Enhancing Clinical Decision Support Systems through Hospital Information System Integration and Machine Learning in a Context of the Emergency Department

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Abstract

This study conducts design science research (DSR) aimed at addressing the challenge of improving clinical decision support (CDS) in Emergency Departments (EDs). Making timely decisions by physicians to meet the diverse demands within hospital EDs is a challenge as the inadequacies of current Hospital Information Systems (HIS) can host fragmented Electronic Health Record (EHR) data across multiple sub-systems. The advancement of Information Technology (IT), notably machine learning (ML), brings new initiatives for addressing this issue. To tackle this complexity, this research deploys DSR to design a novel system integration architecture. This architecture provides a comprehensive framework that orchestrates HIS integration across multiple strata, encompassing the business, application, and technology layers, to facilitate the integration of ML-based Clinical Decision Support Systems (CDSS) within the ED setting.

Two design artefacts are developed as outcomes of DSR: firstly, the development of the system integration architecture, and secondly, the creation of the ML-based CDSS. The former serves as a meticulously designed blueprint for HIS integration, ensuring the effective functioning of ML-based CDSS at the point of care. The latter represents a pioneering CDSS system, harnessing the power of ML algorithms to furnish real-time, context-aware decision support.

The impact of the ML-based CDSS on ED efficiency is subjected to rigorous evaluation. This evaluation is conducted by leveraging historical Electronic Health Record (EHR) data within a simulated ED environment. The simulation, calibrated with parameters drawn from a real-world hospital ED setting, yields promising results. These findings underscore the feasibility and the manifold benefits of integrating ML-based CDSS to augment ED efficiency.

Furthermore, this research makes a noteworthy contribution to the theoretical underpinnings of information system design. It achieves this by pioneering the development of a novel system integration architecture. This architecture serves as a bridge, alleviating the knowledge gap that traditionally separates HIS integration from ML-based CDSS. The study advances the understanding of strategic design and integration of hospital information systems to support ML and CDSS. Ultimately, this advancement holds the potential to catalyse substantial improvements in patient care and outcomes, especially within the intricate and high-stakes environment of the Emergency Department.

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List of Abbreviations

Adam	Adaptive moment estimation
ANN	Artificial neural network
API	Application programming interface
AUC	Area Under the Curve
CDS	Clinical decision support
CDSS	Clinical decision support system
CEMS	Clinical examination management system
CNN	Convolutional neural network
CPT	Current procedural terminology
CR	Creatinine
CT	Computerised tomography
DES	Discrete-event simulation
DHB	District health board
DNN	Deep neural network
DRG	Diagnosis-related groups
DS	Design science
DSR	Resign science research
ECG	Electrocardiogram
ED	Emergency department
EHR	Electronic
EMR	Electronic medical records
ERP	Enterprise resource planning
FEAF	Federal Enterprise Architecture framework
FN	False negative

FNN	Feedforward neural networks
FP	False positive
FPR	False positive rate
GST	General systems theory
HIS	Hospital information system
HL7	Health Level 7
HNZW	Te Whatu Ora health New Zealand Waikato
ICD	International Classification of Diseases
ISDT	Information system design theory
IT	Information technology
LIS	Laboratory information systems
ML	Machine learning
MLM	Medical logic module
MRI	Magnetic resonance imaging
NCKUH	National Cheng Kung University Hospital
NHI	National health index
NIST	National Institute of Standards and Technology
PACS	Picture archiving and communication systems
PCA	Principal component analysis
PIS	Pharmacy information systems
ReLU	Rectified linear unit
RIS	Radiology information systems
RNN	Recurrent neural networks
ROC	Receiver operating characteristic
SGD	Stochastic gradient descent

SNOMED	Systematised Nomenclature of Medicine
SOA	Service-oriented architecture
SYSH	Sun Yat-Sen Memorial Hospital
TN	True negative
TOGAF	The open group architecture framework
TP	True positive
TPR	Ture positive rate
t-SNE	T-Distributed Stochastic Neighbour Embedding
WDHB	Waikato district health board

Chapter 1 Introduction

1.1 Background

In the ever-evolving landscape of healthcare, the proficient management of information and clinical decision-making processes has emerged as a pivotal determinant of patient outcomes. Hospital information systems (HIS) and clinical decision support systems (CDSS) play integral roles in shaping the quality of healthcare service, exerting a profound impact on patient safety and healthcare efficiency.

Within this context, emergency departments (EDs) stand as critical hubs of healthcare delivery, often serving as the initial point of contact for individuals seeking medical attention in urgent situations. The demands placed on EDs are multifaceted, encompassing rapid triage and diagnosis to facilitate timely treatment decisions. The unique challenges faced by EDs, including the imperatives for swift and accurate information dissemination, efficient workflows, and the management of diverse and intricate patient cases, underscore the paramount importance of robust HIS and CDSSs.

In 2013, the Ministry of Health in New Zealand published an ED utilisation report, which included a survey revealing that approximately 14% of the population had utilised A&E services in the preceding 12 months. After this report, in 2016, a more recent publication based on data from District Health Boards (DHBs) in New Zealand demonstrated a steady increase in ED utilisation. Specifically, between 2010 and 2011, and 2014 and 2015, the number of patients seeking care at an ED at least once in a 12-month period rose from around 640,000 to 690,000. Furthermore, the rate of ED utilisation increased from 14.4% to 14.9% during the same timeframe.

One of the most prevalent challenges stemming from this heightened demand is the prolonged waiting times experienced by patients in EDs. This issue significantly impedes hospitals' efforts to achieve quality healthcare, clinical expertise, and customer satisfaction. The reports also underscore the impact of escalating demand on the length of stay for patients within New Zealand's EDs. The duration of a patient's stay in the ED constitutes a pivotal performance indicator, encompassing the time elapsed from the patient's initial presentation at the ED to their subsequent admission, discharge, or transfer.

The survey conducted in the 2013 report divulges that in the year 2011–2012, over 80% of ED visits culminated in a stay of less than three hours. However, the 2016 report reveals a notable shift in this trend, with over 40% of patients experiencing a lengthier stay exceeding three hours in 2014–2015. In 2009, the New Zealand government introduced a key performance target for EDs, stipulating that

95% of patients should undergo admission, discharge, or transfer within six hours of their ED arrival. Regrettably, the 2016 report by the Ministry of Health indicates that only 92% of patient visits at EDs in New Zealand met this benchmark. Extended lengths of stay frequently result in overcrowding within EDs, thereby compromising healthcare outcomes for patients, as many seek urgent care within this critical healthcare setting.

Amidst the challenges posed by increasing patient numbers and prolonged waiting times in EDs, the implementation of diagnosis-related groups (DRG) or similar systems further intensifies the necessity for cost efficiency (Anessi-Pessina et al., 2019; Chok et al., 2018; Van Wilder et al., 2018). DRG is a system designed to classify hospital cases into groups based on similar clinical conditions and treatment, aiming to standardise healthcare billing and payment (Jiao, 2018). Physicians working in EDs are now tasked not only with providing high-quality care but also with making decisions that align with the financial implications of DRG classifications. This added layer of complexity requires careful consideration of resource utilisation and the allocation of medical services, ensuring that patient care remains of the utmost priority while navigating the intricacies of cost-effectiveness in the healthcare landscape.

Emergency healthcare, by its very nature, demands rapid responses and well-informed clinical decisions. These decisions can be greatly enhanced by the integration of HIS and CDS. HIS provides a comprehensive platform for managing patient records, streamlining administrative tasks, and facilitating communication among healthcare providers (Nilashi et al., 2016). Meanwhile, CDS leverages data-driven insights and machine learning (ML) algorithms to assist clinicians in diagnosing, prescribing treatments, and making critical decisions in real-time (Levy-Fix et al., 2019).

The significance of this integration extends beyond the immediate care of patients within the ED; it permeates the entire healthcare ecosystem. Smooth data flow and decision support in the ED can lead to improved patient outcomes, reduced healthcare costs, and enhanced resource allocation throughout the healthcare continuum.

Despite the evident advantages of HIS and CDS integration in EDs, the implementation of such systems is not without its challenges. Technical complexities, data security concerns, and the necessity for adaptability to the dynamic nature of emergency care all warrant meticulous consideration. Furthermore, the evolving landscape of healthcare technology, regulations, and patient expectations necessitates a comprehensive examination of current research and practices in this domain.

