. Analysis of a random forests model. *The Journal of Machine Learning Research*, 13 (1): 1063-1095.

Biru, A., Birhan, D., Melkamu, G., Gebeyehu, A. and Omer, A. M. 2022. Pathways to improve health information systems in Ethiopia: current maturity status and implications. *Health Res Policy Syst*, 20 (1): 78.

Blower, P. E. and Cross, K. P. 2006. Decision tree methods in pharmaceutical research. *Current Topics in Medicinal Chemistry*, 6 (1): 31-39.

Boerma, T., Requejo, J., Victora, C. G., Amouzou, A., George, A., Agyepong, I., Barroso, C., Barros, A. J., Bhutta, Z. A., Black, R. E. and Borghi, J. 2018. Countdown to 2030: tracking progress towards universal coverage for reproductive, maternal, newborn, and child health. *The Lancet*, 391 (10129): 1538-1548.

Bogaert, P., For, H. V. and Hlth, B. 2017. An integrated and sustainable EU health information system: national public health institutes' needs and possible benefits. *Archives of Public Health*, 75.

Bogaert, P., van Oers, H. and Van Oyen, H. 2018. Towards a sustainable EU health information system infrastructure: A consensus driven approach. *Health Policy*, 122 (12): 1340-1347.

Bogaert, P. and Van Oyen, H. 2017. An integrated and sustainable EU health information system: national public health institutes' needs and possible benefits. *Archives of Public Health*, 75 (1): 1-5.

Boikos, C., Imran, M., De Lusignan, S., Ortiz, J. R., Patriarca, P. A. and Mansi, J. A. 2022. Integrating Electronic Medical Records and Claims Data for Influenza Vaccine Research. *Vaccines (Basel)*, 10 (5).

Bosch-Capblanch, X., Oyo-Ita, A., Muloliwa, A. M., Yapi, R. B., Auer, C., Samba, M., Gajewski, S., Ross, A., Krause, L. K., Ekpenyong, N., Nwankwo, O., Njepuome, A. N., Lee, S. M., Sacarlal, J., Madede, T., Berté, S., Matsinhe, G., Garba, A. B. and Brown, D. W. 2021. Does an innovative paper-based health information system (PHISICC) improve data quality and use in primary healthcare? Protocol of a multicountry, cluster randomised controlled trial in sub-Saharan African rural settings. *BMJ Open*, 11 (7): e051823.

Bouhaddou, O., Bennani Othmani, M. and Diouny, S. 2013. Medical informatics in morocco. *Yearbook of medical informatics*, 8: 190-196.

Bozorgmehr, K., Goosen, S., Mohsenpour, A., Kuehne, A., Razum, O. and Kunst, A. E. 2017. How Do Countries' Health Information Systems Perform in Assessing Asylum Seekers' Health Situation? Developing a Health Information Assessment Tool on Asylum Seekers (HIATUS) and Piloting It in Two European Countries. *International Journal of Environmental Research and Public Health*, 14 (8).

Braa, J. and Sahay, S. 2012. *Participatory Design within the HISP network*. Routledge, New York.

Braithwaite, J., Churruca, K., Ellis, L. A., Long, J., Clay-Williams, R., Damen, N., Herkes, J., Pomare, C. and Ludlow, K. 2017. Complexity science in healthcare. *Sydney: Australian Institute of Health Innovation, Macquarie University*, Article ID.

Braunack-Mayer, A., Fabrianesi, B., Street, J., O'Shaughnessy, P., Carter, S. M., Engelen, L., Carolan, L., Bosward, R., Roder, D. and Sproston, K. 2021. Sharing Government Health Data With the Private Sector: Community Attitudes Survey. *Journal of Medical Internet Research*, 23 (10): 14.

Braveman, P. 2014. What are health disparities and health equity? We need to be clear. *Public health reports*, 129 (1_suppl2): 5-8.

Breiman, L. 2001. Random forests. *Machine learning*, 45 (1): 5-32.

Breiman, L., Friedman, J., Olshen, R. and Stone, C. 1984. *Classification and regression trees. Monterey, CA: wadsworth & Brooks/Cole advanced books & software*.

Bygholm, A. 2018. Staff Training on the Use of Health Information Systems: What Do We Know? *Stud Health Technol Inform*, 247: 191-195.

Chaney, S. C., Mechael, P., Thu, N. M., Diallo, M. S. and Gachen, C. 2021. Every Child on the Map: A Theory of Change Framework for Improving Childhood Immunization Coverage and Equity Using Geospatial Data and Technologies. *Journal of Medical Internet Research*, 23 (8): 9.

Chanyalew, M. A., Yitayal, M., Atnafu, A., Mengiste, S. A. and Tilahun, B. 2022. The Effectiveness of the Capacity Building and Mentorship Program in Improving Evidence-Based Decision-making in the Amhara Region, Northwest Ethiopia: Difference-in-Differences Study. *JMIR Med Inform*, 10 (4): e30518.

Chaudhry, B., Wang, J., Wu, S. Y., Maglione, M., Mojica, W., Roth, E., Morton, S. C. and Shekelle, P. G. 2006. Systematic review: Impact of health information technology on quality, efficiency, and costs of medical care. *Annals of Internal Medicine*, 144 (10): 742-752.

Chen, H., Yu, P., Hailey, D. and Cui, T. R. 2020. Identification of the essential components of quality in the data collection process for public health information systems. *Health Informatics Journal*, 26 (1): 664-682.

Chen, H., Yu, P., Hailey, D. and Cui, T. R. 2021. Validation of 4D Components for Measuring Quality of the Public Health Data Collection Process: Elicitation Study. *Journal of Medical Internet Research*, 23 (5): 16.

Chen, J. I. Z. and Hengjinda, P. 2021. Early prediction of coronary artery disease (CAD) by machine learning method-a comparative study. *Journal of Artificial Intelligence*, 3 (01): 17-33.

Chen, L., Baird, A. and Straub, D. W. 2019. An analysis of the evolving intellectual structure of health information systems research in the information systems discipline. In: Proceedings of. Association for Information Systems,

Chumachenko, D., Meniailov, I., Bazilevych, K., Chumachenko, T. and Yakovlev, S. 2022. Investigation of statistical machine learning models for COVID-19 epidemic process simulation: Random forest, K-nearest neighbors, gradient boosting. *Computation*, 10 (6): 86.

Citrin, D., Thapa, P., Nirola, I., Pandey, S., Kunwar, L. B., Tenpa, J., Acharya, B., Rayamazi, H., Thapa, A., Maru, S., Raut, A., Poudel, S., Timilsina, D., Dhungana, S. K., Adhikari, M., Khanal, M. N., Pratap, K. C. N., Acharya, B., Karki, K. B., Singh, D. R., Bangura, A. H., Wacksman, J., Storisteanu, D., Halliday, S., Schwarz, R., Schwarz, D., Choudhury, N., Kumar, A., Wu, W. J., Kalaunee, S. P., Chaudhari, P. and Maru, D. 2018. Developing and deploying a community healthcare worker-driven, digitally-enabled integrated care system for municipalities in rural Nepal. *Healthcare-the Journal of Delivery Science and Innovation*, 6 (3): 197-204.

Clay-Williams, R. and Braithwaite, J. 2019. *Resilient Health Care: A Determinant Framework for Understanding Variation in Everyday Work and Designing Sustainable Digital Health Systems* (Article). IOS Press. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85071189718&doi=10.3233%2fSHTI190118&partnerID=40&md5=d58e717749483e12d3396c04bc726dd6 https://ebooks.iospress.nl/pdf/doi/10.3233/SHTI190118 (Accessed 10 October 2022).

Colais, P., Agabiti, N., Davoli, M., Buttari, F., Centonze, D., De Fino, C., Di Folco, M., Filippini, G., Francia, A., Galgani, S., Gasperini, C., Giuliani, M., Mirabella, M., Nociti, V., Pozzilli, C. and Bargagli, A. 2017. Identifying Relapses in Multiple Sclerosis Patients through Administrative Data: A Validation Study in the Lazio Region, Italy. *Neuroepidemiology*, 48 (3-4): 171-178.

Colais, P., Bontempi, K., Pinnarelli, L., Piscicelli, C., Mappa, I., Fusco, D. and Davoli, M. 2018. Vaginal birth after caesarean birth in Italy: variations among areas of residence and hospitals. *BMC Pregnancy Childbirth*, 18 (1): 383.

Combi, C. and Pozzi, G. 2019. Clinical Information Systems and Artificial Intelligence: Recent Research Trends. *Yearb Med Inform*, 28 (1): 83-94.

Cook, E. J., Randhawa, G., Sharp, C., Ali, N., Guppy, A., Barton, G., Bateman, A. and Crawford-White, J. 2016. Exploring the factors that influence the decision to adopt and engage with an integrated assistive telehealth and telecare service in Cambridgeshire, UK: a nested qualitative study of patient 'users' and 'non-users'. *Bmc Health Services Research*, 16.

Cotlear, D., Nagpal, S., Smith, O., Tandon, A. and Cortez, R. 2015. *Going universal: how 24 developing countries are implementing universal health coverage from the bottom up*. World Bank Publications.

Craig, A. T., Joshua, C. A., Sio, A. R., Lauri, M., Kaldor, J., Rosewell, A. E. and Schierhout, G. 2018. Towards effective outbreak detection: a qualitative study to identify factors affecting nurses' early warning surveillance practice in Solomon Islands. *BMC health services research*, 18 (1): 702.

Crepaldi, N. Y., de Lima, I. B., Vicentine, F. B., Rodrigues, L. M. L., Sanches, T. L. M., Ruffino-Netto, A., Alves, D. and Rijo, R. 2018. Towards a Clinical Trial Protocol to Evaluate Health Information Systems: Evaluation of a Computerized System for Monitoring Tuberculosis from a Patient Perspective in Brazil. *Journal of Medical Systems*, 42 (6): 8.

Crepaldi, N. Y., de Lima, I. B., Vicentine, F. B., Rodrigues, L. M. L., Yamaguti, V. H., Sanches, T. L. M., Ruffino-Netto, A., Alves, D. and Rijo, R. P. C. L. 2017. Satisfaction evaluation of health professionals in the usability of software for monitoring the tuberculosis treatment. *Procedia Computer Science*, 121: 889-896.

Cresswell, K. and Sheikh, A. 2013. Organizational issues in the implementation and adoption of health information technology innovations: An interpretative review. *International Journal of Medical Informatics*, 82 (5): E73-E86.

Crooks, S., Hanisch, R., Edwards, B., Chao, A., Armstrong, H., Kohler, B., Michels, F., Soerjomataram, I. and Mery, L. 2022. Cancer registry operations in the Caribbean during the COVID-19 pandemic: a report of lessons learned and opportunities identified to support strong and sustainable health systems. *The Lancet. Oncology*, 23: S38.

Curtis, S. and Brandow, A. M. 2017. Responsiveness of Patient-Reported Outcome Measurement Information System (PROMIS) pain domains and disease-specific patient-reported outcome measures in children and adults with sickle cell disease. *Hematology Am Soc Hematol Educ Program*, 2017 (1): 542-545.

de Carvalho Junior, M. A. and Bandiera-Paiva, P. 2018. Health Information System Role-Based Access Control Current Security Trends and Challenges. *J Healthc Eng*, 2018: 6510249.

de Carvalho, M. A. and Bandiera-Paiva, P. 2020. Towards unobtrusive patient-centric access-control for Health Information System. *Concurrency and Computation-Practice & Experience*, 32 (22).

de Oliveira, V. C., Guimaraes, E. A. D., Perez, G., Zacharias, F. C. M., Cavalcante, R. B., Gontijo, T. L., Quites, H. F. D., Amaral, G. G., Silva, B. S. and Pinto, I. C. 2020. Factors related to the adoption of the Brazilian National Immunization Program Information System. *Bmc Health Services Research*, 20 (1): 10.

de Quiros, F. G. B., Dawidowski, A. R. and Figar, S. 2017. Representation of People's Decisions in Health Information Systems.* A Complementary Approach for Understanding Health Care Systems and Population Health. *Methods Inf Med*, 56 (S 01): e13-e19.

de Sanjose, S. and Tsu, V. D. 2019. Prevention of cervical and breast cancer mortality in low- and middle-income countries: a window of opportunity. *International Journal of Womens Health*, 11: 381-386.

Dehnavieh, R., Haghdoost, A., Khosravi, A., Hoseinabadi, F., Rahimi, H., Poursheikhali, A., Khajehpour, N., Khajeh, Z., Mirshekari, N. and Hasani, M. 2019. The District Health Information System (DHIS2): A literature review and meta-synthesis of its strengths and operational challenges based on the experiences of 11 countries. *Health Information Management Journal*, 48 (2): 62-75.

Delnord, M., Abboud, L. A., Costa, C. and Van Oyen, H. 2021. Developing a tool to monitor knowledge translation in the health system: results from an international Delphi study. *European Journal of Public Health*, 31 (4): 695-702.

Dhillon, A. and Singh, A. 2019. Machine learning in healthcare data analysis: a survey. *Journal of Biology and Today's World*, 8 (6): 1-10.

Digan, W., Neveol, A., Neuraz, A., Wack, M., Baudoin, D., Burgun, A. and Rance, B. 2021. Can reproducibility be improved in clinical natural language processing? A study of 7 clinical NLP suites. *Journal of the American Medical Informatics Association*, 28 (3): 504-515.