1.2 Theoretical Motivation

Physicians working in the ED confront formidable challenges in decision-making due to the prevalence of high uncertainty and clinical diversity. Consider, for instance, scenarios involving accidental injuries, where a patient may sustain multiple injuries, some of which may escape initial detection. Acute conditions can swiftly evolve, complicating the diagnostic process. Furthermore, EDs often lack immediate feedback to evaluate the accuracy of their initial diagnoses, given that more precise assessments often occur after a patient's transfer to another department. In life-threatening situations, physicians must make decisions with minimal information and limited time (Zavala et al., 2018). Moreover, in their decision-making, ED physicians must also account for resource availability and backup capabilities (Stout & Tawney, 2005).

ML, as an emerging technology in data analytics, holds promise for augmenting CDSS by furnishing a practical decision-making mechanism. Within the domain of medical information technology, ML's application has garnered considerable interest, particularly for its capabilities in image recognition. For example, diabetic retinopathy-induced blindness can be mitigated with timely intervention. In a study by Gulshan et al. (2016), a deep-learning algorithm was developed to aid in the diagnosis of diabetic retinopathy in regions where expert detection is scarce. Similarly, when examining small bowel diseases using capsule endoscopy, the traditional manual analysis of copious image and video data for each patient typically consumes one to two hours of a physician's time. The introduction of a convolutional neural network (CNN)-based deep learning algorithm by Ding et al. (2019) reduced the average diagnosis time by up to 90%. In both instances, the application of deep learning models exhibited diagnostic sensitivity on par with human specialists. However, despite numerous studies endorsing ML for clinical informatics tasks (Choi et al., 2016; Miotto et al., 2016; Ravì et al., 2016; Shickel et al., 2018), research on the application of ML to enhance clinical decision-making in EDs is notably lacking.

The relevance of this research transcends the confines of the ED, resonating with a broader audience concerned with the convergence of healthcare and technology. At its core, this research addresses fundamental questions in healthcare—how can the wealth of data within electronic health records (EHRs) be leveraged for clinical decision support (CDS)? And how can ML technology be devised to achieve this purpose? Given the escalating healthcare costs and the mounting pressures on healthcare systems, answers to these questions assume paramount importance. The potential to enhance the promptness and accuracy of decision-making holds the promise of not only saving lives but also optimising resource allocation, reducing healthcare expenditures, and enhancing overall healthcare quality.

The present landscape of healthcare decision support systems underscores significant deficiencies and gaps. Presently, EHR data remains underutilised in ED decision-making. Despite the vast repository of patient data within EHRs, the potential for effective data mining to support decision-making remains largely unexplored. Furthermore, the application of ML to enhance ED efficiency, especially concerning EHR data, remains relatively uncharted territory. These knowledge gaps present an opportunity to explore the development of an ML-based CDSS tailored for EDs, offering timely, data-driven decision support. The pressing need is to bridge these gaps and transform the healthcare decision support landscape.

An outstanding question in the healthcare domain concerns the inadequate integration of HISs with EHR data (Parks et al., 2019). Unlike industrial enterprise systems, HIS comprises multiple sub-systems serving distinct purposes that are not necessarily aligned in objectives. Administrative systems may prioritise cost efficiency, while clinical systems emphasise optimal medical outcomes (Reichertz, 2006). In hospitals, these sub-systems are often deployed as separate applications highly optimised for specific departments, neglecting integration with a centralised data repository (Kuhn & Giuse, 2001). This fragmented system structure leads to the segregation of EHR data, with different components stored within various HISs. Successful integration of these systems is pivotal to harnessing the full potential of EHR data for decision support.

1.3 Research Objective and Research Question

To address the prevailing challenges within the current HIS and the formidable obstacles confronting ED physicians, the primary research objective of this study is to design a system integration architecture aimed at augmenting CDS capabilities within the HIS through the application of ML. The potency of ML in processing substantial volumes of data and discerning intricate patterns and insights stands poised to substantially enhance the efficacy and celerity of clinical decision-making within the demanding milieu of emergency healthcare.

The central research inquiry steering this undertaking is as follows: "How to design an integrated architectural framework for hospital information systems to provide machine learning-based clinical decision support capabilities tailored to the exigencies of an ED setting?" This query encapsulates the core challenge of integrating ML-driven CDS functionalities into the pre-existing HIS infrastructure, custom-tailored to the fast-paced and unpredictable landscape of ED operations.

In the decomposition of this overarching research question, the study is systematically organised around two subordinate investigative pursuits. The first is articulated as follows:

"How to design a clinical decision support system imbued with machine learning capabilities?"

This sub-investigation centres on the creation of a CDSS that harnesses the power of ML to provide real-time insights and recommendations to ED physicians, thereby enhancing their clinical acumen with data-driven perspectives.

The second subordinate research question is phrased as follows:

" How can an integration architecture for hospital information systems be designed to accommodate the incorporation of machine learning-driven clinical decision support functionality?"

This inquiry delves deeply into the technical aspects of system architecture, with the aim of ensuring an integrated and resource-efficient assimilation of ML-driven decision support within the existing HIS, all the while ensuring no disruption to the daily operations of the ED.

1.4 Key Concepts

Emergency Department (ED)

The emergency department (ED) serves as an indispensable pillar within a hospital's infrastructure, functioning 24/7 to provide immediate medical assistance to individuals grappling with severe injuries or illnesses. Typically located within public healthcare institutions, these departments are staffed with highly skilled medical professionals who perform critical assessments, administer treatment, and initiate essential care for patients in dire medical circumstances (Healthdirect Australia, 2023).

Hospital Information System (HIS)

A hospital information system (HIS) stands as a central cornerstone of contemporary healthcare infrastructure, encompassing a diverse array of information technology applications designed to enhance hospital operations (Gartner Inc., 2020). Tailored specifically for healthcare environments, a HIS is dedicated to the processing of data, information, and knowledge. It orchestrates these activities to collect, process, report, and leverage health-related information and knowledge for policymaking, program execution, and research purposes (Jakovljević, 2008).

Clinical Decision Support System (CDSS)

Clinical decision support systems (CDSSs) are computer applications with the primary goal of advancing patient outcomes and reducing hospital costs by delivering pertinent clinical guidance to healthcare providers (Berner & La Lande, 2007). Essentially, a CDSS is a computer-based system that furnishes healthcare professionals with essential knowledge and information, ultimately elevating the quality of healthcare services and patient well-being (Greenes, 2011).

Machine Learning (ML)

Machine learning (ML) represents a specialised field dedicated to the development of computer systems that autonomously improves their performance through experiential learning. It revolves around the foundational principles underpinning learning systems, with application across diverse real-world domains (Jordan & Mitchell, 2015).

Artificial Neural Network (ANN)

Artificial neural networks (ANNs) are computer simulations inspired by the structural intricacies of the human brain. They employ algorithms to emulate the behaviour of model neurons (nodes), classifying data through hyperplane separation (Krogh, 2008). ANNs draw upon the complex connections present in biological neural networks to replicate parallel and distributed information processing. Comprising interconnected, simplistic units that process real-valued inputs and yield real-valued outputs, ANNs essentially emulate the neural architecture of the human brain to facilitate learning and address a broad spectrum of issues through these interconnected processing units (Mitchell, 1997).

System Integration

System integration entails the intricate process of constructing a complex information system. This involves the creation of a customised architecture or application and its seamless integration with a combination of both new and existing hardware, off-the-shelf, and bespoke software. The ultimate objective is to establish seamless communication and cohesiveness among all interconnected components (Gartner, n.d.).

Design Science Research

Design science research serves as a framework within the realm of information systems research, addressing two pivotal issues: the role of information technology artefacts and the practical relevance of information services research (A. Hevner & S. Chatterjee, 2010b). Design science research amalgamates artefact creation with a robust emphasis on practical usability, bridging this divide and evolving into a methodological approach aimed at resolving real-world challenges through the development of functional solutions.

1.5 Research Method

The research methodology employed in this study is design science research. Design science research is the chosen methodology for addressing the research inquiries and objectives of this study. The primary research objective is the development of a system integration architecture that enhances CDS capabilities within the HIS through the application of ML.

Design science research is aptly suited for this research endeavour due to its emphasis on generating innovative artefacts, notably the system integration architecture and ML models, and their evaluation in real-world contexts. This methodology aligns with the overarching goal of crafting a pragmatic solution to enhance CDS within the healthcare system.

To establish a robust foundation for this study, an extensive and comprehensive literature review was conducted. This encompassed a wide array of topics, including ED, CDS, ML, HIS, and system integration. This thorough review facilitated a profound comprehension of the existing landscape and revealed gaps and opportunities for enhancement.

In adherence to design science research principles, this research employs the observation method to scrutinise the interaction between physicians and the existing HISs in the ED environment. This method is pivotal in gaining insights into the current state of the CDSS and pinpointing areas where ML integration can offer the greatest advantages.

Data collection is a cornerstone of this research and serves a dual purpose: training the ML model and constructing the simulation model. The data procured from a collaborating hospital ED is invaluable as it mirrors real-world clinical scenarios and patient interactions within the ED.

The selection of the dataset from the collaborating hospital is a deliberate one. It adheres to the strict criteria of completeness, accuracy, and consistency, rendering it a fitting dataset for the training and validation of the ML models. This dataset forms a dependable foundation for the development of the system integration architecture and the simulation of its impact on CDS.

Following data acquisition, a pivotal phase of data pre-processing is executed. During this phase, raw data is refined, normalised, and purged of redundancies and outliers. This is imperative to ensure that the data used for training the ML models is of the highest quality, capable of producing precise results.

EHR data is then harnessed to construct and train the ML models. These models are tailored to predict the outcomes of laboratory tests, an integral element of CDS. The results generated by these models are juxtaposed with historical data to evaluate their accuracy and effectiveness.

The trained ML models undergo further scrutiny through their integration into the clinical workflow within a simulated environment. This step is critical in assessing how the system integration architecture enhances efficiency in the ED by reducing superfluous tests and furnishing more precise CDS.

To ensure the veracity and dependability of the research findings, the simulation model has undergone an iterative refinement process, incorporating feedback from physicians in the hospital ED. This iterative approach guarantees that the system integration architecture is honed and enhanced based on the insights and expertise of medical professionals.

The simulation model has been rigorously validated by cross-referencing its outcomes with historical patient visit data. This validation procedure substantiates that the system integration architecture faithfully replicates real-world scenarios. Furthermore, configuration parameters from the actual hospital ED have been integrated to further validate the simulation model, ensuring its faithful representation of the clinical environment.

This study places considerable emphasis on ethical considerations. It is conducted under the auspices of ethical approval from the University of Waikato Human Research Ethics Committee, thereby assuring that the research adheres rigorously to ethical principles and guidelines. The access and utilisation of EHR data are facilitated by the Institutional Review Board at the collaborating hospital, assuring that patient data is handled with the utmost security and ethical integrity, respecting the principles of privacy and confidentiality.

1.6 Significance

This research holds substantial implications, primarily centred around the incorporation of ML-based CDSSs within the context of the ED and the development of a system integration architecture for HISs.

Foremost, this study addresses a critical knowledge gap by offering a pragmatic resolution to healthcare-related challenges. The integration of ML-based CDSSs at the point of care in the ED is geared towards augmenting operational efficiency. By harnessing ML technology, this research illustrates how ED physicians can make data-informed clinical decisions, leading to more judicious resource allocation and ultimately elevating the quality of patient care. This serves as a pertinent response to the persistent challenge in the healthcare industry where physicians grapple with the task of optimising resource usage, such as diagnostic tests, while ensuring precision in diagnoses and patient stability.

Furthermore, the study highlights the potential for substantial cost savings due to a marked reduction in unnecessary diagnostic tests, all while preserving diagnostic accuracy. The findings also underscore improved patient flow within the ED. The inclusion of the ML model, in conjunction with a simulation experiment, substantiates the prospect of a more streamlined patient experience within the ED, which proves invaluable within the bustling environment of healthcare facilities.

Another vital implication resides within the realm of Information System Design Theory (ISDT) in healthcare. The study advocates for the integration of ISDT in healthcare information systems, underlining the necessity for a systematic and theory-driven approach to system design. By accentuating the significance of General Systems Theory and enterprise architecture within the theoretical framework, this research promotes a comprehensive view of healthcare information technology constructs, where usability, effectiveness, and efficiency take centre stage.

This theoretical transition bears practical implications for the design and implementation of healthcare information systems. It urges healthcare institutions to consider the interrelated nature of different components within the healthcare ecosystem, extending from patient care procedures to HIS integration. Through alignment of processes and technologies with strategic objectives via enterprise architecture, the research underscores the demand for information technology solutions that enrich patient care and operational efficiency, without causing disruption to the broader mission of healthcare organisations.

To summarise, this research not only furnishes practical solutions for enhancing ED operations through ML-based CDSS and system integration architecture for HISs but also advances the theoretical underpinnings of ISDT in the healthcare domain. It emphasises the importance of adopting a comprehensive perspective on healthcare information technology constructs and aligning technology with strategic objectives, ultimately leading to enhanced patient care, cost-effectiveness, and improved resource allocation within the ED and beyond. These implications are particularly significant as the healthcare landscape continues to evolve, underscoring the centrality of data-driven decision-making and information technology integration.

1.7 Publications

The research conducted in this study has undergone rigorous validation and refinement through extensive engagement with the academic community, including presentations at prestigious conferences. These interactions with fellow researchers and subject-matter experts have significantly contributed to the enrichment of our work, providing us with invaluable feedback.

Poster:

In 2019, an initial conceptualisation of this study was showcased as a poster presentation at the International Conference on Information Resources Management (Conf–IRM 2019). The primary objective at that stage was to enhance clinical decision-making by applying a data analytics approach that leveraged both Electronic Health Record (EHR) data and resource capacity data.

> Jiang H., Wang YC., Goh T. (2019). Enhancing decision making in a hospital emergency department with data analytics. *International Conference on Information Resources Management (Conf–IRM). Auckland, New Zealand.*

As the research progressed and understanding evolved, the focus shifted toward integrating EHR data from various HISs to facilitate machine learning for CDSS. This pivot was prompted by subsequent research activities that uncovered the challenges associated with system integration.

Conference Proceedings:

Amidst the unprecedented challenges posed by the COVID-19 pandemic in 2020, a comprehensive paper was published and presented as part of the conference proceedings at the 4th International Conference on Medical and Health Informatics (ICMHI 2020). This paper elucidated the potential of the system design to assist physicians in making more informed clinical decisions, particularly in the context of unexpected public health emergency.