Dixon-Woods, M., Redwood, S., Leslie, M., Minion, J., Martin, G. P. and Coleman, J. J. 2013. Improving Quality and Safety of Care Using "Technovigilance": An Ethnographic Case Study of Secondary Use of Data from an Electronic Prescribing and Decision Support System. *Milbank Quarterly*, 91 (3): 424-454.

Dixon, B. E., McGowan, J. J. and Cravens, G. D. 2009. Knowledge sharing using codification and collaboration technologies to improve health care: lessons from the public sector. *Knowledge Management Research & Practice*, 7 (3): 249-259.

Donoho, D. 2017. 50 years of data science. *Journal of Computational and Graphical Statistics*, 26 (4): 745-766.

Doorn, N., Gardoni, P. and Murphy, C. 2019. A multidisciplinary definition and evaluation of resilience: The role of social justice in defining resilience. *Sustainable and Resilient Infrastructure*, 4 (3): 112-123.

Dortmans, E. and Punter, T. 2022. Behavior Trees for Smart Robots Practical Guidelines for Robot Software Development. *Journal of Robotics*, 2022.

Dresch, A., Lacerda, D. P., Antunes Jr, J. A. V., Dresch, A., Lacerda, D. P. and Antunes, J. A. V. 2015. *Design science research*. Springer International Publishing.

Dudley, L., Mamdoo, P., Naidoo, S. and Muzigaba, M. 2022. Towards a harmonised framework for developing quality of care indicators for global health: a scoping review of existing conceptual and methodological practices. *Bmj Health & Care Informatics*, 29 (1): 9.

Dunn, T. J., Browne, A., Haworth, S., Wurie, F. and Campos-Matos, I. 2021. Service Evaluation of the English Refugee Health Information System: Considerations and Recommendations for Effective Resettlement. *Int J Environ Res Public Health*, 18 (19).

Dunstan, J., Villena, F., Pérez, J. and Lagos, R. 2021. Supporting the classification of patients in public hospitals in Chile by designing, deploying and validating a system based on natural language processing. *BMC medical informatics and decision making*, 21 (1): 1-11.

Dye, C., Reeder, J. C. and Terry, R. F. 2013. Research for Universal Health Coverage. *Science Translational Medicine*, 5 (199): 199ed113-199ed113.

Ebnehoseini, Z., Tabesh, H., Deghatipour, A. and Tara, M. 2022. Development an extended-information success system model (ISSM) based on nurses' point of view for hospital EHRs: a combined framework and questionnaire. *BMC medical informatics and decision making*, 22 (1): 71.

Ebnehoseini, Z., Tara, M., Meraji, M., Deldar, K., Khoshronezhad, F. and Khoshronezhad, S. 2018. Usability Evaluation of an Admission, Discharge, and Transfer Information System: A Heuristic Evaluation. *Open Access Maced J Med Sci*, 6 (11): 1941-1945.

Efron, B. and Hastie, T. 2021. *Computer age statistical inference, student edition: algorithms, evidence, and data science*. Cambridge University Press.

El Khatib, M., Hamidi, S., Al Ameeri, I., Al Zaabi, H. and Al Marqab, R. 2022. Digital Disruption and Big Data in Healthcare- Opportunities and Challenges. *Clinicoeconomics and Outcomes Research*, 14: 563-574.

English, R., Masilela, T., Barron, P. and Schonfeldt, A. 2011. Health information systems in South Africa. *South African health review*, 2011 (1): 81-89.

Epizitone, A. 2021. Critical success factors within an Enterprise Resource Planning System implementation designed to support financial functions of a public higher education institution. Article ID.

Epizitone, A. 2022. Framework to Develop a Resilient and Sustainable Integrated Information System for Health Care Applications: A Review. *International Journal of Advanced Computer Science and Applications(IJACSA)* ,, 13 (7): 477-481.

Epizitone, A., Moyane, S. and Agbehadji, I. 2023. A Systematic Literature Review of Health Information Systems for Healthcare. . *Healthcare* 11 (959): 1-13. Available: https://doi.org/10.3390/healthcare11070959

Epizitone, A., Moyane, S. P. and Agbehadji, I. E. 2022. Health Information System and Health Care Applications Performance in the Healthcare Arena: A Bibliometric Analysis. *Healthcare*, 10 (11): 2273.

Epizitone, A. and Olugbara, O. O. 2020. Mixed method approach to determination critical success factors for successful financial ERP system implementation. *Academy of Accounting and Financial Studies Journal*, 24 (2): 1-10.

Eslami Andargoli, A., Scheepers, H., Rajendran, D. and Sohal, A. 2017. Health information systems evaluation frameworks: A systematic review. *Int J Med Inform*, 97: 195-209.

Eslami, M., Firoozabadi, M. and Homayounvala, E. 2018. User preferences for adaptive user interfaces in health information systems. *Universal Access in the Information Society*, 17 (4): 875-883.

Faridah, L., Rinawan, F. R., Fauziah, N., Mayasari, W., Dwiartama, A. and Watanabe, K. 2020. Evaluation of Health Information System (HIS) in The Surveillance of Dengue in Indonesia: Lessons from Case in Bandung, West Java. *Int J Environ Res Public Health*, 17 (5).

Farnham, A., Utzinger, J., Kulinkina, A. V. and Winkler, M. S. 2020. Using district health information to monitor sustainable development. *Bulletin of the World Health Organization*, 98 (1): 69.

Farrahi, R., Jeddi, F. R., Nabovati, E., Jabali, M. S. and Khajouei, R. 2019. The relationship between user interface problems of an admission, discharge and transfer module and usability features: a usability testing method. *Bmc Medical Informatics and Decision Making*, 19 (1).

Farzandipour, M., Nabovati, E. and Sadeqi Jabali, M. 2022. Comparison of usability evaluation methods for a health information system: heuristic evaluation versus cognitive walkthrough method. *BMC Med Inform Decis Mak*, 22 (1): 157.

Faujdar, D. S., Sahay, S., Singh, T., Kaur, M. and Kumar, R. 2020. Field testing of a digital health information system for primary health care: a quasi-experimental study from India. *International Journal of Medical Informatics*, 141: 104235.

Feldman, J., Thomas-Bachli, A., Forsyth, J., Patel, Z. H. and Khan, K. 2019. Development of a global infectious disease activity database using natural language processing, machine learning, and human expertise. *Journal of the American Medical Informatics Association*, 26 (11): 1355-1359.

Fernandes, C. O., Miles, S., De Lucena, C. J. P. and Cowan, D. 2019. Artificial Intelligence Technologies for Coping with Alarm Fatigue in Hospital Environments Because of Sensory Overload: Algorithm Development and Validation. *Journal of Medical Internet Research*, 21 (11): 19.

Ferreira, A. J. and Figueiredo, M. A. 2012. Boosting algorithms: A review of methods, theory, and applications. *Ensemble machine learning: Methods and applications*, Article ID: 35-85.

Feteira-Santos, R., Camarinha, C., Nobre, M. D., Elias, C., Bacelar-Nicolau, L., Costa, A. S., Furtado, C. and Nogueira, P. J. 2022. Improving morbidity information in Portugal: Evidence from data linkage of COVID-19 cases surveillance and mortality systems. *International Journal of Medical Informatics*, 163: 9.

Fine, S. L., Kane, J. C., Spiegel, P. B., Tol, W. A. and Ventevogel, P. 2022. Ten years of tracking mental health in refugee primary health care settings: an updated analysis of data from UNHCR's Health Information System (2009-2018). *BMC Med*, 20 (1): 183.

Finet, P., Gibaud, B., Dameron, O. and Jeannes, R. L. 2018. Interoperable Infrastructure and Implementation of a Health Data Model for Remote Monitoring of Chronic Diseases with Comorbidities. *Irbm*, 39 (3): 151-159.

Flora, O. C., Margaret, K. and Dan, K. 2017. Perspectives on utilization of community based health information systems in Western Kenya. *Pan African Medical Journal*, 27.

Forkan, A. R. M., Khalil, I. and Atiquzzaman, M. 2017. ViSiBiD: A learning model for early discovery and real-time prediction of severe clinical events using vital signs as big data. *Computer Networks*, 113: 244-257.

Fox, E. W., Hill, R. A., Leibowitz, S. G., Olsen, A. R., Thornbrugh, D. J. and Weber, M. H. 2017. Assessing the accuracy and stability of variable selection methods for random forest modeling in ecology. *Environmental monitoring and assessment*, 189 (7): 1-20.

Gäbler, G., Lycett, D. and Gall, W. 2022. Integrating a New Dietetic Care Process in a Health Information System: A System and Process Analysis and Assessment. *Int J Environ Res Public Health*, 19 (5).

Gamal, A., Barakat, S. and Rezk, A. 2021. Letter to Editor (Response from author): Toward a universal electronic health record system. *Journal of Biomedical Informatics*, 117: 103770.

Ganie, S. M. and Malik, M. B. 2022. An ensemble machine learning approach for predicting type-II diabetes mellitus based on lifestyle indicators. *Healthcare Analytics*, 2: 100092.

Garcia, A. P., De la Vega, S. F. and Mercado, S. P. 2022. Health Information Systems for Older Persons in Select Government Tertiary Hospitals and Health Centers in the Philippines: Cross-sectional Study. *Journal of Medical Internet Research*, 24 (2): 12.

Gardner-Lubbe, S. 2021. Linear discriminant analysis for multiple functional data analysis. *Journal of Applied Statistics*, 48 (11): 1917-1933.

Gardoni, P. 2018. Promoting societal well-being by designing sustainable and resilient infrastructure: Engineering tools and broader interdisciplinary considerations. In: Proceedings of *Life Cycle Analysis and Assessment in Civil Engineering:*

Towards an Integrated Vision: Proceedings of the Sixth International Symposium on Life-Cycle Civil Engineering (IALCCE 2018), 28-31 October 2018, Ghent, Belgium. CRC Press, 25.

Gardoni, P. 2019. *Routledge handbook of sustainable and resilient infrastructure*. Routledge New York, NY.

Gardoni, P. and Murphy, C. 2020. Society-based design: promoting societal well-being by designing sustainable and resilient infrastructure. *Sustainable and Resilient Infrastructure*, 5 (1-2): 4-19.

Gasso, G. 2019. Logistic regression. *INSA Rouen-ASI Departement Laboratory: Saint-Etienne-du-Rouvray, France*, Article ID: 1-30.

Gatta, R., Vallati, M., Fernandez-Llatas, C., Martinez-Millana, A., Orini, S., Sacchi, L., Lenkowicz, J., Marcos, M., Munoz-Gama, J., Cuendet, M. A., de Bari, B., Marco-Ruiz, L., Stefanini, A., Valero-Ramon, Z., Michielin, O., Lapinskas, T., Montvila, A., Martin, N., Tavazzi, E. and Castellano, M. 2020. What Role Can Process Mining Play in Recurrent Clinical Guidelines Issues? A Position Paper. *International journal of environmental research and public health*, 17 (18).

Gebre-Mariam, M. and Fruijtier, E. 2018. Countering the "dam effect": the case for architecture and governance in developing country health information systems. *Information Technology for Development*, 24 (2): 333-358.

Geerts, G. L. 2011. A design science research methodology and its application to accounting information systems research. *International journal of accounting Information Systems*, 12 (2): 142-151.

Geiger, B. C. 2021. On Information Plane Analyses of Neural Network Classifiers--A Review. *IEEE Transactions on Neural Networks and Learning Systems*, Article ID.

Gesicho, M. B. and Babic, A. 2018. Using Innovation-Decision Model to Describe the Adoption to Utilization of HIV-Data for Decision-Making in LMICs. *Stud Health Technol Inform*, 251: 117-120.

Geurts, P., Irrthum, A. and Wehenkel, L. 2009. Supervised learning with decision tree-based methods in computational and systems biology. *Molecular Biosystems*, 5 (12): 1593-1605.

Ghaffari, F., Jeddi, F. R., Farrahi, R. and Nabovati, E. 2021. Design, development, and evaluation of an interactive training simulator for teaching hospital information systems. *Journal of Education and Health Promotion*, 10: 205.

Ghalibaf, A. K., Jangi, M., Habibi, M. R. M., Zangouei, S. and Khajouei, R. 2018. Usability evaluation of obstetrics and gynecology information system using cognitive walkthrough method. *Electron Physician*, 10 (4): 6682-6688.

Gil-Borrelli, C., Velasco, C., Martí-Pastor, M. and Latasa, P. 2018. Gender identity, a factor of inequality forgotten by Spanish health information systems. *Gac Sanit*, 32 (2): 184-186.

Giussi Bordoni, M. V., Baum, A., García, G., Moriñigo, P., Luna, D., Otero, P., Otero, C. and de Quirós, F. B. G. 2019. Change Management in Healthcare Organizations: Soft Skills Training Strategies Through Blended Learning Environments. *Stud Health Technol Inform*, 264: 1999-2000.

Gouda, H. N., Flaxman, A. D., Brolan, C. E., Joshi, R., Riley, I. D., AbouZahr, C., Firth, S., Rampatige, R. and Lopez, A. D. 2017. New challenges for verbal autopsy: Considering the ethical and social implications of verbal autopsy methods in routine health information systems. *Social Science & Medicine*, 184: 65-74.

Gregor, S. 2006. The nature of theory in information systems. *MIS quarterly*, Article ID: 611-642.

Grenha Teixeira, J., Pinho, N. F. and Patrício, L. 2019. Bringing service design to the development of health information systems: The case of the Portuguese national electronic health record. *Int J Med Inform*, 132: 103942.

Grosjean, S., Bate, E. and Mestre, T. 2020. Designing socially acceptable mHealth technologies for Parkinson's disease self-management. *Finnish Journal of eHealth and eWelfare*, 12 (3): 163-178.

Grosjean, S., Ciocca, J.-L., Gauthier-Beaupré, A., Poitras, E., Grimes, D. and Mestre, T. 2022. Co-designing a digital companion with people living with Parkinson's to support self-care in a personalized way: The eCARE-PD Study. *Digital Health*, 8: 20552076221081695.

Guidotti, R., Chmielewski, H., Unnikrishnan, V., Gardoni, P., McAllister, T. and van de Lindt, J. 2016. Modeling the resilience of critical infrastructure: The role of network dependencies. *Sustainable and resilient infrastructure*, 1 (3-4): 153-168.

Guzella, T. S. and Caminhas, W. M. 2009. A review of machine learning approaches to Spam filtering. *Expert Systems with Applications*, 36 (7): 10206-10222.

Hancock, J. T. and Khoshgoftaar, T. M. 2021. Gradient boosted decision tree algorithms for medicare fraud detection. *SN Computer Science*, 2 (4): 268.

Hansrajh, A., Adeliyi, T. T. and Wing, J. 2021. Detection of online fake news using blending ensemble learning. *Scientific Programming*, 2021: 1-10.

Hariyanto, H., Denison, T. and Stillman, L. 2018. Understanding health information system implementation in an Indonesian primary health centre: A sociotechnical perspective. In: Tanabu, M. and Senoo, D. eds. Proceedings of *22nd Pacific Asia Conference on Information Systems - Opportunities and Challenges for the Digitized Society: Are We Ready?, PACIS 2018*. Association for Information Systems, Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85089238231&partnerID=40&md5=8de3b4e267f6de6f88eed853c2855bba (Accessed 26 June 2018 through 30 June 2018).

Harjai, S. and Khatri, S. K. 2019. An intelligent clinical decision support system based on artificial neural network for early diagnosis of cardiovascular diseases in rural areas. In: Proceedings of *2019 Amity International conference on artificial intelligence (AICAI)*. IEEE, 729-736.

Haule, C. D., Muhanga, M. and Ngowi, E. 2022. The what, why, and how of health information systems: a systematic review. Article ID.

Haux, R. 2006. Health information systems–past, present, future. *International journal of medical informatics*, 75 (3-4): 268-281.

He, L., Chen, X. H., Xu, C., Liu, J. and Johnson, M. T. 2018. Local Pairwise Linear Discriminant Analysis for Speaker Verification. *Ieee Signal Processing Letters*, 25 (10): 1575-1579.

Helwig, J. E., Bishop-Williams, K. E., Berrang-Ford, L., Lwasa, S., Namanya, D. B. and Grp, I. R. 2020. Doing More Than Asking for Opinions: A Framework for Participation and Ecohealth in Health Information System Evaluations. *International Journal of Healthcare Information Systems and Informatics*, 15 (3): 22-46.

Hevner, A. and Chatterjee, S. 2010. Design science research in information systems. In: *Design research in information systems*. Springer, 9-22.

Hevner, A., Chatterjee, S., Hevner, A. and Chatterjee, S. 2010. Design science research in information systems. *Design research in information systems: theory and practice*, Article ID: 9-22.

Hevner, A., Chatterjee, S. and Iivari, J. 2010. Twelve Theses on Design Science Research in Information Systems. *Design research in information systems: Theory and practice*, Article ID: 43-62.

Hevner, A. R. and Wickramasinghe, N. 2018. Design science research opportunities in health care. *Theories to inform superior health informatics research and practice*, Article ID: 3-18.

Hewapathirana, R. and Sahay, S. 2017. OPEN SOURCE ADOPTION IN HEALTH SECTOR: UNDERSTANDING THE STAKEHOLDER RELATIONSHIPS IN A RESOURCE CONSTRAINED SETTING. *Electronic Journal of Information Systems in Developing Countries*, 81 (1).

Higman, S., Dwivedi, V., Nsaghurwe, A., Busiga, M., Rulagirwa, H. S., Smith, D., Wright, C., Nyinondi, S. and Nyella, E. 2019. Designing interoperable health information systems using Enterprise Architecture approach in resource-limited countries: A literature review. *International Journal of Health Planning and Management*, 34 (1): E85-E99.

Hochgesang, M., Zamudio-Haas, S., Moran, L., Nhampossa, L., Packel, L., Leslie, H., Richards, J. and Shade, S. B. 2017. Scaling-up health information systems to improve HIV treatment: An assessment of initial patient monitoring systems in Mozambique. *Int J Med Inform*, 97: 322-330.

Hoque, M. R. 2016. An empirical study of mHealth adoption in a developing country: the moderating effect of gender concern. *Bmc Medical Informatics and Decision Making*, 16.

Høstgaard, A. M. B., Bertelsen, P. and Nøhr, C. 2017. Constructive eHealth evaluation: lessons from evaluation of EHR development in 4 Danish hospitals. *BMC medical informatics and decision making*, 17 (1): 45.

Hoxha, K., Hung, Y. W., Irwin, B. R. and Grepin, K. A. 2022. Understanding the challenges associated with the use of data from routine health information systems in low- and middle-income countries: A systematic review. *Health Information Management Journal*, 51 (3): 135-148.

Hughes-Lartey, K., Qin, Z., Botchey, F. E. and Dsane-Nsor, S. 2020. An Assessment of Data Location Vulnerability for Human Factors Using Linear Regression and Collaborative Filtering. *Information*, 11 (9).

Hung, M. C. and Jen, W. Y. 2012. The Adoption of Mobile Health Management Services: An Empirical Study. *Journal of Medical Systems*, 36 (3): 1381-1388.

Hurtado-Salgado, E., Ortiz-Panozo, E., Salmerón, J., Saavedra-Lara, N., Kuri-Morales, P., Pesqueira-Villegas, E., Luna-Gordillo, R., Franco, E. L. and Lazcano-Ponce, E. 2018. Use of HPV testing in cervical cancer screening services in Mexico, 2008-2018: a nationwide database study. *Salud publica de Mexico*, 60 (6): 722-733.

Hypponen, H., Kaipio, J., Heponiemi, T., Laaveri, T., Aalto, A. M., Vanska, J. and Elovainio, M. 2019. Developing the National Usability-Focused Health Information System Scale for Physicians: Validation Study. *Journal of Medical Internet Research*, 21 (5): 18.

Hyppönen, H., Lumme, S., Reponen, J., Vänskä, J., Kaipio, J., Heponiemi, T. and Lääveri, T. 2019. Health information exchange in Finland: Usage of different access types and predictors of paper use. *Int J Med Inform*, 122: 1-6.

Ifinedo, P. 2018. Empirical Study of Nova Scotia Nurses' Adoption of Healthcare Information Systems: Implications for Management and Policy-Making. *Int J Health Policy Manag*, 7 (4): 317-327.

Ijaz, M., Lan, L., Zahid, M. and Jamal, A. 2021. A comparative study of machine learning classifiers for injury severity prediction of crashes involving three-wheeled motorized rickshaw. *Accident Analysis and Prevention*, 154.

Iofrida, N., De Luca, A. I., Strano, A. and Gulisano, G. 2018. Can social research paradigms justify the diversity of approaches to social life cycle assessment? *The International Journal of Life Cycle Assessment*, 23 (3): 464-480.

Isleyen, F. and Ulgu, M. M. 2020. Data Transfer Model for HIS and Developers Opinions in Turkey. *Stud Health Technol Inform*, 270: 557-561.

Jabareen, H., Khader, Y. and Taweel, A. 2020. Health information systems in Jordan and Palestine: the need for health informatics training. *Eastern Mediterranean Health Journal*, 26 (11): 1323-1330.

Jauk, S., Kramer, D., Avian, A., Berghold, A., Leodolter, W. and Schulz, S. 2021. Technology Acceptance of a Machine Learning Algorithm Predicting Delirium in a Clinical Setting: a Mixed-Methods Study. *Journal of medical systems*, 45 (4): 48.

Jawa, R. S., Tharakan, M. A., Tsai, C., Garcia, V. L., Vosswinkel, J. A., Rutigliano, D. N., Rubano, J. A. and Stony Brook Med Enterprise, A. T. 2020. A reference guide to rapidly implementing an institutional dashboard for resource allocation and oversight during COVID-19 pandemic surge. *Jamia Open*, 3 (4): 518-522.

Jayaratne, M., Nallaperuma, D., De Silva, D., Alahakoon, D., Devitt, B., Webster, K. E. and Chilamkurti, N. 2019. A data integration platform for patient-centered e-healthcare and clinical decision support. *Future Generation Computer Systems*, 92: 996-1008.

Jeddi, F. R., Nabovati, E., Bigham, R. and Khajouei, R. 2020. Usability evaluation of a comprehensive national health information system: relationship of quality components to users' characteristics. *International Journal of Medical Informatics*, 133: 7.

Jeffery, C., Pagano, M., Hemingway, J. and Valadez, J. J. 2018. Hybrid prevalence estimation: Method to improve intervention coverage estimations. *Proc Natl Acad Sci U S A*, 115 (51): 13063-13068.

Jena, M. and Dehuri, S. 2020. Decision Tree for Classification and Regression: A State-of-the Art Review. *Informatica-an International Journal of Computing and Informatics*, 44 (4): 405-420.

Jeyakumar, T., McClure, S., Lowe, M., Hodges, B., Fur, K., Javier-Brozo, M., Tassone, M., Anderson, M., Tripp, T. and Wiljer, D. 2021. An Education Framework for Effective Implementation of a Health Information System: Scoping Review. *J Med Internet Res*, 23 (2): e24691.

Jinabhai, C. C., Onwubu, S. C., Sibiya, M. N. and Thakur, S. 2021. Accelerating implementation of District Health Information Systems: Perspectives from healthcare workers from KwaZulu-Natal, South Africa. *South African Journal of Information Management*, 23 (1).

Johnson, M., Burgess, N. and Sethi, S. 2020. Temporal pacing of outcomes for improving patient flow: design science research in a national health service Hospital. *Journal of Operations Management*, 66 (1-2): 35-53.

Johnson, R. B., Russo, F. and Schoonenboom, J. 2019. Causation in mixed methods research: The meeting of philosophy, science, and practice. *Journal of Mixed Methods Research*, 13 (2): 143-162.

Jolliffe, I. T., Morgan, B. J. T. and Young, P. J. 1996. A simulation study of the use of principal components in linear discriminant analysis. *Journal of Statistical Computation and Simulation*, 55 (4): 353-366.

Joseph, A. L., Stringer, E., Borycki, E. M. and Kushniruk, A. W. 2022. Evaluative Frameworks and Models for Health Information Systems (HIS) and Health Information Technologies (HIT). *Stud Health Technol Inform*, 289: 280-285.

Jurkeviciute, M., van Velsen, L., Eriksson, H., Lifvergren, S., Trimarchi, P. D., Andin, U. and Svensson, J. 2020. Identifying the Value of an eHealth Intervention Aimed at Cognitive Impairments: Observational Study in Different Contexts and Service Models. *Journal of Medical Internet Research*, 22 (10): 14.

Kabari, L. G. and Onwuka, U. C. 2019. Comparison of bagging and voting ensemble machine learning algorithm as a classifier. *International Journals of Advanced Research in Computer Science and Software Engineering*, 9 (3): 19-23.

Kala, J. R., Kre, D. M., Gnassou, A. N. G., Kala, J. R. K., Akpablin, Y. M. A. and Coulibaly, T. 2020. Assets management on electrical grid using Faster-RCNN. *Annals of Operations Research*, Article ID: 1-14.

Kalong, N. A. and Yusof, M. 2017. Waste in health information systems: a systematic review. *International Journal of Health Care Quality Assurance*, 30 (4): 341-357.

Kang, H., Yoo, S. J. and Han, D. 2012. Senti-lexicon and improved Naive Bayes algorithms for sentiment analysis of restaurant reviews. *Expert Systems with Applications*, 39 (5): 6000-6010.

Kao, H.-Y., Yu, M.-C., Masud, M., Wu, W.-H., Chen, L.-J. and Wu, Y.-C. J. 2016. Design and evaluation of hospital-based business intelligence system (HBIS): A foundation for design science research methodology. *Computers in Human Behavior*, 62: 495-505.

Kapepo, M. I. and Yashik, S. 2018. A process analysis of the Namibian Health System: An exploratory case study. *Ethiopian Journal of Health Development*, 32 (4): 200-209.

Karuri, J., Waiganjo, P., Daniel, O. and Manya, A. 2014. DHIS2: the tool to improve health data demand and use in Kenya. *Journal of Health Informatics in Developing Countries*, 8 (1).

Kasthurirathne, S. N., Biondich, P. G., Grannis, S. J., Purkayastha, S., Vest, J. R. and Jones, J. F. 2019. Identification of Patients in Need of Advanced Care for Depression Using Data Extracted From a Statewide Health Information Exchange: A Machine Learning Approach. *Journal of medical Internet research*, 21 (7): e13809.