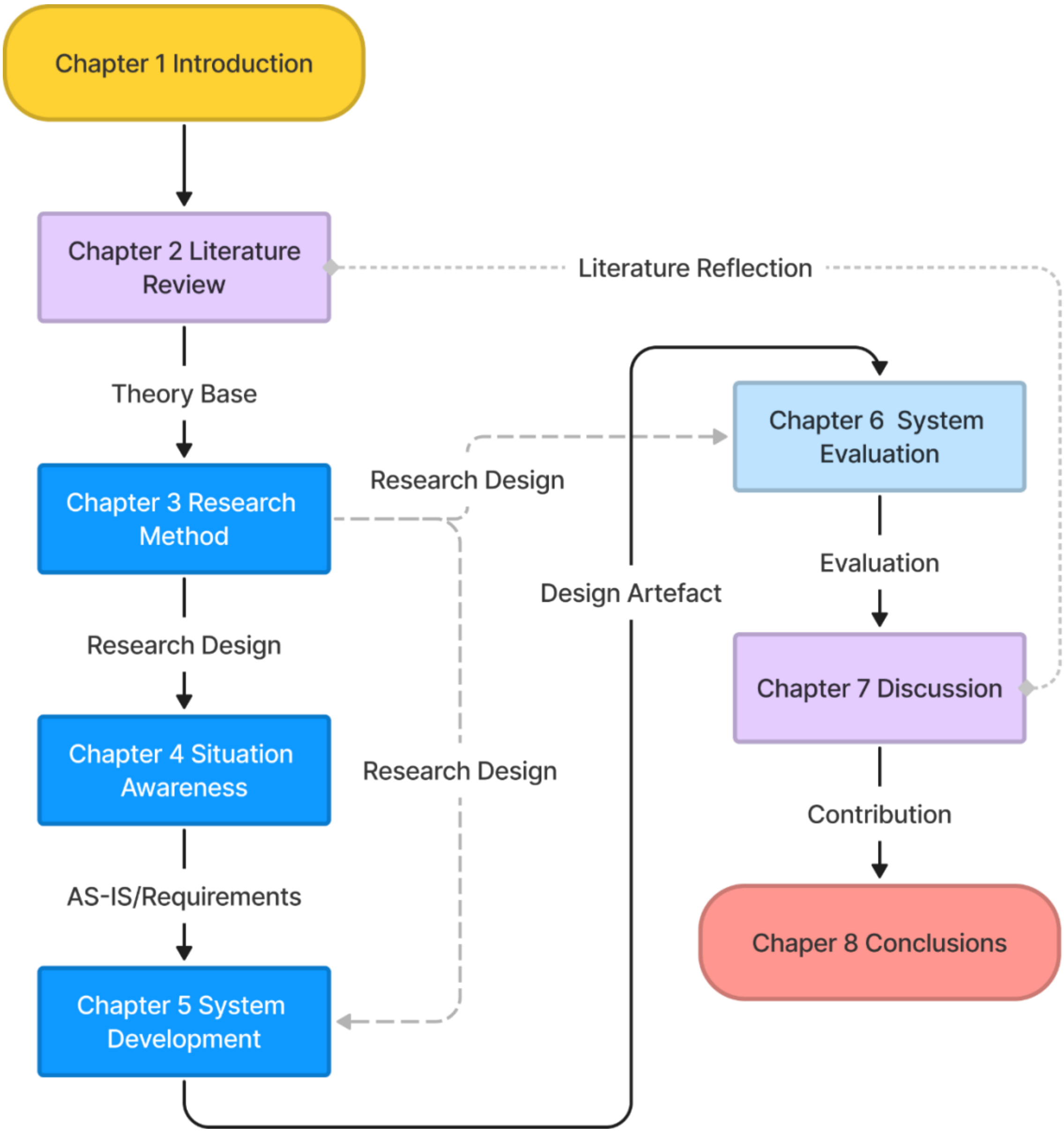
> Jiang, H., Wang, W. Y. C., Goh, T. T., & Zhu, J. (2020, August). Enhancing Decision Making with Deep Reinforcement Learning in a Context of Novel Coronavirus Outbreak: an Example in Emergency Department. In *Proceedings of the 4th International Conference on Medical and Health Informatics* (pp. 113-117).

In 2022, the system design artefact was further elucidated and disseminated as part of the conference proceedings at the 6th International Conference on Medical and Health Informatics (ICMHI 2022). This particular publication delved deeply into the challenges associated with the integration of HISs, a significant obstacle in the implementation of ML-based CDSS. Furthermore, it introduced a systematic integration architecture design artefact as a pivotal solution to these challenges.

> Wang, W. Y. C., Jiang, P. H. W., Tiong, T. G., & Hsieh, C. C. (2022, May). Gauging the Gaps for Decision Support-Data integration in the Hospital Information Systems with Machine Learning. In *Proceedings of the 6th International Conference on Medical and Health Informatics* (pp. 43-47).

1.8 Thesis Structure

Figure 1-1: Thesis structure



As illustrated in Figure 1-1, the structure of this thesis provides a well-defined roadmap, ensuring a logical and coherent progression from the initial literature review to the intricate research methodology. Subsequently, it guides the reader through the detailed exploration and discussion of situation awareness, system development, system simulation, and the resulting conclusions. Each chapter builds upon the knowledge and discoveries of the preceding chapters, facilitating a smooth transition from theoretical underpinnings to practical applications and analytical insights.

Chapter 2, the Literature Review, serves as the cornerstone of this research endeavour. This segment examines the existing body of literature pertaining to situation awareness and system development. It forms the theoretical framework, emphasising pivotal concepts and pertinent theories. Additionally, it identifies gaps in the existing literature that this research aims to address. By revealing the knowledge gap, the research questions are thoughtfully formulated, drawing from the identified problems and the theoretical context.

Chapter 3 elaborates on the research methodology employed in this study. This section expounds upon the chosen approach, the methods employed for data collection, and the rationale that underpins these methodological choices. In doing so, this chapter effectively bridges the transition from the literature review to the ensuing chapters by detailing how the research will be conducted.

Chapter 4 delves comprehensively into the concept of situation awareness, offering an in-depth analysis of its current state (AS-IS). This chapter presents a thorough comprehension of prevailing practices and technologies related to situation awareness.

Chapter 5 marks the transition into the development phase. It focuses on the design and creation of a system aimed at augmenting situation awareness. This section offers insights into the design process, addresses implementation challenges, and presents the resulting design artefact. Importantly, it builds upon the knowledge gathered in Chapter 4 and establishes a critical link to the subsequent chapter on system simulation.

Chapter 6 is dedicated to the utilisation of system simulation as a method for evaluating the system design. It discusses the design artefact introduced in Chapter 5 and its integration into a comprehensive simulation framework. Detailed explanations of the simulation process, including parameters and objectives, are thoughtfully provided. This chapter, therefore, serves as a bridge to the final chapter, where research results and findings are subjected to thorough analysis.

Chapter 7 consolidates the results and findings derived from the system simulation. It critically assesses the impact of the designed system on situation awareness, addressing the implications of the research and providing answers to the research questions posed in Chapter 2. The chapter also reflects upon the significance of the findings, their practical applications, and potential avenues for further research.

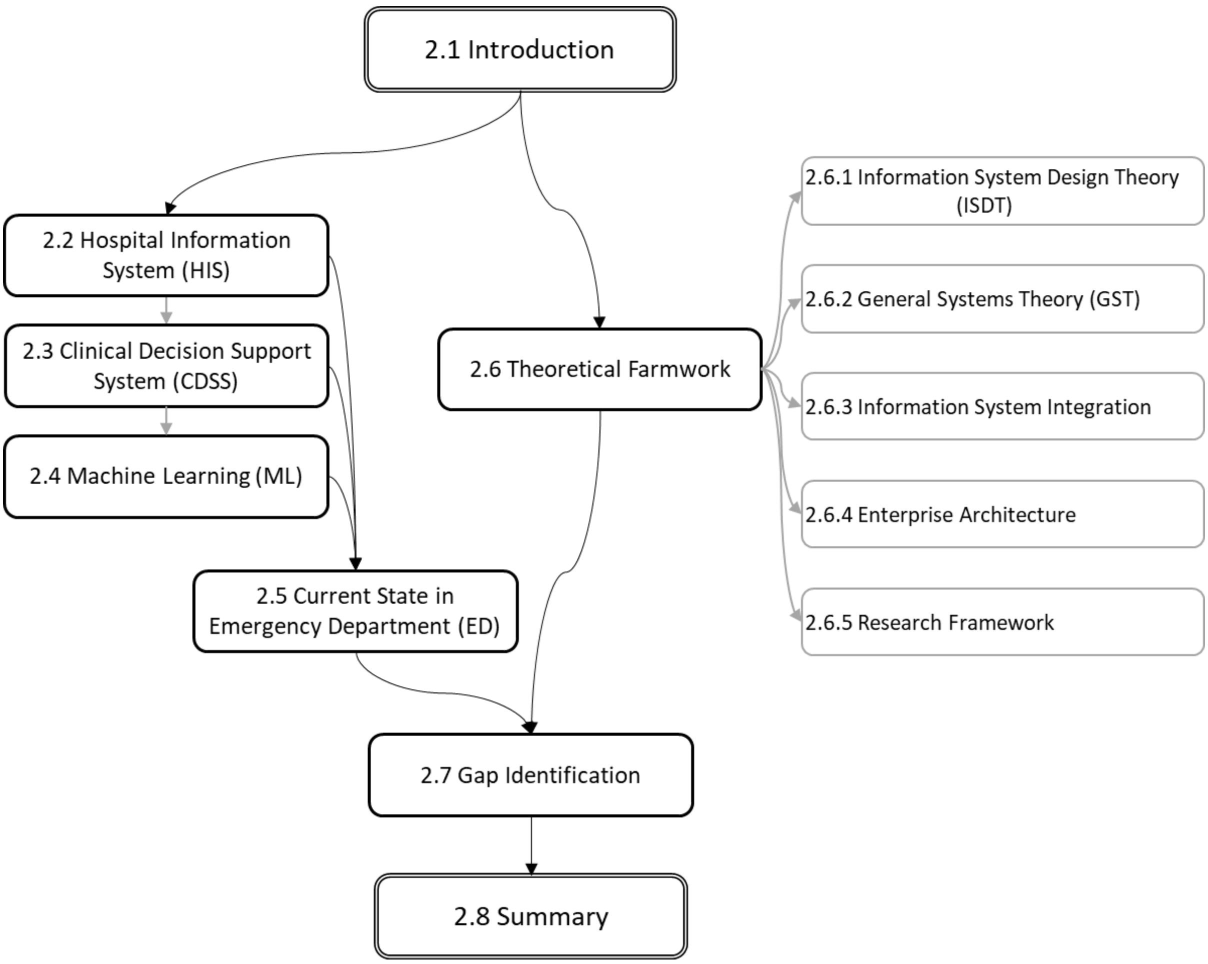
Finally, Chapter 8 culminates in a comprehensive conclusion to this study. It succinctly encapsulates the contributions made to the field, discusses their implications for practical application, and proposes future research directions. This chapter artfully weaves together the threads of the research, offering a coherent and holistic conclusion to the thesis.