Katarahweire, M., Bainomugisha, E. and Mughal, K. A. 2020. Data classification for secure mobile health data collection systems. *Development Engineering*, 5: 100054.

Kaur, K. and Mittal, S. 2020. Classification of mammography image with CNN-RNN based semantic features and extra tree classifier approach using LSTM. *Materials Today: Proceedings*, Article ID.

Kaur, P., Kumar, R. and Kumar, M. 2019. A healthcare monitoring system using random forest and internet of things (IoT). *Multimedia Tools and Applications*, 78 (14): 19905-19916.

Ker, J. I., Wang, Y. C. and Hajli, N. 2018. Examining the impact of health information systems on healthcare service improvement: The case of reducing in patient-flow delays in a US hospital. *Technological Forecasting and Social Change*, 127: 188-198.

Khader, Y., Jabareen, H., Alzyoud, S., Awad, S., Rumeileh, N. A., Manasrah, N., Mudallal, R. and Taweel, A. 2018. Perception and acceptance of health informatics learning among health-related students in Jordan and Palestine. In: Proceedings of *2018 IEEE/ACS 15th International Conference on Computer Systems and Applications (AICCSA)*. IEEE, 1-6.

Khan, M. S. I., Islam, N., Uddin, J., Islam, S. and Nasir, M. K. 2022. Water quality prediction and classification based on principal component regression and gradient boosting classifier approach. *Journal of King Saud University-Computer and Information Sciences*, 34 (8): 4773-4781.

Kharwar, A. R. and Thakor, D. V. 2022. An ensemble approach for feature selection and classification in intrusion detection using extra-tree algorithm. *International Journal of Information Security and Privacy (IJISP)*, 16 (1): 1-21.

Khorshed, M. S., Lindsay, D., McAuliffe, M., West, C. and Wild, K. 2022. Factors Affecting Quality of Care in Maternal and Child Health in Timor-Leste: A Scoping Review. *Health Services Insights*, 15: 12.

Kien, V. D., Minh, H. V., Giang, K. B., Ng, N., Nguyen, V., Tuan, L. T. and Eriksson, M. 2018. Views by health professionals on the responsiveness of commune health stations regarding non-communicable diseases in urban Hanoi, Vietnam: a qualitative study. *Bmc Health Services Research*, 18: 12.

Kim, Y. M., Newby-Bennett, D. and Song, H. J. 2012. Knowledge sharing and institutionalism in the healthcare industry. *Journal of Knowledge Management*, Article ID.

Kivinen, T. and Lammintakanen, J. 2013. The success of a management information system in health care–A case study from Finland. *International Journal of Medical Informatics*, 82 (2): 90-97.

Koliou, M., van de Lindt, J. W., McAllister, T. P., Ellingwood, B. R., Dillard, M. and Cutler, H. 2020. State of the research in community resilience: Progress and challenges. *Sustainable and resilient infrastructure*, 5 (3): 131-151.

Koumamba, A. P., Bisvigou, U. J., Ngoungou, E. B. and Diallo, G. 2021. Health information systems in developing countries: case of African countries. *BMC Med Inform Decis Mak*, 21 (1): 232.

Kpobi, L., Swartz, L. and Ofori-Atta, A. L. 2018. Challenges in the use of the mental health information system in a resource-limited setting: lessons from Ghana. *Bmc Health Services Research*, 18: 8.

Krasuska, M., Williams, R., Sheikh, A., Franklin, B., Hinder, S., TheNguyen, H., Lane, W., Mozaffar, H., Mason, K., Eason, S., Potts, H. and Cresswell, K. 2021. Driving digital health transformation in hospitals: a formative qualitative evaluation of the English Global Digital Exemplar programme. *Bmj Health & Care Informatics*, 28 (1): 10.

Krishna, C. L. and Reddy, P. V. S. 2019. An efficient deep neural network multilayer perceptron based classifier in healthcare system. In: Proceedings of *2019 3rd*

International Conference on Computing and Communications Technologies (ICCCT). IEEE, 1-6.

Kujala, S., Ammenwerth, E., Kolanen, H. and Ervast, M. 2020. Applying and extending the FITT framework to identify the challenges and opportunities of successful eHealth services for patient self-management: qualitative interview study. *Journal of Medical Internet Research*, 22 (8): e17696.

Kumar, M., Gotz, D., Nutley, T. and Smith, J. B. 2018. Research gaps in routine health information system design barriers to data quality and use in low- and middle-income countries: A literature review. *Int J Health Plann Manage*, 33 (1): e1-e9.

Kumar, M., Mostafa, J. and Ramaswamy, R. 2018. Federated health information architecture: Enabling healthcare providers and policymakers to use data for decision-making. *Health Inf Manag*, 47 (2): 85-93.

Kumar, P., Singh, S. N. and Dawra, S. 2022. Software component reusability prediction using extra tree classifier and enhanced Harris hawks optimization algorithm. *International Journal of System Assurance Engineering and Management*, 13 (2): 892-903.

Kumar, R. 2018. *Research methodology: A step-by-step guide for beginners*. Sage.

Kuo, J. W. and Kuo, A. M. 2017. Integration of Health Information Systems Using HL7: A Case Study. *Stud Health Technol Inform*, 234: 188-194.

Ladas, N., Franz, S., Haarbrandt, B., Sommer, K. K., Kohler, S., Ballout, S., Fiebeck, J., Marschollek, M. and Gietzelt, M. 2022. openEHR-to-FHIR: Converting openEHR Compositions to Fast Healthcare Interoperability Resources (FHIR) for the German Corona Consensus Dataset (GECCO). *Stud Health Technol Inform*, 289: 485-486.

Lal, A., Ashworth, H. C., Dada, S., Hoemeke, L. and Tambo, E. 2022. Optimizing Pandemic Preparedness and Response Through Health Information Systems: Lessons Learned From Ebola to COVID-19. *Disaster Med Public Health Prep*, 16 (1): 333-340.

Lapão, L. V., Da Silva, M. M. and Gregório, J. 2017. Implementing an online pharmaceutical service using design science research. *BMC medical informatics and decision making*, 17 (1): 1-14.

Lee, A. S., Thomas, M. and Baskerville, R. L. 2015. Going back to basics in design science: from the information technology artifact to the information systems artifact. *Information Systems Journal*, 25 (1): 5-21.

Li, X. and Akagi, M. 2019. Improving multilingual speech emotion recognition by combining acoustic features in a three-layer model. *Speech Communication*, 110: 1-12.

Lin, G., Lin, A. and Gu, D. 2022. Using support vector regression and K-nearest neighbors for short-term traffic flow prediction based on maximal information coefficient. *Information Sciences*, 608: 517-531.

Lindberg, M. H., Venkateswaran, M., Abu Khader, K., Awwad, T., Ghanem, B., Hijaz, T., Morkrid, K. and Froen, J. F. 2019. eRegTime, Efficiency of Health Information Management Using an Electronic Registry for Maternal and Child Health: Protocol for a Time-Motion Study in a Cluster Randomized Trial. *Jmir Research Protocols*, 8 (8): 11.

Lippeveld, T. 2001. Routine health information systems: the glue of a unified health system. In: Proceedings of *Keynote address at the Workshop on Issues and Innovation in Routine Health Information in Developing Countries, Potomac, March*. 14-16.

Liu, G., Tsui, E. and Kianto, A. 2022. An emerging knowledge management framework adopted by healthcare workers in China to combat COVID-19. *Knowledge and Process Management*, Article ID.

Lluch, M. 2011. Healthcare professionals' organisational barriers to health information technologies—A literature review. *International journal of medical informatics*, 80 (12): 849-862.

Luna, D., Almerares, A., Mayan, J. C., 3rd, Gonzalez Bernaldo de Quiros, F. and Otero, C. 2014. Health Informatics in Developing Countries: Going beyond Pilot Practices to Sustainable Implementations: A Review of the Current Challenges. *Healthcare informatics research*, 20 (1): 3-10.

Lv, H., Xu, W. J., You, J. and Xiong, S. B. 2017. Classification of freshwater fish species by linear discriminant analysis based on near infrared reflectance spectroscopy. *Journal of near Infrared Spectroscopy*, 25 (1): 54-62.

Lynch, J., Ramjan, L. M., Glew, P. J. and Salamonson, Y. 2021. How to embed a conceptual or theoretical framework into a dissertation study design. *Nurse researcher*, 29 (2).

Magdon-Ismail, Z., Sherman, B. R., Fillmore, H. and Straussman, J. 2019. The Leadership Style of "The People's Doctor": A Contemporary Look Back at New York State Commissioner of Health David Axelrod, MD. *Am J Public Health*, 109 (1): 85-91.

Mahendrawathi, E. 2015. Knowledge management support for enterprise resource planning implementation. *Procedia Computer Science*, 72: 613-621.

Maheswari, S. and Pitchai, R. 2019. Heart Disease Prediction System Using Decision Tree and Naive Bayes Algorithm. *Current Medical Imaging*, 15 (8): 712-717.

Maier, O., Wilms, M., von der Gablentz, J., Krämer, U. M., Münte, T. F. and Handels, H. 2015. Extra tree forests for sub-acute ischemic stroke lesion segmentation in MR sequences. *Journal of neuroscience methods*, 240: 89-100.

Makombe, G. 2017. An expose of the relationship between paradigm, method and design in research. *The qualitative report*, 22 (12): 3363-3383.

Malaquias, R. S. and Filho, I. M. B. 2021. *Middleware for Healthcare Systems: A Systematic Mapping* (Conference Paper). Springer Science and Business Media Deutschland GmbH. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85115710819&doi=10.1007%2f978-3-030-87013-3_30&partnerID=40&md5=de79cb9d4d5d393eec57b140679c4557 (Accessed 13 September 2021 through 16 September 2021).

Malekzadeh, S., Hashemi, N., Sheikhtaheri, A. and Hashemi, N. S. 2018. Barriers for Implementation and Use of Health Information Systems from the Physicians' Perspectives. *Stud Health Technol Inform*, 251: 269-272.

Malik, M., Kazi, A. F. and Hussain, A. 2021. Adoption of health technologies for effective health information system: Need of the hour for Pakistan. *PloS one*, 16 (10): e0258081.

Mandacaru, P. M. P., Andrade, A. L., Rocha, M. S., Aguiar, F. P., Nogueira, M. S. M., Girodo, A. M., Pedrosa, A. A. G., Oliveira, V. L. A. D., Alves, M. M. M., Paixão, L. M. M. M., Malta, D. C., Silva, M. M. A. and Morais Neto, O. L. D. 2017. Qualifying information on deaths and serious injuries caused by road traffic in five Brazilian capitals using record linkage. *Accident Analysis and Prevention*, 106: 392-398.

Maramba, I., Chatterjee, A. and Newman, C. 2019. Methods of usability testing in the development of eHealth applications: A scoping review. *International Journal of Medical Informatics*, 126: 95-104.

Mardani, A., Saraji, M. K., Mishra, A. R. and Rani, P. 2020. A novel extended approach under hesitant fuzzy sets to design a framework for assessing the key challenges of digital health interventions adoption during the COVID-19 outbreak. *Appl Soft Comput*, 96: 106613.

Martikainen, S., Kaipio, J. and Laaveri, T. 2020. End-user participation in health information systems (HIS) development: Physicians' and nurses' experiences. *International Journal of Medical Informatics*, 137: 11.

Martins, B., Ferreira, D., Neto, C., Abelha, A. and Machado, J. 2021. Data Mining for Cardiovascular Disease Prediction. *Journal of Medical Systems*, 45 (1): 8.

Martins, J., Bandiera-Paiva, P., Neto, A. R. B., de Carvalho, L. R. B., Padrini-Andrade, L., Machado, V. T., da Silva Junior, A. C. and Sun, S. Y. 2022. Development and validation of a health information system for assistance and research in gestational trophoblast disease. *BMC Med Inform Decis Mak*, 22 (1): 173.

Mayer, F., Faglioni, L., Agabiti, N., Fenu, S., Buccisano, F., Latagliata, R., Ricci, R., Spiriti, M. A. A., Tatarelli, C., Breccia, M., Cimino, G., Fianchi, L., Criscuolo, M., Gumenyuk, S., Mancini, S., Maurillo, L., Nobile, C., Niscola, P., Piccioni, A. L., Tafuri, A., Trapè, G., Andriani, A., De Fabritiis, P., Voso, M. T., Davoli, M. and Zini, G. 2017. A Population-Based Study on Myelodysplastic Syndromes in the Lazio Region (Italy), Medical Miscoding and 11-Year Mortality Follow-Up: the Gruppo Romano-Laziale Mielodisplasie Experience of Retrospective Multicentric Registry. *Mediterr J Hematol Infect Dis*, 9 (1): e2017046.

Mayr, A., Binder, H., Gefeller, O. and Schmid, M. 2014. The evolution of boosting algorithms. *Methods of information in medicine*, 53 (06): 419-427.

Mazur, L. M., Mosaly, P. R., Moore, C. and Marks, L. 2019. Association of the Usability of Electronic Health Records With Cognitive Workload and Performance Levels Among Physicians. *JAMA Netw Open*, 2 (4): e191709.

McAllister, T. and McAllister, T. 2013. *Developing guidelines and standards for disaster resilience of the built environment: A research needs assessment*. US Department of Commerce, National Institute of Standards and Technology ….

McPherson, A., Durham, J., Richards, N., Gouda, H., Rampatige, R. and Whittaker, M. 2017. Strengthening health information systems for disability-related rehabilitation in LMICs. *Health Policy Plan*, 32 (3): 384-394.

Medic, G., Kosaner KlieSs, M., Atallah, L., Weichert, J., Panda, S., Postma, M. and El-Kerdi, A. 2019. Evidence-based Clinical Decision Support Systems for the prediction and detection of three disease states in critical care: A systematic literature review. *F1000Research*, 8: 1728.

Mejia Medina, F., Cucaita Vergara, Z., Dario Castro Acuña, R. and Tellez, J. 2019. EXPLORING USER EXPERIENCES OF INFORMATION SYSTEMS IN HEALTH OF PATIENT SAFETY PROGRAMS: A RAPID SYSTEMATIC REVIEW. *Int J Med Biomed Stud*, 3 (9): 181-187.

Mensah, R., Agyemang, F., Acquah, A., Babah, P. and Dontoh, J. 2020. Discourses on Conceptual and Theoretical Frameworks in Research: Meaning and Implications for Researchers. *Journal of African Interdisciplinary Studies*, 4 (5): 53-64.

Meribole, E. C., Makinde, O. A., Oyemakinde, A., Oyediran, K. A., Atobatele, A., Fadeyibi, F. A., Azeez, A., Ogbokor, D., Adebayo, O., Adebayo, W., Abatta, E., Adoghe, A., Adebayo, S. B., Mahmoud, Z., Ashefor, G., Adebayo, S. B., Yisa, I. O., Balogun, A., Chukwujekwu, O., Dalhatu, I., Jahun, I., Bamidele, S., Johnson, D. O., Ibrahim, M., Akpan, F., Aiyenigba, B., Omaha, O. I., Terpase, A., Ottih, C., Adelakin, O., Mullen, S. and Orobaton, N. 2018. The Nigerian health information system policy review of 2014 : the need, content, expectations and progress. *Health Info Libr J*, 35 (4): 285-297.

Mezarina, L. R., Silva-Valencia, J., Escobar-Agreda, S., Herrera, D. H. E., Egoavil, M. S., Kuljich, M. M., Inga-Berrospi, F. and Ronceros, S. 2020. Need for the Development of a Specific Regulatory Framework for Evaluation of Mobile Health Apps in Peru: Systematic Search on App Stores and Content Analysis. *Jmir Mhealth and Uhealth*, 8 (7): 11.

Mills, S., Lee, J. K. and Rassekh, B. M. 2019. Benefits of linking civil registration and vital statistics with identity management systems for measuring and achieving Sustainable Development Goal 3 indicators. *Journal of health, population, and nutrition*, 38 (Suppl 1): 18.

Mills, S., Lee, J. K., Rassekh, B. M., Zorko Kodelja, M., Bae, G., Kang, M., Pannarunothai, S. and Kijsanayotin, B. 2019. Unique health identifiers for universal health coverage. *Journal of health, population, and nutrition*, 38 (Suppl 1): 22.

Mnyawi, R., Kombe, C., Sam, A. and Nyambo, D. 2022. Blockchain-based Data Storage Security Architecture for e-Health Care Systems: A Case of Government of Tanzania Hospital Management Information System. *International Journal of Computer Science and Network Security*, 22 (3): 364-374.

Moghaddasi, H., Mohammadpour, A., Bouraghi, H., Azizi, A. and Mazaherilaghab, H. 2018. Hospital Information Systems: The status and approaches in selected countries of the Middle East. *Electronic physician*, 10 (5): 6829-6835.

Mohamadali, N. A., Aziz, N. F. A. and Zahari, N. A. M. 2017. A novel conceptual framework of Health information systems (HIS) sustainability. In: Proceedings of *5th International Conference on Research and Innovation in Information Systems, ICRIIS 2017*. IEEE Computer Society, Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85029944298&doi=10.1109%2fICRIIS.2017.8002458&partnerID=40&md5=5ab1b18644e78e325620ec3e33fe45f7 (Accessed 16 July 2017 through 17 July 2017).

Mohd Nor, N. A., Taib, N. A., Saad, M., Zaini, H. S., Ahmad, Z., Ahmad, Y. and Dhillon, S. K. 2019. Development of electronic medical records for clinical and research purposes: the breast cancer module using an implementation framework in a middle income country- Malaysia. *BMC bioinformatics*, 19 (Suppl 13): 402.

Mohd Yusof, M., Takeda, T., Mihara, N. and Matsumura, Y. 2020. Process Approach for Managing Health Information System-Induced Medication Errors. *Stud Health Technol Inform*, 270: 1036-1040.

Mohd. Yusof, M., Takeda, T., Mihara, N. and Matsumura, Y. 2020. *Process approach for managing health information system-induced medication errors* (Conference Paper). IOS Press. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85086938234&doi=10.3233%2fSHTI200319&partnerID=40&md5=3102239c954267724bbeeaa223b7296a (Accessed 28 April 2020 through 1 May 2020).

Moloczij, N., Gough, K., Solomon, B., Ball, D., Mileshkin, L., Duffy, M. and Krishnasamy, M. 2018. Development of a hospital-based patient-reported outcome framework for lung cancer patients: a study protocol. *Health and Quality of Life Outcomes*, 16: 8.

Momany, M. C., Martinez-Gutierrez, J., Soto, M., Capurro, D., Ciampi, F., Thompson, B. and Puschel, K. 2017. Development of mobile technologies for the prevention of cervical cancer in Santiago, Chile study protocol: a randomized controlled trial. *BMC Cancer*, 17 (1): 847.

Morid, M. A., Kawamoto, K., Ault, T., Dorius, J. and Abdelrahman, S. 2017. Supervised learning methods for predicting healthcare costs: systematic literature review and empirical evaluation. In: Proceedings of *AMIA annual symposium proceedings*. American Medical Informatics Association, 1312.

Mozaffar, H., Williams, R., Cresswell, K. and Sheikh, A. 2018. Anglicization of hospital information systems: Managing diversity alongside particularity. *International Journal of Medical Informatics*, 119: 88-93.

Mqadi, N. M., Naicker, N. and Adeliyi, T. 2021. Solving misclassification of the credit card imbalance problem using near miss. *Mathematical Problems in Engineering*, 2021: 1-16.

Mujiono, S. 2020. *EHR Dataset for Patient Treatment Classification*: Mendeley Available: https://data.mendeley.com/datasets/7kv3rctx7m/1

Munoz, R., Olivares, R., Taramasco, C., Villarroel, R., Soto, R., Barcelos, T. S., Merino, E. and Alonso-Sanchez, M. F. 2018. Using Black Hole Algorithm to Improve EEG-Based Emotion Recognition. *Computational Intelligence and Neuroscience*, 2018.

Murad, A. 2018. Planning and location of health care services in Jeddah City, Saudi Arabia: Discussion of the constructive use of geographical information systems. *Geospatial Health*, 13 (2): 322-329.

Muriel Fernandez, J., Sánchez Ledesma, M. J., López Millan, M. and García Cenador, M. B. 2017. Study of the uses of Information and Communication Technologies by Pain Treatment Unit Physicians. *Journal of medical systems*, 41 (5): 78.

Mussi, C. C., Pereira, C. D. D., Lacerda, R. T. D. and dos Santos, E. M. 2018. Pre-Implementation evaluation of a nationwide information system for university hospitals: lessons learned from a study in Brazil. *Behaviour & Information Technology*, 37 (3): 217-231.

Mutale, W., Cleary, S., Olivier, J., Chilengi, R. and Gilson, L. 2018. Implementing large-scale health system strengthening interventions: experience from the better health outcomes through mentoring and assessments (BHOMA) project in Zambia. *Bmc Health Services Research*, 18: 11.

Mutanga, R. T., Naicker, N. and Olugbara, O. O. 2022. Detecting Hate Speech on Twitter Network using Ensemble Machine Learning. *International Journal of Advanced Computer Science and Applications*, 13 (3).

Mwilu, O. S., Comyn-Wattiau, I. and Prat, N. 2016. Design science research contribution to business intelligence in the cloud—A systematic literature review. *Future Generation Computer Systems*, 63: 108-122.

Nabee, S. G. and Walters, J. 2018. Liner shipping cascading effect on Southern African Development Community port strategies. *Journal of Transport and Supply Chain Management*, 12 (1): 1-12.

Nadri, H., Rahimi, B., Timpka, T. and Sedghi, S. 2017. The top 100 articles in the medical informatics: a bibliometric analysis. *Journal of medical systems*, 41 (10): 1-12.

Najimudeen, M., Aldheleai, H. F. and Ubaidullah, M. 2021. Health Care Professionals' Use of Health Information Systems (HIS) in Indian Hospitals. *International Journal of Computer Applications*, 975: 8887.

Namageyo-Funa, A., Aketch, M., Tabu, C., MacNeil, A. and Bloland, P. 2018. Assessment of select electronic health information systems that support immunization data capture - Kenya, 2017. *Bmc Health Services Research*, 18: 7.

Naraei, P., Abhari, A. and Sadeghian, A. 2016. Application of multilayer perceptron neural networks and support vector machines in classification of healthcare data. In: Proceedings of *2016 Future Technologies Conference (FTC)*. IEEE, 848-852.

Natekin, A. and Knoll, A. 2013. Gradient boosting machines, a tutorial. *Frontiers in neurorobotics*, 7: 21.

Negro-Calduch, E., Azzopardi-Muscat, N., Krishnamurthy, R. S. and Novillo-Ortiz, D. 2021. Technological progress in electronic health record system optimization: Systematic review of systematic literature reviews. *International Journal of Medical Informatics*, 152: 8.

Neto, C., Senra, F., Leite, J., Rei, N., Rodrigues, R., Ferreira, D. and Machado, J. 2021. Different Scenarios for the Prediction of Hospital Readmission of Diabetic Patients. *Journal of medical systems*, 45 (1): 11.

Ng'etich, A. K. S., Voyi, K. and Mutero, C. M. 2021. Development and validation of a framework to improve neglected tropical diseases surveillance and response at sub-national levels in Kenya. *Plos Neglected Tropical Diseases*, 15 (10).

Nguyen, S. 2015. User acceptance of instant messaging in DHIS 2. Master's thesis in computer science 27th May 2015, Halden, Norway: Ostfold university college, pp1-96.

Nicol, E., Hanmer, L. A., Mukumbang, F. C., Basera, W., Zitho, A. and Bradshaw, D. 2021. Is the routine health information system ready to support the planned national health insurance scheme in South Africa? *Health Policy and Planning*, 36 (5): 639-650.

Nocera, F., Tabandeh, A., Guidotti, R., Boakye, J. and Gardoni, P. 2018. Physics-based fragility functions: Their mathematical formulation and use in the reliability and resilience analysis of transportation infrastructure. In: *Routledge handbook of sustainable and resilient infrastructure*. Routledge, 239-262.

Noel, R., Taramasco, C. and Marquez, G. 2022. Standards, Processes, and Tools Used to Evaluate the Quality of Health Information Systems: Systematic Literature Review. *Journal of Medical Internet Research*, 24 (3): 11.

Nøhr, C., Kuziemsky, C. E., Elkin, P. L., Marcilly, R. and Pelayo, S. 2019. Sustainable Health Informatics: Health Informaticians as Alchemists. *Studies in health technology and informatics*, 265: 3-11.

Nsaghurwe, A., Dwivedi, V., Ndesanjo, W., Bamsi, H., Busiga, M., Nyella, E., Massawe, J. V., Smith, D., Onyejekwe, K., Metzger, J. and Taylor, P. 2021. One country's journey to interoperability: Tanzania's experience developing and implementing a national health information exchange. *BMC Med Inform Decis Mak*, 21 (1): 139.

Nwankwo, B. and Sambo, M. N. 2020. Effect of Training on Knowledge and Attitude of Health Care Workers towards Health Management Information System in Primary Health Centres in Northwest Nigeria. *West Afr J Med*, 37 (2): 138-144.

Nyangena, J., Rajgopal, R., Ombech, E. A., Oloo, E., Luchetu, H., Wambugu, S., Kamau, O., Nzioka, C., Gwer, S. and Ndirangu, M. N. 2021. Maturity assessment of Kenya's health information system interoperability readiness. *Bmj Health & Care Informatics*, 28 (1): 7.

O'Connor, Y., Andreev, P. and O'Reilly, P. 2020. MHealth and perceived quality of care delivery: a conceptual model and validation. *BMC medical informatics and decision making*, 20 (1): 41.

Oberschmidt, K., Grunloh, C., Nijboer, F. and van Velsen, L. 2022. Best Practices and Lessons Learned for Action Research in eHealth Design and Implementation: Literature Review. *Journal of Medical Internet Research*, 24 (1): 18.

Omar, A., Ellenius, J. and Lindemalm, S. 2017. Evaluation of Electronic Prescribing Decision Support System at a Tertiary Care Pediatric Hospital: The User Acceptance Perspective. *Studies in health technology and informatics*, 234: 256-261.

Orellana, A., Estrada, V. and Alfonso, D. 2018. MVD: A Model for the Detection of Variability in Hospital Processes Using Process Mining. *Ieee Latin America Transactions*, 16 (3): 966-974.

Ossai, C. I. and Wickramasinghe, N. 2022. GLCM and statistical features extraction technique with Extra-Tree Classifier in Macular Oedema risk diagnosis. *Biomedical Signal Processing and Control*, 73: 103471.