Chapter 2 Literature Review

2.1 Introduction

This chapter of the literature review establishes a solid foundation for this explanatory research, thereby providing valuable insights into the functions of information systems, hospital information systems (HIS), clinical decision support systems (CDSS), and machine learning (ML) within the intricate context of an emergency department (ED). Through the utilisation of a sound theoretical underpinning in this pertinent domain, its primary objective is to address current knowledge gaps and formulate a robust research framework. This framework, in turn, will serve as a guiding beacon for the ensuing design science research activities within the scope of this study.

Figure 2-1: Chapter structure



The chapter's structure, as depicted in Figure 2-1, unfolds systematically. It begins with an exploration of the pivotal role of HIS in the hospital operations, encompassing electronic health records (EHR) and administrative systems, emphasising their evolution and impact on workflow and healthcare. Subsequently, it delves into the historical development of CDSS, elucidating their essential functionalities and significance in providing healthcare professionals with evidence-based recommendations, particularly in EDs.

Following this, the chapter transitions to an examination of ML applications within EDs, focusing on the technological advancements of ML and its relevance in the healthcare sector, along with an overview of commonly used ML techniques. It proceeds to provide an encompassing view of contemporary challenges faced by EDs and the emerging technological trends that affect patient care.

The theoretical underpinnings of the chapter are introduced through discussions of Information System Design Theory (ISDT), General Systems Theory (GST), information system integration, and enterprise architecture, establishing a robust theoretical foundation. This groundwork sets the stage for the introduction of a research framework, which integrates these theories into a cohesive model tailored for ED information systems, offering a strategic roadmap for practical application.

Culminating from an exhaustive review of the existing literature, this study has conclusively substantiated critical knowledge gaps. These revelations hold profound implications for both practical applications and theoretical advancements. Furthermore, these identified knowledge gaps serve as the foundational framework for forthcoming research endeavours, specifically focusing on the exploration of real-world business challenges.

2.2 Hospital Information Systems

The HIS holds a central position within contemporary healthcare infrastructure. It encompasses an array of information technology applications meticulously designed to enhance efficiency and oversee various dimensions of hospital operations (Gartner Inc., 2020). In certain contexts, the HIS is portrayed as an extensive computer network serving as the foundational infrastructure for all medical, organisational, and administrative functions within a hospital setting (Schneider & Feussner, 2017). Broadly within the healthcare domain, the term "health information system" is often used interchangeably (Haux, 2006). An HIS is characterised as an information system meticulously tailored to process data, information, and knowledge within healthcare environments. It constitutes a cohesive effort aimed at aggregating, processing, reporting, and leveraging health information and knowledge to inform policymaking, drive programmatic actions, and facilitate research initiatives (Jakovljević, 2008).

It is noteworthy that the utilisation of HIS and health information system nomenclature may exhibit variances contingent upon the specific context in which they are used. While some academic discourses consider HIS and health information system to be synonymous, others demarcate HIS as a constituent or specialised branch within the broader health information system framework (Jakovljević, 2008). Given the research scope of this study, which concentrates on information systems deployed within the clinical workflows of hospital EDs, with a primary objective of enhancing clinical decision-making processes, it is appropriate to employ the term "hospital information system".

Despite most HISs nowadays being implemented with computer technology, the concept of HISs, which can take any form of structured repository of data, information, or knowledge repository used to support healthcare delivery or to promote health development, originates from the 18th century, more than two centuries before the integration of information technology (Panerai, 2014). It is only in recent decades that HISs have evolved from paper-based to computer-based processing and storage, coinciding with a significant proliferation of data in the healthcare sector (Haux, 2006). The impetus for the development of information systems in hospitals is to optimise operational efficiency (Reichertz, 2006). Since introduced into the healthcare sector, information systems in healthcare have transitioned from paper-based data storage to computer-based processing, expanding from local departmental focus to global architectures encompassing all hospital services. Information systems/information technology have become indispensable for healthcare planning and research, shifting from technical priorities to addressing organisational and strategic management issues. This transformation has also involved adapting to new data types and technologies, such as wearables (Fernandes et al., 2022). In response to technological advancements and evolving system scope, information systems/information technology in healthcare has undergone significant transformations over the decades.

1960s to 1970s: Emergence of Administrative Systems

During the 1960s and 1970s, healthcare executives primarily concentrated on automating administrative and financial processes (Wager, 2017). These early systems aimed to streamline patient billing and support accurate Medicare cost reporting. However, their adoption was mainly confined to large hospitals and academic medical centres due to their resource-intensive nature.

1970s to 1990s: Departmental Systems

The late 1970s and 1980s marked a shift towards the development of departmental systems, such as clinical laboratory and pharmacy systems (Wager, 2017). These systems were more affordable and catered to revenue-generating departments within healthcare organisations. However, they often operated as stand-alone systems, lacking interoperability with other clinical and administrative systems (Haux, 2006).

1990s to present: Patient-Centred Information Systems

Starting in the 1990s and continuing into the 2000s, there was a significant shift towards patient-centred information processing within health care regions, reflecting a more global perspective (Haux, 2006). The introduction of new information technology in the healthcare sector has invoked digital transformation, changing the organisation paradigm and improving the healthcare service quality (Tuzii, 2017). With HIS studies focusing on integrated management, medical images, and EHR, there have been advancements in internal access, mobile access, and efficient EHR storage and retrieval with digital transformation (Marques & Ferreira, 2020). Such technological improvements in HISs have also enabled what is called e-health, where healthcare is transferred from the intimacy and confines of the doctor-patient relationship to a complex network of both human and non-human actors, including databases, HISs, digital health records, electronic health cards, online patient communities, health-related apps, smart homes with ambient-assisted living technologies, etc.

HISs have now gained widespread adoption within hospital settings, serving multifaceted roles in supporting clinical, administrative, and financial operations (Nilashi et al., 2016). These systems constitute a vital component of contemporary healthcare delivery, revolutionising the management, sharing, and utilisation of patient data to enhance healthcare outcomes. In the specific context of EDs, where swift and precise decision-making is imperative, HISs assume a pivotal role in augmenting patient care, streamlining workflow efficiency, and facilitating resource allocation.

In contrast to enterprise systems in other sectors, an HIS in a hospital consists of multiple subsystems with varying objectives, often giving rise to challenges related to internal integration (Kuhn & Giuse, 2001). Within HIS, administrative systems emphasise cost reduction, while clinical systems prioritise achieving the best medical outcomes (Reichertz, 2006). Frequently, in a hospital environment, these subsystems are implemented as distinct applications tailored for specific departments, with limited attention given to their integration into a centralised data repository (Kuhn & Giuse, 2001).

A pivotal component of modern HISs is the EHR, which functions as a centralised repository for a wide array of clinical data, encompassing patient demographics, diagnoses, laboratory results, prescriptions, radiological images, and allergies (Birkhead et al., 2015). Research indicates that EHRs surpass traditional paper-based records by enhancing the accessibility of medical data, resulting in time savings for data retrieval and maintenance, as well as cost reductions through the prevention of redundant admissions (Ben-Assuli et al., 2013; Poissant et al., 2005).