Ostern, N., Perscheid, G., Reelitz, C. and Moormann, J. 2021. Keeping pace with the healthcare transformation: a literature review and research agenda for a new decade of health information systems research. *Electronic Markets*, 31 (4): 901-921.

Oza, S., Wing, K., Sesay, A. A., Boufkhed, S., Houlihan, C., Vandi, L., Sebba, S. C., McGowan, C. R., Cummings, R. and Checchi, F. 2019. Improving health information systems during an emergency: lessons and recommendations from an Ebola treatment centre in Sierra Leone. *BMC Med Inform Decis Mak*, 19 (1): 100.

Palojoki, S., Pajunen, T., Lehtonen, L. and Saranto, K. 2017. FIN-TIERA: A Tool for Assessing Technology Induced Errors. *Methods Inf Med*, 56 (1): 1-12.

Panerai, R. 2014. Health Information Systems. *Global Perspective of Heath. Department of Medical Physics, University of Leicester, UK. 6pp*, Article ID.

Paré, G. and Kitsiou, S. 2017. Methods for literature reviews. In: *Handbook of eHealth Evaluation: An Evidence-based Approach [Internet]*. University of Victoria.

Park, H.-A. 2016. Are we ready for the fourth industrial revolution? *Yearbook of medical informatics*, 25 (01): 1-3.

Paul, M. M., Greene, C. M., Newton-Dame, R., Thorpe, L. E., Perlman, S. E., McVeigh, K. H. and Gourevitch, M. N. 2015. The state of population health surveillance using electronic health records: a narrative review. *Population health management*, 18 (3): 209-216.

Pavão, A. L. B., Barcellos, C., Pedroso, M., Boccolini, C. and Romero, D. 2017. The role of Brazilian National Health Information Systems in assessing the impact of Zika virus outbreak. *Rev Soc Bras Med Trop*, 50 (4): 450-457.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R. and Dubourg, V. 2011. Scikit-learn: Machine learning in Python. *the Journal of machine Learning research*, 12: 2825-2830.

Peffers, K., Tuunanen, T., Rothenberger, M. A. and Chatterjee, S. 2007. A design science research methodology for information systems research. *Journal of management information systems*, 24 (3): 45-77.

Penfold, R. B., Burgess, J. F., Jr., Lee, A. F., Li, M., Miller, C. J., Nealon Seibert, M., Semla, T. P., Mohr, D. C., Kazis, L. E. and Bauer, M. S. 2018. Space-Time Cluster Analysis to Detect Innovative Clinical Practices: A Case Study of

Aripiprazole in the Department of Veterans Affairs. *Health services research*, 53 (1): 214-235.

Peng, L., Yuan, R., Shen, L., Gao, P. and Zhou, L. 2021. LPI-EnEDT: an ensemble framework with extra tree and decision tree classifiers for imbalanced lncRNA-protein interaction data classification. *BioData Mining*, 14: 1-22.

Persano, H. L., Kugler, M. V., Gutnisky, D. A. and Alul, M. F. 2021. [Public telemental health during COVID-19 pandemic: preliminary approaches on mental-health help-line program (MHLP)]. *Vertex*, Xxxii (151): 25-31.

Pineros, M., Saraiya, M., Baussano, I., Bonjour, M., Chao, A. and Bray, F. 2021. The role and utility of population-based cancer registries in cervical cancer surveillance and control. *Preventive Medicine*, 144.

Pisner, D. A. and Schnyer, D. M. 2020. Support vector machine. In: *Machine learning*. Elsevier, 101-121.

Postnikov, E. B., Esmedljaeva, D. A. and Lavrova, A. I. 2020. A CatBoost machine learning for prognosis of pathogen's drug resistance in pulmonary tuberculosis. In: Proceedings of *2020 IEEE 2nd Global Conference on Life Sciences and Technologies (LifeTech)*. IEEE, 86-87.

Prasser, F., Kohlbacher, O., Mansmann, U., Bauer, B., Kuhn, K. A. and Consortium, D. 2018. Data Integration for Future Medicine (DIFUTURE) An Architectural and Methodological Overview. *Methods of Information in Medicine*, 57: E57-E65.

Price, C., Green, W. and Suhomlinova, O. 2019. Twenty-five years of national health IT: exploring strategy, structure, and systems in the English NHS. *Journal of the American Medical Informatics Association*, 26 (3): 188-197.

Priestley, J. L. and McGrath, R. J. 2019. The evolution of data science: A new mode of knowledge production. *International Journal of Knowledge Management (IJKM)*, 15 (2): 97-109.

Prodinger, B. and Taylor, P. 2018. Improving quality of care through patient-reported outcome measures (PROMs): expert interviews using the NHS PROMs Programme and the Swedish quality registers for knee and hip arthroplasty as examples. *Bmc Health Services Research*, 18: 13.

Provost, F. and Fawcett, T. 2013. Data science and its relationship to big data and data-driven decision making. *Big data*, 1 (1): 51-59.

Rachmani, E., Lin, M. C., Hsu, C. Y., Jumanto, J., Iqbal, U., Shidik, G. F. and Noersasongko, E. 2020. The implementation of an integrated e-leprosy framework in a leprosy control program at primary health care centers in Indonesia. *Int J Med Inform*, 140: 104155.

Rai, H. M., Trivedi, A. and Shukla, S. 2013. ECG signal processing for abnormalities detection using multi-resolution wavelet transform and Artificial Neural Network classifier. *Measurement*, 46 (9): 3238-3246.

Rani, P., Kumar, R. and Jain, A. 2021. Coronary artery disease diagnosis using extra tree-support vector machine: ET-SVMRBF. *International Journal of Computer Applications in Technology*, 66 (2): 209-218.

Raza, A., Siddiqui, H. U. R., Munir, K., Almutairi, M., Rustam, F. and Ashraf, I. 2022. Ensemble learning-based feature engineering to analyze maternal health during pregnancy and health risk prediction. *Plos one*, 17 (11): e0276525.

Reubens, R. 2016. To craft, by design, for sustainability: Towards holistic sustainability design for developing-country enterprises. Article ID.

Reynolds, H. W., Salentine, S., Silvestre, E., Millar, E., Strahley, A., Cannon, A. C. and Bobrow, E. A. 2022. A learning agenda to build the evidence base for strengthening global health information systems. *Health Inf Manag*, 51 (2): 79-88.

Riley, P. L., Zuber, A., Vindigni, S. M., Gupta, N., Verani, A. R., Sunderland, N. L., Friedman, M., Zurn, P., Okoro, C., Patrick, H. and Campbell, J. 2012. Information systems on human resources for health: a global review. *Human Resources for Health*, 10.

Rogova, G. 2008. Combining the results of several neural network classifiers. *Classic Works of the Dempster-Shafer Theory of Belief Functions*, Article ID: 683-692.

Rohani, N. and Yusof, M. M. 2022. Evaluating Unintended Consequences in Health Information Systems. *Stud Health Technol Inform*, 294: 269-270.

Roth, J. A., Goebel, N., Sakoparnig, T., Neubauer, S., Kuenzel-Pawlik, E., Gerber, M., Widmer, A. F., Abshagen, C., Padiyath, R., Hug, B. L. and Grp, P. S. 2018. Secondary use of routine data in hospitals: description of a scalable analytical platform based on a business intelligence system. *Jamia Open*, 1 (2): 172-177.

Roy, M. S., Gupta, R., Chandra, J. K., Sharma, K. D. and Talukdar, A. 2018. Improving photoplethysmographic measurements under motion artifacts using artificial neural network for personal healthcare. *IEEE Transactions on Instrumentation and Measurement*, 67 (12): 2820-2829.

Rudd, K. E., Puttkammer, N., Antilla, J., Richards, J., Heffron, M., Tolentino, H., Jacobs, D. J., KatjivanJo, P., Prybylski, D., Shepard, M., Kumalija, J. C., Katuma, H. L., Leon, B. K., Mgonja, N. G. and Santas, X. M. 2019. Building workforce capacity for effective use of health information systems: Evaluation of a blended eLearning course in Namibia and Tanzania. *International Journal of Medical Informatics*, 131: 6.

Sadoughi, F., Hemmat, M., Valinejadi, A., Mohammadi, A. and Majdabadi, H. A. 2017. Assessment of Health Information Technology Knowledge, Attitude, and Practice among Healthcare Activists in Tehran Hospitals. *International Journal of Computer Science and Network Security*, 17 (1): 155-158.

Sahay, S., Nielsen, P. and Latifov, M. 2018. Grand challenges of public health: How can health information systems support facing them? *Health policy and technology*, 7 (1): 81-87.

Sahay, S., Rashidian, A. and Doctor, H. V. 2020. Challenges and opportunities of using DHIS2 to strengthen health information systems in the Eastern Mediterranean Region: A regional approach. *The Electronic Journal of Information Systems in Developing Countries*, 86 (1): e12108.

Saigi-Rubio, F., Pereyra-Rodriguez, J. J., Torrent-Sellens, J., Eguia, H., Azzopardi-Muscat, N. and Novillo-Ortiz, D. 2021. Routine Health Information Systems in the European Context: A Systematic Review of Systematic Reviews. *International Journal of Environmental Research and Public Health*, 18 (9).

Sajedul Alam, A., Reza, R., Abrar, A., Ahmed, T., Ahmed, S., Sharar, S. and Alim Rasel, A. 2022. Patients' Severity States Classification based on Electronic Health Record (EHR) Data using Multiple Machine Learning and Deep Learning Approaches. *arXiv e-prints*, Article ID: arXiv: 2209.14907.

Salleh, M. I. M., Abdullah, R. and Zakaria, N. 2020. Quality Predictors and Clinician Performance in Using Health Information Systems: A Test of Mediating Effect. *Pertanika Journal of Social Science and Humanities*, 28 (4): 3235-3251.

Salminen-Karlsson, M. and Golay, D. 2022. Information systems in nurses' work: Technical rationality versus an ethic of care. *New Technology Work and Employment*, 37 (2): 270-287.

Samra, H., Li, A. and Soh, B. 2020. G3DMS: Design and Implementation of a Data Management System for the Diagnosis of Genetic Disorders. *Healthcare*, 8 (3): 34.

Sanchez-Franco, M. J., Navarro-Garcia, A. and Rondan-Cataluna, F. J. 2019. A naive Bayes strategy for classifying customer satisfaction: A study based on online reviews of hospitality services. *Journal of Business Research*, 101: 499-506.

Sancho-Gomez, J. L., Martinez-Garcia, J. A., Ahalt, S. C. and Figueiras-Vidal, A. R. 2018. Linear discriminants described by disjoint tangent configurations. *Neurocomputing*, 316: 345-356.

Sandag, G. A. 2020. A prediction model of company health using bagging classifier. *JITK (Jurnal Ilmu Pengetahuan Dan Teknologi Komputer)*, 6 (1): 41-46.

Santana, V. S., Salvi, L., Cavalcante, F., Campos, F. and Algranti, E. 2021. Underreporting of mesothelioma, asbestosis and pleural plaques in Brazil. *Occup Med (Lond)*, 71 (4-5): 223-230.

Sari, A. D. and Prayoga, N. 2018. *Enhancing citizen engagement in the face of climate change risks: A case study of the flood early warning system and health information system in Semarang city, Indonesia* (Book Chapter). Springer. Available:https://www.scopus.com/inward/record.uri?eid=2-s2.0-85060718333&doi=10.1007%2f978-3-319-65003-6_7&partnerID=40&md5=57d01593e1789bdc3d4fbe4f0e0988e3 https://link.springer.com/chapter/10.1007/978-3-319-65003-6_7

Sarmiento-Suárez, R., Padron-Monedero, A., Bogaert, P., Abboud, L., Van Oyen, H., Tolonen, H., Tijhuis, M., Seeling, S., Haneef, R., Zaletel, M., Palmieri, L., Gallay, A., Lapão, L. V., Nogueira, P., Ziese, T., Vukovic, J., Beja, A., Saso, M. and Noguer-Zambrano, I. 2022. The InfAct proposal for a sustainable European health information infrastructure on population health: the

Distributed Infrastructure on Population Health (DIPoH). *Arch Public Health*, 80 (1): 139.

Sawadogo-Lewis, T., Keita, Y., Wilson, E., Sawadogo, S., Téréra, I., Sangho, H. and Munos, M. 2021. Can We Use Routine Data for Strategic Decision Making? A Time Trend Comparison Between Survey and Routine Data in Mali. *Glob Health Sci Pract*, 9 (4): 869-880.

Saxena, A. and Saad, A. 2007. Evolving an artificial neural network classifier for condition monitoring of rotating mechanical systems. *Applied Soft Computing*, 7 (1): 441-454.

Scheplitz, T. 2021. Pathway-Supporting Health Information Systems: A Review. *Stud Health Technol Inform*, 279: 87-94.

Schmidt, A. E., Abboud, L. A. and Bogaert, P. 2021. Making the case for strong health information systems during a pandemic and beyond. *Arch Public Health*, 79 (1): 13.

Schreiner, J. H., Thurston, D. L. and Willemsen-Dunlap, A. 2020. Readmission Risk Assessment Technologies and the Anchoring and Adjustment Heuristic. *Journal of medical systems*, 44 (3): 61.

Scott, V. and Gilson, L. 2017. Exploring how different modes of governance act across health system levels to influence primary healthcare facility managers' use of information in decision-making: experience from Cape Town, South Africa. *Int J Equity Health*, 16 (1): 159.

See, E. J., Bello, A. K., Levin, A., Lunney, M., Osman, M. A., Ye, F., Ashuntantang, G. E., Bellorin-Font, E., Benghanem Gharbi, M., Davison, S., Ghnaimat, M., Harden, P., Htay, H., Jha, V., Kalantar-Zadeh, K., Kerr, P. G., Klarenbach, S., Kovesdy, C. P., Luyckx, V., Neuen, B., O'Donoghue, D., Ossareh, S., Perl, J., Rashid, H. U., Rondeau, E., Syed, S., Sola, L., Tchokhonelidze, I., Tesar, V., Tungsanga, K., Kazancioglu, R. T., Wang, A. Y., Yang, C. W., Zemchenkov, A., Zhao, M. H., Jager, K. J., Caskey, F., Perkovic, V., Jindal, K. K., Okpechi, I. G., Tonelli, M., Feehally, J., Harris, D. C. and Johnson, D. W. 2021. Availability, coverage, and scope of health information systems for kidney care across world countries and regions. *Nephrol Dial Transplant*, 37 (1): 159-167.

Seo, K., Kim, H. N. and Kim, H. 2019. Current Status of the Adoption, Utilization and Helpfulness of Health Information Systems in Korea. *Int J Environ Res Public Health*, 16 (12).

Shan, R., Xiao, X. F., Che, J. W., Du, J. F. and Li, Y. W. 2022. Data Mining Optimization Software and Its Application in Financial Audit Data Analysis. *Mobile Information Systems*, 2022.

Sharaff, A. and Gupta, H. 2019. Extra-tree classifier with metaheuristics approach for email classification. In: Proceedings of *Advances in Computer Communication and Computational Sciences: Proceedings of IC4S 2018*. Springer, 189-197.

Sharma, D., Kumar, R. and Jain, A. 2022. Breast cancer prediction based on neural networks and extra tree classifier using feature ensemble learning. *Measurement: Sensors*, 24: 100560.

Sharma, R. K. and Prashar, R. 2019. FEASIBILITY OF EHEALTH IMPLEMENTATION IN INDIA LEARNING FROM GLOBAL EXPERIENCE. *Asia Pacific Journal of Health Management*, 14 (3): 12-23.

Shimpi, N., McRoy, S., Zhao, H. M., Wu, M. and Acharya, A. 2020. Development of a periodontitis risk assessment model for primary care providers in an interdisciplinary setting. *Technology and Health Care*, 28 (2): 143-154.

Sik, A. S., Aydinoglu, A. U. and Son, Y. A. 2021. Assessing the readiness of Turkish health information systems for integrating genetic/genomic patient data: System architecture and available terminologies, legislative, and protection of personal data. *Health Policy*, 125 (2): 203-212.

Şimşek, E. S., Atila, G., Aydın, A., Reisoğlu, İ. and Göktaş, Y. 2022. Comparison of theoretical frameworks of doctoral theses on the field of instructional technology: The Turkey-US case. *Library & Information Science Research*, Article ID: 101138.

Sivarajah, U., Kamal, M. M., Irani, Z. and Weerakkody, V. 2017. Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, 70: 263-286.

Sligo, J., Gauld, R., Roberts, V. and Villa, L. 2017. A literature review for large-scale health information system project planning, implementation and evaluation. *International Journal of Medical Informatics*, 97: 86-97.

Soltysik-Piorunkiewicz, A. and Morawiec, P. 2022. The Sustainable e-Health System Development in COVID 19 Pandemic–The Theoretical Studies of Knowledge Management Systems and Practical Polish Healthcare Experience. Article ID.

Sordo, M. 2002. Introduction to neural networks in healthcare. *Open clinical: Knowledge management for medical care*, Article ID.

Srimaneekarn, N., Hayter, A., Liu, W. and Tantipoj, C. 2022. Binary response analysis using logistic regression in dentistry. *International Journal of Dentistry*, 2022.

Srivastava, S. K., Singh, S. K. and Suri, J. S. 2020. A healthcare text classification system and its performance evaluation: A source of better intelligence by characterizing healthcare text. In: *Cognitive informatics, computer modelling, and cognitive science*. Elsevier, 319-369.

Steil, J., Finas, D., Beck, S., Manzeschke, A. and Haux, R. 2019. Robotic Systems in Operating Theaters: New Forms of Team-Machine Interaction in Health Care On Challenges for Health Information Systems on Adequately Considering Hybrid Action of Humans and Machines. *Methods of Information in Medicine*, 58: E14-E25.

Stoltzfus, J. C. 2011. Logistic regression: a brief primer. *Academic emergency medicine*, 18 (10): 1099-1104.

Stout, A., Wood, S., Namagembe, A., Kaboré, A., Siddo, D. and Ndione, I. 2018. Designing a global monitoring system for pilot introduction of a new contraceptive technology, subcutaneous DMPA (DMPA-SC). *Eval Program Plann*, 68: 185-193.

Suresh, L. and Singh, S. N. 2014. Studies in ICT and Health Information System. *International Journal of Information Library and Society*, 3 (1): 16.

Suthaharan, S. and Suthaharan, S. 2016. Support vector machine. *Machine learning models and algorithms for big data classification: thinking with examples for effective learning*, Article ID: 207-235.

Talekar, B. and Agrawal, S. 2020. A Detailed Review on Decision Tree and Random Forest. *Bioscience Biotechnology Research Communications*, 13 (14): 245-248.

Tamm, A., Jones, H. J. S., Perry, W., Campbell, D., Carten, R., Davies, J., Galdikas, A., English, L., Garbett, A., Glampson, B., Harris, S., Khan, K., Little, S., Malcomson, L., Matharu, S., Mayer, E., Mercuri, L., Morris, E. J. A., Muirhead, R., Norris, R., O'Hara, C., Papadimitriou, D., Peek, N., Renehan, A., Roadknight, G., Starling, N., Teare, M., Turner, R., Varnai, K. A., Wasan, H., Woods, K. and Cunningham, C. 2022. Establishing a colorectal cancer research database from routinely collected health data: the process and potential from a pilot study. *Bmj Health & Care Informatics*, 29 (1): 8.

Tangcharoensathien, V., Mills, A. and Palu, T. 2015. Accelerating health equity: the key role of universal health coverage in the Sustainable Development Goals. *BMC medicine*, 13 (1): 1-5.

Tappis, H., Ramadan, M., Vargas, J., Kahi, V., Hering, H., Schulte-Hillen, C. and Spiegel, P. 2021. Neonatal mortality burden and trends in UNHCR refugee camps, 2006-2017: a retrospective analysis. *BMC Public Health*, 21 (1): 390.

Taye, G. 2021. Improving health care services through enhanced Health Information System: Human capacity development Model. *Ethiopian Journal of Health Development*, 35 (1).

Teixeira, J. G., de Pinho, N. F. and Patricio, L. 2019. Bringing service design to the development of health information systems: The case of the Portuguese national electronic health record. *International Journal of Medical Informatics*, 132: 8.

Teixeira, J. G., Patrício, L. and Tuunanen, T. 2019. Advancing service design research with design science research. *Journal of Service Management*, 30 (5): 577-592.

Teles, G., Rodrigues, J., Saleem, K., Kozlov, S. and Rabelo, R. A. L. 2020. Machine learning and decision support system on credit scoring. *Neural Computing & Applications*, 32 (14): 9809-9826.

Thomas, J., Carlson, R., Cawley, M., Yuan, Q., Fleming, V. and Yu, F. 2022. The Gap Between Technology and Ethics, Especially in Low-and Middle-Income Country Health Information Systems: A Bibliometric Study. *Studies in health technology and informatics*, 290: 902-906.

Tilahun, B., Gashu, K. D., Mekonnen, Z. A., Endehabtu, B. F., Asressie, M., Minyihun, A., Mamuye, A., Atnafu, A., Ayele, W., Gutema, K., Abera, A., Abera, M., Gebretsadik, T., Abate, B., Mohammed, M., Animut, N., Belay, H., Alemu, H., Denboba, W., Gebeyehu, A., Wondirad, N. and Tadesse, L. 2021. Strengthening the national health information system through a capacity-building and mentorship partnership (CBMP) programme: a health system and university partnership initiative in Ethiopia. *Health Res Policy Syst*, 19 (1): 141.

Tossy, T. 2014. Major challenges and constraint of integrating health information systems in african countries: A Namibian experience. *International Journal of Information and Communication Technology*, 4 (7).

Tsangaratos, P. and Benardos, A. 2014. Estimating landslide susceptibility through a artificial neural network classifier. *Natural Hazards*, 74: 1489-1516.

Tummers, J., Tekinerdogan, B., Tobi, H., Catal, C. and Schalk, B. 2021a. Obstacles and features of health information systems: A systematic literature review. *Comput Biol Med*, 137: 104785.

Tummers, J., Tobi, H., Catal, C. and Tekinerdogan, B. 2021b. Designing a reference architecture for health information systems. *BMC Med Inform Decis Mak*, 21 (1): 210.

Tummers, J., Tobi, H., Schalk, B., Tekinerdogan, B. and Leusink, G. 2021c. State of the practice of health information systems: a survey study amongst health care professionals in intellectual disability care. *Bmc Health Services Research*, 21 (1): 9.

Tweedie, D., Polli, J. W., Berglund, E. G., Huang, S. M., Zhang, L., Poirier, A., Chu, X., Feng, B. and Int Transporter, C. 2013. Transporter Studies in Drug Development: Experience to Date and Follow-Up on Decision Trees From the International Transporter Consortium. *Clinical Pharmacology & Therapeutics*, 94 (1): 113-125.

Tyagi, A. and Singh, P. 2018. Health information system. In: *Healthcare Policy and Reform: Concepts, Methodologies, Tools, and Applications*. IGI Global, 1554-1564. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85059719653&doi=10.4018%2f978-1-5225-6915-2.ch070&partnerID=40&md5=ca60d1810fa6de276648fb67db2e7aa0

Vaganova, E., Ishchuk, T., Zemtsov, A. and Zhdanov, D. 2017. Health Information Systems: Background and Trends of Development Worldwide and in Russia. In: Proceedings of *HEALTHINF*. 424-428.

Van Aken, J., Chandrasekaran, A. and Halman, J. 2016. Conducting and publishing design science research: Inaugural essay of the design science department of the Journal of Operations Management. *Journal of Operations Management*, 47: 1-8.

van Bussel, M. J. P., Odekerken-Schröder, G. J., Ou, C., Swart, R. R. and Jacobs, M. J. G. 2022. Analyzing the determinants to accept a virtual assistant and use cases among cancer patients: a mixed methods study. *BMC health services research*, 22 (1): 890.

Van der Voort, H., Klievink, A., Arnaboldi, M. and Meijer, A. J. 2019. Rationality and politics of algorithms. Will the promise of big data survive the dynamics of public decision making? *Government Information Quarterly*, 36 (1): 27-38.

van der Voort, H., van Bulderen, S., Cunningham, S. and Janssen, M. 2021. Data science as knowledge creation a framework for synergies between data analysts and domain professionals. *Technological Forecasting and Social Change*, 173: 121160.

Venable, J., Pries-Heje, J. and Baskerville, R. 2016. FEDS: a framework for evaluation in design science research. *European journal of information systems*, 25 (1): 77-89.

Verikas, A., Gelzinis, A. and Bacauskiene, M. 2011. Mining data with random forests: A survey and results of new tests. *Pattern recognition*, 44 (2): 330-349.

Wahyuni, D. 2012. The research design maze: Understanding paradigms, cases, methods and methodologies. *Journal of applied management accounting research*, 10 (1): 69-80.

Waterson, P., Hoonakker, P. L. T. and Carayon, P. 2013. Special issue on human factors and the implementation of health information technology (HIT): Comparing approaches across nations. *International Journal of Medical Informatics*, 82 (5): 277-280.

Weber, J. H. and Ho, J. 2020. Applying Bidirectional Transformations to the Design of Interoperable EMR Systems. *Journal of Healthcare Informatics Research*, 4 (2): 138-150.

WHO. 2013. *Consultative expert working group on research and development: financing and coordination: Report of regional technical consultation, Bangkok, thailand, 15-17 August 2012*. WHO Regional Office for South-East Asia.

Wickramasinghe, I. and Kalutarage, H. 2021. Naive Bayes: applications, variations and vulnerabilities: a review of literature with code snippets for implementation. *Soft Computing*, 25 (3): 2277-2293.

Wieringa, R. J. 2014. *Design science methodology for information systems and software engineering*. Springer.

Willis, C. D., Riley, B. L., Herbert, C. P. and Best, A. 2013. Networks to Strengthen Health Systems for Chronic Disease Prevention. *American Journal of Public Health*, 103 (11): E39-E48.

Worku, A., Alemu, H., Belay, H., Mohammedsanni, A., Denboba, W., Mulugeta, F., Omer, S., Abate, B., Mohammed, M., Ahmed, M., Wondarad, Y. and Abebaw, M. 2022. Contribution of health information system to child immunization services in Ethiopia: baseline study of 33 woredas. *BMC Med Inform Decis Mak*, 22 (1): 64.