In recent decades, there has been a substantial global upswing in EHR adoption within healthcare facilities. For instance, in the United States, data from the Office of the National Coordinator for Health Information Technology (2018) reveals that by 2017, more than 95% of all types of hospitals had embraced certified EHR technology. A survey conducted by the China Hospital Information Network Conference (CHINC) in 2015 disclosed that 72.57% of a sample of 2622 hospitals had integrated EHR systems (chinabaogao.com, 2019). Similarly, in New Zealand, EHR adoption is now ubiquitous, with all general practices fully using this technology (Protti & Bowden, 2010).

In addition to the EHR system, hospitals with well-established HISs often incorporate several other critical components, including laboratory information systems (LISs) for precise management of laboratory data and results (Sepulveda & Young, 2013), radiology information systems (RISs), or picture archiving and communication systems (PACSs) for organised storage and distribution of medical images, such as X-rays, MRIs, and CT scans (Boochever, 2004; Nance Jr et al., 2013), and pharmacy information systems (PISs) for streamlined medication management (Alanazi et al., 2018). These integrated systems collectively enhance patient care, improve diagnostic capabilities, and streamline healthcare operations within the facility.

The landscape of HISs has been continually evolving beyond the existing systems, driven by the emergence of new technologies. For instance, IoT devices, such as wearable health monitors and connected medical equipment, are becoming increasingly prevalent (Selvaraj & Sundaravaradhan, 2020). These devices can collect real-time patient data and transmit it to HISs for analysis (Iqbal et al., 2021). Blockchain technology is gaining traction for its potential to improve data security and interoperability in healthcare. HISs can benefit from blockchain by ensuring the integrity and privacy of patient records (Yaqoob et al., 2021). Patients can also have more control over their health data, granting permissions to healthcare providers as needed (Shen et al., 2019).

2.3 Clinical Decision Support Systems

CDSSs represent computer applications designed to enhance patient outcomes and reduce hospital operating costs by furnishing pertinent clinical decision support (CDS) to physicians (Berner & Lande, 2007). It can also be describe as the computer system to provide pertinent knowledge and information for the enhancement of healthcare service and patient well-being (Greenes, 2011). Modern CDSSs typically consist of three integral components: a knowledge base, an inference engine, and an interface for input and output management (Cheerkoot-Jalim et al., 2019; Spooner, 2016). The knowledge base encompasses predefined rules or formulas, often articulated as IF-THEN rules. Patient data, obtained from manual entry, EHR data, or a combination of both, serves as the input for the system. The inference engine processes this patient data in conjunction with the preset rules to generate informative output. Such output may encompass cautions or recommendations regarding potential interventions.

The adoption of CDSSs within the healthcare sector is motivated by several significant factors, including addressing the intricacies of knowledge management, leveraging EHR data effectively, and delivering personalised healthcare services (Musen et al., 2021). While CDS is a concept that does not inherently require association with information technologies like computer hardware or software, this study specifically focuses on computer based CDSSs.

The early development of CDSSs can trace back to the 1990s, when departmental HISs were widely adopted in hospitals, where an attempt was taken to design and implement CDS capabilities within the various systems (Middleton et al., 2016). At this stage, CDS functionalities are binding with the departmental system for specific clinical tasks in pharmacy (Bates et al., 1999; Evans et al., 1998; Nielsen et al., 2014), resource allocation (Manrique-Rodríguez et al., 2012; Schmidt et al., 2013), point of care (Hibbs et al., 2015), and documentation (Embi et al., 2004; Fitzmaurice et al., 2002).

In addition to the various system orientations, lack of standardisation in both technology and terminology is another obstacle to the early adoption of CDSSs as it is difficult to share knowledge across systems. And much effort has been made to solve the issue. To establish a common language and format to represent medical knowledge and clinical guidelines independent from the choice of HIS applications, Arden Syntax was developed as a specification which addresses the technical issue by enabling interoperability of the knowledge within various systems (Samwald et al., 2012). In addition to the data exchange standard established by Arden Syntax, development has also been made in terminology. Substantial advancements have been made in the establishment of robust standards for various healthcare domains, such as International Classification of Diseases (ICD-9-CM/10), Systematized Nomenclature of Medicine (SNOMED), and Current Procedural Terminology (CPT), contributing to improved data interoperability and communication within the healthcare sector (Middleton et al., 2016).

The various CDSSs can be categorised along different dimensions, with one fundamental dimension being their functionality. Basic CDSSs primarily serve as tools for healthcare practitioners to access clinical knowledge or information in response to specific queries (Metzger & MacDonald, 2002). This information retrieval process can be initiated either through explicit user-driven searches or through semi-automated searches prompted by user interactions with the system or its outputs (Greenes, 2011).

Another prevalent category of CDSSs actively intervenes in the clinical decision-making process by delivering alerts, reminders, and constraints (Greenes, 2011). This kind of CDSS functions by triggering warnings over the occurrence of inappropriate input value, such as drug-drug interactions, dosage errors or allergies; or abnormal output value, such as clinical test results beyond normal ranges. Some solutions within this category can generate reminders with conditions, such as a schedule test for revisit patient, or when immunisations or mammograms are due (Moore & Loper, 2011).

The increasing adoption of EHR has paved the way for the emergence of data driven CDSSs. With access to extensive repositories of patient data, the utilisation of mathematical models and computer algorithms has become feasible for generating information aimed at augmenting clinical decision-making. These models serve the purpose of capturing valuable insights, identifying trends, and detecting patterns within patient data. For instance, in the realm of CDSS, Bayes' rule, also known as Bayes' theorem, has found widespread application, particularly in aiding diagnosis through a probabilistic reasoning or predictive approach (Miller, 2009). The fundamental premise underlying the use of Bayes' rule involves determining the most likely diagnosis by calculating conditional probabilities associated with a patient's symptoms and their correspondence to various potential disease complexes. These probabilities are influenced by two primary factors: firstly, the likelihood of a patient with a specific combination of diseases exhibiting certain symptoms, primarily linked to the disease's characteristics; and secondly, the overall probability of an individual from a specific population subset having that combination of diseases. This overarching probability may be subject to various contextual factors, such as geographical location, seasonal variations, or the choice of healthcare specialist or clinic visited (Ledley & Lusted, 1959).

It is noteworthy that this approach often necessitates an array of laboratory tests to identify and correlate specific symptoms accurately. To address the potential drawbacks associated with the time-consuming and costly nature of this testing process, Gorry and Barnett (1968) developed an innovative sequential strategy approach. In contrast to the conventional approach that mandates the performance of all diagnostic tests upfront, this sequential strategy allows for the initiation of testing with a limited subset of assessments. Subsequently, additional tests are ordered based on the evolving diagnostic information, ultimately leading to a conclusive diagnosis. Gorry and Barnett's pioneering approach is founded on the premise that, on average, it requires approximately one-third fewer tests to achieve a diagnosis of equivalent accuracy when compared to the conventional Bayes' rule-based approach.

To further extend the capability of CDSSs, an alternative approach is the utilisation of expert systems. An expert system is designed to simulate the reasoning and decision-making processes of human experts (Berner & La Lande, 2007; Greenes, 2011). The early iterations of an expert system combined a diagnostic program with support routines, enabling users to specialise the program for specific domains by incorporating insights gleaned from past experiences, employing Bayesian analysis for inference and providing insights from its application in medical diagnosis (Gorry, 1968). These systems, in contrast to providing definitive answers, aimed to offer interactive advice to healthcare professionals. They facilitated the explanation of decision rationale, with their clinical utility contingent on the continuous acquisition of rules and collaboration with human experts to expand their knowledge base (Shortliffe et al., 1973). Often, these expert systems were implemented with a heuristic model. Rule-based systems, as a heuristic approach, emulate expert reasoning processes by aggregating individual logical statements in the form of production rules, typically derived through observation, interviews, or debriefing of human experts (Greenes, 2011).

Moreover, CDSSs can be further categorised along additional dimensions, including their timing of intervention in the clinical process, whether they operate actively or passively, and the extent to which their recommendations are tailored to specific clinical scenarios and individual patients (Metzger & MacDonald, 2002; Sutton et al., 2020).

In terms of their underlying decision-making processes, CDSSs can be categorised as either knowledge-based or non-knowledge-based systems (Berner & Lande, 2007). Most of the CDSSs discussed above in this section fall into the category of knowledge-based systems. A knowledge-based CDSS draws upon existing knowledge concerning the relationships between patient data and diagnostic outcomes. This knowledge is described and encoded in a programming language to address clinical challenges (Spooner, 2016). For instance, Arden Syntax serves as a prominent markup language for managing medical knowledge within the widely adopted Health Level 7 (HL7) standard (Samwald et al., 2012). Arden Syntax furnishes a standardised method for representing medical knowledge, clinical rules, and decision support logic. It employs a consistent syntax and structure, thereby enabling diverse systems to comprehend and interpret the same medical knowledge in a uniform manner. Arden Syntax is devised to be machine-readable, facilitating easy parsing and interpretation of encoded medical knowledge by computer systems such as CDSSs. Within the framework of Arden Syntax, each rule is encapsulated as a medical logic module (MLM), incorporating predefined variables, IF-THEN rules, and output specifications (Musen et al., 2021). A knowledge-based CDSS may exhibit several inherent limitations. Firstly, the maintenance of its knowledge base can prove to be a laborious undertaking. Empirical research has consistently indicated that one of the primary challenges in this context lies in the acquisition of knowledge, which is inherently a time-intensive process (Ash et al., 2007). Secondly, the inflexibility inherent in knowledge-based systems constitutes a significant concern. These systems are designed to rigidly adhere to predefined rules, which can limit their adaptability to evolving clinical contexts and nuances (Sutton et al., 2020). Furthermore, a knowledge-based CDSS is susceptible to inherent biases. Since the rules governing its decision-making processes are devised by human experts, the knowledge obtained from one specific population or setting may not be universally applicable or suitable for another distinct population or context (Bright et al., 2012).

In contrast, non-knowledge-based CDSSs obviate the necessity for explicit rule maintenance. Instead, ML techniques are employed to discern unexpected patterns within historical data extracted from EHR systems (Sutton et al., 2020), the assimilation of statistical technology within the ambit of extensive EHR databases, underpinned by access to comprehensive and well-structured datasets. This facilitates precise patient matching, thereby enabling the examination of treatment responses in analogous patients, thereby informing the appropriate course of action for the current patient (Greenes, 2011). Nevertheless, as the scale and intricacy of EHR data burgeoned, statistical methods exhibited constraints attributable to their hypothesis-driven nature. Subsequently, the introduction of ML approaches became imperative to cope with the enormity of datasets and to unveil salient patterns devoid of heavy reliance on predefined hypotheses (Peiffer-Smadja et al., 2020). Furthermore, empirical studies have demonstrated the efficacy of ML, even in the presence of data of suboptimal quality (Zheng et al., 2017).

2.4 Machine Learning

ML is a discipline dedicated to the development of computer systems capable of autonomous improvement through experiential learning. Its core focus is rooted in comprehending the fundamental principles governing learning systems, which find practical applications across diverse domains (Jordan & Mitchell, 2015). The inception of ML can be traced back to endeavours aimed at instructing a digital computer to emulate human learning processes. This pursuit held the promise of diminishing the reliance on intricate manual problem-solving techniques by enabling computers to assimilate knowledge from their experiences, eventually surpassing human capabilities (Samuel, 1959). According to Mitchell (1997, p. 2), ML can be defined as "a computer program [that] is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E".

Despite the existence of numerous techniques, the majority of ML algorithms can be categorised into three fundamental paradigms: supervised learning, unsupervised learning, and reinforcement learning (Jordan & Mitchell, 2015).

Supervised learning represents a pivotal machine learning paradigm wherein the objective is to establish mapping from input data to corresponding output values, as gleaned from a provided dataset containing known input-output pairs (Mahesh, 2020; Nasteski, 2017). In this context, the dataset in question, which includes paired input and output data points, is commonly referred to as labelled data. Within this the realm of ML, the input elements serve as the features used to forecast the associated output values, which are, in turn, designated as the labels. At its core, supervised learning is fundamentally centred on the task of training a computational model to formulate predictions grounded in the patterns and relationships discerned within labelled data. This framework holds widespread applicability across various domains, exemplified by its deployment in healthcare for tasks such as disease diagnosis (Rajkomar et al., 2019), in finance for the identification of fraudulent activities (Sailusha et al., 2020), and in recommendation systems to facilitate the tailored delivery of service to users (Portugal et al., 2018).

In practical applications, linear regression stands as a fundamental and widely employed technique within the realm of supervised ML, primarily employed for the construction of predictive models, where it endeavours to establish a relationship between a dependent variable, denoted as 'y', and a set of independent variables, collectively represented as 'x'. (Maulud & Abdulazeez, 2020) This relationship is typically expressed mathematically as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_m x_m + \epsilon$$

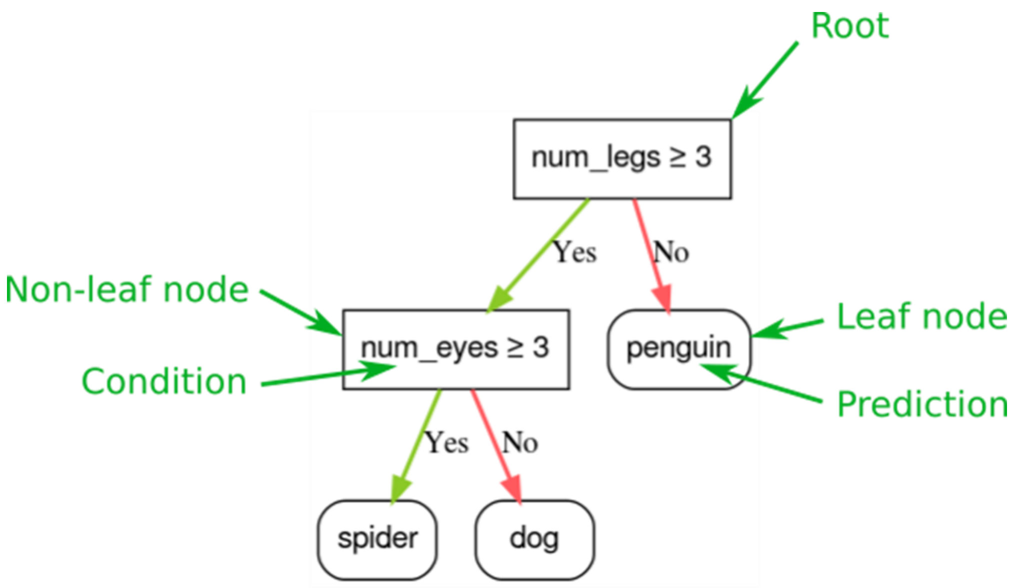
Where:

- y represents the dependent variable of interest.
- $X_1, X_2, \ldots, X_m$ denote the independent variables.
- $\beta_0, \beta_1, \ldots, \beta_m$ signify the regression coefficients associated with the respective independent variables.
- ϵ denotes the error term, representing the deviation between the predictions and the actual observed values.

In the context of ML, the dependent variable (y) corresponds to the label, the independent variables ($X_1, X_2, \ldots, X_m$) represent the features, and the error term (ϵ) mirrors the concept of loss. A linear regression model, within this context, is cultivated through the pursuit of the optimal linear relationship between input features and a designated target label. This process is chiefly characterised by the minimisation of the disparity between predicted and actual values (Wang et al., 2022). It is initiated by the random initialisation of coefficients 'β0, β1, …, βm', followed by iterative refinement through optimisation techniques such as gradient descent (El Misilmani et al., 2020).

An alternative approach to the linear regression in supervised learning is a decision tree. A decision tree models the data through a hierarchical structure of nodes and branches (Navada et al., 2011). At each node, a decision is made based on the values of a specific feature, and this decision directs the traversal down one of the branches to the next node (Myles et al., 2004). This process continues until a terminal node, or leaf, is reached, providing the final prediction.

Figure 2-2: A simple classification decision tree



Note. A simple classification decision tree. From Google for Developers, by Google, Google for Developers (https://developers.google.com/machine-learning/decision-forests/decision-trees). CC BY 4.0

As depicted in Figure 2-2, a basic decision tree is employed for the prediction of potential species associated with a given creature from a predefined set of options. This predictive model takes into account specific attributes, such as the number of legs and the number of eyes (Google, 2022a). Functioning within the paradigm of supervised learning, the training of a decision tree model necessitates a meticulously organised dataset featuring well-defined feature inputs and corresponding labelled classifications for each entity within the dataset (Navada et al., 2011). The training procedure for a decision tree can be delineated into two pivotal phases: the growth phase and the subsequent pruning phase (Kotsiantis, 2011). During the growth phase, the tree is systematically constructed through the recursive partitioning of the training data. This partitioning continues until each leaf node exclusively represents a single class or further partitioning would yield child nodes below a predetermined threshold (Jadhav & Channe, 2016). It is worth noting that this phase may involve optional pre-pruning measures to forestall unnecessary splits. The subsequent pruning phase is primarily geared towards refining the tree created during the growth phase (Song & Lu, 2015). Its overarching goal is to enhance the generalisation capabilities of the model and mitigate the risk of overfitting. This is achieved through various post-pruning techniques (Kotsiantis, 2011).