Yang, S., Wei, R., Guo, J. and Xu, L. 2017a. Semantic Inference on Clinical Documents: Combining Machine Learning Algorithms with an Inference Engine for Effective Clinical Diagnosis and Treatment. *IEEE Access*, 5: 3529-3546.

Yang, S., Wei, R., Guo, J. Z. and Xu, L. D. 2017b. Semantic Inference on Clinical Documents: Combining Machine Learning Algorithms With an Inference Engine for Effective Clinical Diagnosis and Treatment. *Ieee Access*, 5: 3529-3546.

Ye, J. 2021. Health Information System's Responses to COVID-19 Pandemic in China: A National Cross-sectional Study. *Appl Clin Inform*, 12 (2): 399-406.

You, Y., Doubova, S. V., Pinto-Masis, D., Pérez-Cuevas, R., Borja-Aburto, V. H. and Hubbard, A. 2019. Application of machine learning methodology to assess the performance of DIABETIMSS program for patients with type 2 diabetes in family medicine clinics in Mexico. *BMC medical informatics and decision making*, 19 (1): 221.

Youngs, H. and Piggot-Irvine, E. 2012. The application of a multiphase triangulation approach to mixed methods: The research of an aspiring school principal development program. *Journal of Mixed Methods Research*, 6 (3): 184-198.

Yousaf, M. S., Ahmad, I., Khurshid, A. and Ikram, M. 2020. Machine assisted classification of chicken, beef and mutton tissues using optical polarimetry and Bagging model. *Photodiagnosis and Photodynamic Therapy*, 31: 101779.

Yusof, M. M. 2019. *A socio-technical and lean approach towards a framework for health information systems-induced error* (Article). IOS Press. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85061236878&doi=10.3233%2f978-1-61499-951-5-508&partnerID=40&md5=7e20e2e6cc3ba1efedad66a3283af06f

Zane, P., Gieschen, H., Kersten, E., Mathias, N., Ollier, C., Johansson, P., Van den Bergh, A., Van Hemelryck, S., Reichel, A., Rotgeri, A., Schafer, K., Mullertz, A. and Langguth, P. 2019. In vivo models and decision trees for formulation development in early drug development: A review of current practices and recommendations for biopharmaceutical development. *European Journal of Pharmaceutics and Biopharmaceutics*, 142: 222-231.

Zareapoor, M. and Shamsolmoali, P. 2015. Application of credit card fraud detection: Based on bagging ensemble classifier. *Procedia computer science*, 48 (2015): 679-685.

Zhai, X., Ali, A. A. S., Amira, A. and Bensaali, F. 2016. MLP neural network based gas classification system on Zynq SoC. *IEEE Access*, 4: 8138-8146.

Zhang, R., Chen, Y., Liu, S. L., Liang, S. X., Wang, G., Li, L., Luo, X. N. and Li, Y. 2020. Progress of equalizing basic public health services in Southwest China--- health education delivery in primary healthcare sectors. *Bmc Health Services Research*, 20 (1): 13.

Zhang, W.-J. and Lin, Y. 2010. On the principle of design of resilient systems–application to enterprise information systems. *Enterprise Information Systems*, 4 (2): 99-110.

Zhang, Z. 2016. Introduction to machine learning: k-nearest neighbors. *Annals of translational medicine*, 4 (11).

Zheng, J., Lin, D., Gao, Z., Wang, S., He, M. and Fan, J. 2020. Deep learning assisted efficient AdaBoost algorithm for breast cancer detection and early diagnosis. *IEEE Access*, 8: 96946-96954.

Zotov, E., Hills, A. F., de Mello, F. L., Aram, P., Sayers, A., Blom, A. W., McCloskey, E. V., Wilkinson, J. M. and Kadirkamanathan, V. 2020. JointCalc: A web-based personalised patient decision support tool for joint replacement. *International Journal of Medical Informatics*, 142: 8.

Zuske, M. K., Auer, C., Oliver, S., Eyers, J. and Bosch-Capblanch, X. 2022. Framework synthesis to inform the ideation and design of a paper-based health information system (PHISICC). *Int J Health Plann Manage*, 37 (4): 1953-1972.

APPENDIX

Certificates and abstracts of published articles


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CERTIFICATE OF ACCEPTANCE

Certificate of acceptance for the manuscript (**healthcare-1996401**) titled:

Health Information System and Health Care Applications Performance in the Healthcare Arena: A Bibliometric Analysis

Authored by:

Ayogeboh Epizitone; Smangele Pretty Moyane; Israel Edem Agbehadji

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Open Access Review

A Systematic Literature Review of Health Information Systems for Healthcare

by Ayogeboh Epizitone [1,*], Smangele Pretty Moyane [2] and Israel Edem Agbehadji [3]

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Abstract

Health information system deployment has been driven by the transformation and digitalization currently confronting healthcare. The need and potential of these systems within healthcare have been tremendously driven by the global instability that has affected several interrelated sectors. Accordingly, many research studies have reported on the inadequacies of these systems within the healthcare arena, which have distorted their potential and offerings to revolutionize healthcare. Thus, through a comprehensive review of the extant literature, this study presents a critique of the health information system for healthcare to supplement the gap created as a result of the lack of an in-depth outlook of the current health information system from a holistic slant. From the studies, the health information system was ascertained to be crucial and fundament in the drive of information and knowledge management for healthcare. Additionally, it was asserted to have transformed and shaped healthcare from its conception despite its flaws. Moreover, research has envisioned that the appraisal of the current health information system would influence its adoption and solidify its enactment within the global healthcare space, which is highly demanded.

Keywords: health information system; information system; knowledge management; healthcare

Open Access Article

Health Information System and Health Care Applications Performance in the Healthcare Arena: A Bibliometric Analysis

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Abstract

There have been several studies centred on health information systems with many insights provided to enhance health care applications globally. These studies have provided theoretical schemes for fortifying the enactment and utilisation of the Health Information System (HIS). In addition, these research studies contribute greatly to the development of HIS in alignment with major stakeholders such as health practitioners and recipients of health care. Conversely, there has been trepidation about HIS' sustainability and resilience for healthcare applications in the era of digitalization and globalization. Hence, this paper investigates research on HIS with a primary focus on health care applications to ascertain its sustainability and resilience amidst the transformation of the global healthcare space. Therefore, using a bibliometric approach, this paper measures the performance of health information systems and healthcare for health care applications using bibliometric data from the web of science database. The findings reveal solid evidence of the constructive transformation of health information systems and health care applications in the healthcare arena, providing ample evidence of the adaptation of HIS and health care applications within the healthcare arena to the fourth industrial revolution and, additionally, revealing the resilient alignment of health care applications and health information systems.

Keywords: health information system; health care applications; healthcare; HIS applications

Article Details

Framework to Develop a Resilient and Sustainable Integrated Information System for Health Care Applications: A Review

Author 1: Ayogeboh Epizitone

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Abstract: The reconstruction of the health sector amidst the forth industrial revolution has been confronted with many challenges. Many benefits have been attributed to the vital role played by technology in realizing and constructing a robust health information system. However, amidst the digitalization in the healthcare system, several challenges such as integration and fragmentation have been affecting the structure of the Health Information Systems (HIS) which subsequently influences decision making and resource allocation. Therefore, this paper through a comprehensive systematic review afford a proposition for a develop a resilient and sustainable information system for Health Care applications. The study reveals the parallel impact of health information technology application in the healthcare arena and highlight the need for more in-depth research on HIS that incorporate novel scientific methods. Additional this study also presents a body of evident that reveal the inadequacies of the HIS to tackle the constant transformative changes presently confronting the global healthcare systems.

Keywords: Health information system; integrated information system; e-health; bioinformatics

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ORIGINAL RESEARCH

A Data-Driven Paradigm for a Resilient and Sustainable Integrated Health Information Systems for Health Care Applications

Authors Epizitone A, Moyane SP, Agbehadji IE

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Introduction: Many transformations and uncertainties, such as the fourth industrial revolution and pandemics, have propelled healthcare acceptance and deployment of health information systems (HIS). External and internal determinants aligning with the global course influence their deployments. At the epic is digitalization, which generates endless data that has permeated healthcare. The continuous proliferation of complex and dynamic healthcare data is the digitalization frontier in healthcare that necessitates attention.
Objective: This study explores the existing body of information on HIS for healthcare through the data lens to present a data-driven paradigm for healthcare augmentation paramount to attaining a sustainable and resilient HIS.
Method: Preferred Reporting Items for Systematic Reviews and Meta-Analyses: PRISMA-compliant in-depth literature review was conducted systematically to synthesize and analyze the literature content to ascertain the value disposition of HIS data in healthcare delivery.
Results: This study details the aspects of a data-driven paradigm for robust and sustainable HIS for health care applications. Data source, data action and decisions, data sciences techniques, serialization of data sciences techniques in the HIS, and data insight implementation and application are data-driven features expounded. These are essential data-driven paradigm building blocks that need iteration to succeed.
Discussions: Existing literature considers insurgent data in healthcare challenging, disruptive, and potentially revolutionary. This view echoes the current healthcare quandary of good and bad data availability. Thus, data-driven insights are essential for building a resilient and sustainable HIS. People, technology, and tasks dominated prior HIS frameworks, with few data-centric facets. Improving healthcare and the HIS requires identifying and integrating crucial data elements.
Conclusion: The paper presented a data-driven paradigm for a resilient and sustainable HIS. The findings show that data-driven track and components are essential to improve healthcare using data analytics insights. It provides an integrated footing for data analytics to support and effectively assist health care delivery.

Keywords: health information system, HIS, data, healthcare, analytics

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AYOGEBOH EPIZITONE

For your participation in the DSI - Africa Machine Learning Short Course: UKZN Hub Durban, KwaZulu-Natal

23rd January 2023 - 3rd February 2023.

PROFESSOR HENRY MWAMBI
Principal Investigator: DSI, UKZN

DR NISHA NADESAN-REDDY
Project Manager: DSI, UKZN

Acknowledgement
This training programme is supported by the Fogarty International Center of the National Institutes of Health under Award Number U2RTW012140. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health

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For your participation in the Data Science Initiative short course 1: Statistical computing held in Durban, KwaZulu-Natal
30th May 2022 - 10th June 2022.

PROFESSOR HENRY MWAMBI
Principal Investigator: DSI, UKZN

PROFESSOR HEATHER MATTIE
Training programme director and course facilitator, Harvard

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For your participation in the
Data science initiative: Bootcamp in
Durban, KwaZulu-Natal
23rd May - 27th May 2022

PROFESSOR HENRY MWAMBI
Principal Investigator: DSI, UKZN

DR. ELPHAS OKANGO
Course facilitator

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for your participation in the ***Deep Learning*** short course of the WASHA Takwimu (Working on Applications for Data Science and Health in Africa) Research Training Program on Harnessing Data Science For Global Health Priorities in Africa (DSI-A).

26 June - 07 July 2023
Durban, KwaZulu-Natal

Professor Henry Mwambi
Principal Investigator: DSI, UKZN

DR Nisha Nadesan-Reddy
Project Manager: DSI, UKZN

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for your participation in the ***Health Systems with a focus on health data science*** short course of the WASHA Takwimu (Working on Applications for Data Science and Health in Africa) Research Training Program on Harnessing Data Science For Global Health Priorities in Africa (DSI-A).

21 August 2023 - 01 September 2023
Durban, KwaZulu-Natal

Professor Saloshni Naidoo
Training Director: DSI, UKZN

Dr Nisha Nadesan-Reddy
Project Manager: DSI, UKZN

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FOR COMPLETION OF THE SERIES OF SHORT COURSES IN **HEALTH DATA SCIENCE METHODS** AS PART OF THE NATIONAL INSTITUTES OF HEALTH TRAINING GRANT: WASHA TAKWIMU - RESEARCH TRAINING ON HARNESSING DATA SCIENCE FOR GLOBAL HEALTH PRIORITIES IN AFRICA (DSI-A)

May 2022 - July 2023
Durban, KwaZulu-Natal

PROFESSOR HENRY MWAMBI
PRINCIPAL INVESTIGATOR: DSI, UKZN

DR NISHA NADESAN-REDDY
PROJECT MANAGER: DSI, UKZN

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CERTIFICATE OF COMPETENCY

This NVIDIA DLI Certificate has been awarded to

Ayogeboh Epizitone

for the successful completion of

Fundamentals of Deep Learning

Will Ramey
Senior Director, Developer Programs

July 27,2022

EDITING CERTIFICATE

Mastermind Editorial Service

1 Orilla 12, Somerset Avenue, Glenwood, Durban.
Email: Patrickukzn2016@gmail.com

17th February 2023

Ms Ayogeboh Epizitone
Durban University of Technology.

LETTER FOR DOCTORAL THESIS REVIEW

As the Editor-in-Chief of the Mastermind review/editing services, I confirm that your doctoral thesis, "FRAMEWORK TO DEVELOP A RESILIENT AND SUSTAINABLE INTEGRATED INFORMATION SYSTEM FOR HEALTH CARE APPLICATIONS – A DATA-DRIVEN APPROACH," has gone through our process of editing and review.

We thank you for considering us for this service. We do hope we will work together for your future editorial services.

Regards,

Dr. Hosea Patrick,
Editor in Chief,
School of Built Environment and Development Studies,
University of KwaZulu-Natal,
Durban, KwaZulu-Natal,
South Africa.
Email: patrickh@ukzn.ac.za
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