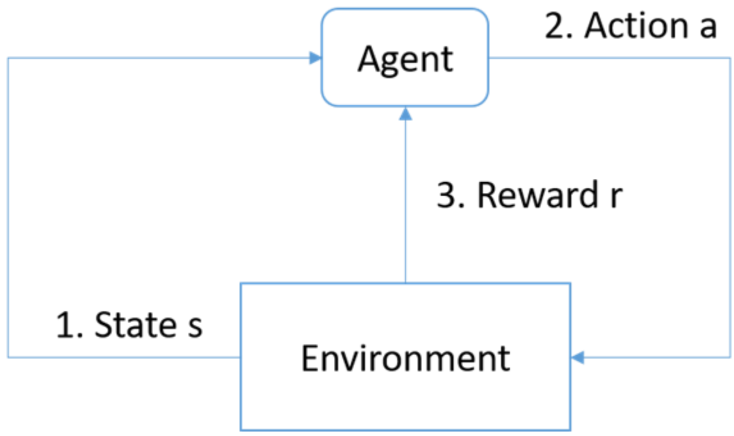
Unsupervised learning is another fundamental branch of ML, aimed at discerning latent patterns, structures, and associations within data, without necessitating the availability of labelled datasets (Ghahramani, 2004). A prominent exemplar of its utility is in clustering, wherein algorithms segregate akin data points into discrete clusters (Raschka, 2015). This method finds applications in diverse domains, including customer segmentation (Narayana et al., 2022), image segmentation(Seo et al., 2020), or document categorisation(Kadhim et al., 2014). Additionally, it is instrumental in anomaly detection, facilitating the identification of outliers or irregularities within a dataset (Syarif et al., 2012), thus extending its relevance to domains such as fraud detection, network security, and quality control.

The K-means algorithm emerges as one of the most prevalent techniques for clustering within unsupervised learning (Sinaga & Yang, 2020). K-Means clustering is a partitional approach that groups data points into K clusters through the optimisation of a mathematical function (Peña et al., 1999). The core objective is the minimisation of the sum of the L^2 distances (square of Euclidean distances) between each data point and its closest cluster centroid. The algorithm initiates by assigning data points to clusters and computing centroids. Subsequently, it iteratively reallocates data points to clusters with the nearest centroids, thereby updating centroids and the square error. This iterative process persists until convergence, when further reduction in the square error becomes unattainable, ensuring each data point is associated with the most appropriate cluster (Ivosev et al., 2008).

Another consequential application of unsupervised learning resides in dimensionality reduction, a procedure wherein data is transformed from a high-dimensional space to a lower-dimensional space while conserving intrinsic properties. This operation assumes paramount importance in domains such as signal processing, image analysis, and bioinformatics due to challenges inherent in managing high-dimensional data, notably sparsity and computational complexity (Lee & Verleysen, 2007). Techniques such as Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE) reduce dimensionality whilst preserving pertinent information, facilitating visualisation and analysis (Anowar et al., 2021).

Reinforcement learning has emerged as a prominent subfield within the realm of ML, garnering considerable attention in recent times. Its foundational premise revolves around the capacity of an agent to acquire the skill of making sequential decisions within an environment with the aim of maximising cumulative rewards (Kaelbling et al., 1996). In contrast to supervised and unsupervised learning paradigms, reinforcement learning places paramount emphasis on interaction with a dynamic and intricate environment. Within the framework of reinforcement learning, four pivotal components are discernible: a policy dictating the actions of an agent contingent on environmental states, a reward signal delineating the objectives of the problem, a value function estimating the long-term desirability of actions, and a model of the environment that simulates environmental dynamics (Sutton & Barto, 2018).

Figure 2-3: A reinforcement learning cycle



As illustrated in Figure 2-3, the reinforcement learning cycle commences with an agent collecting data from the environment, executing actions that could alter the environment, and culminating with the receipt of a reward as feedback for the action. Reinforcement learning is particularly suited to address problems necessitating the formulation of optimal strategies through iterative decision-making, such as in the domains of game playing (Silver et al., 2016), and robotics (Johannink et al., 2019).

In recent decades, artificial neural networks (ANNs) have emerged as a pivotal and transformative advancement in the field of ML. ANNs are computational systems inspired by the human nervous system, with the aim of replicating pattern recognition and intelligence akin to the human brain in automated tasks (Dongare et al., 2012). As an alternative to conventional regression and statistical models, ANNs find wide adoption in ML paradigms, encompassing supervised learning, unsupervised learning, and reinforcement learning, for tasks including classification, clustering, pattern recognition, and prediction (Abiodun et al., 2018).

ANNs are computer simulations inspired by brain models. They employ algorithms to enable networks to learn and solve diverse problems by simulating the functions of model neurons, known as nodes, which classify data based on hyperplane separation (Krogh, 2008). Drawing inspiration from the densely interconnected networks of neurons in biological systems, the study of ANNs endeavours to replicate parallel and distributed information processing observed in neurobiology. This is achieved through interconnected simple units that process real-valued inputs to produce real-valued outputs (Mitchell, 1997). The architecture of an ANN model comprises three key components: an input layer with multiple neurons receiving input values, one or more hidden layers with multiple neurons positioned between the input and output layers, and an output layer typically with a single neuron whose output falls within the range of 0 and 1 (Kukreja et al., 2016).

Activation functions constitute crucial components within ANNs, given their pivotal role in introducing non-linearity. This non-linearity is instrumental in enabling models to effectively represent intricate and complex functions, thereby enhancing their capability to learn and process a broad spectrum of data and establish mappings between input and output variables (Sharma et al., 2017). Common activation functions include the sigmoid function, which outputs values between 0 and 1, the Rectified Linear Unit (ReLU) for handling positive values, and the hyperbolic tangent (tanh) function (Rasamoelina et al., 2020).

In the context of ANNs, the training process involves iteratively updating the neural network architecture and connection weights using available training patterns to enable efficient task performance. This leverages the ability of ANNs to learn underlying rules automatically from examples, which is a significant advantage over traditional ML algorithms (Jain et al., 1996). This iterative process adjusts connection weights to minimise the error (loss) between predicted and actual outputs, often guided by optimisation algorithms, such as gradient descent. In practice, gradient descent has been implemented in various algorithms, including the widely used stochastic gradient descent (SGD) (Ruder, 2016). SGD initiates the training process by random initialisation of model parameters, computes gradients based on small random subsets of the training data, and iteratively updates the model by taking steps in the direction of steepest descent to minimise the loss function (Ketkar, 2017). This process repeats until convergence is achieved to find an optimal set of model parameters. However, SGD presents a challenge in determining an appropriate learning rate—a rate that, if too small, leads to slow convergence, or if too large, disrupts convergence and induces erratic behaviour in the loss function near the minimum or even divergence (Ruder, 2016). To overcome the challenges posed by the limitations of SGD, variants such as RMSprop and Adaptive Moment Estimation (Adam) have been introduced.

Expanding upon ANNs, a deep neural network (DNN) represents a subtype of ANN characterised by multiple hidden layers positioned between the input and output layers. DNNs have gained popularity in recent years, owing to advancements in ML algorithms and improved computational hardware (Hinton et al., 2012). The significance of DNNs lies in their capacity to effectively model complex data patterns and representations, rendering them particularly well-suited for tasks such as image recognition, natural language processing, and speech recognition (LeCun et al., 2015).

2.5 Current State in EDs

An ED within a hospital serves as the primary point of entry for patients requiring immediate medical attention, irrespective of prior appointments. Globally, EDs function as critical components of healthcare systems, offering services beyond standard operating hours. Given the escalating demand for emergency healthcare services and heightened expectations regarding treatment outcomes, many studies have been carried out focusing on their operational management. This improvement is necessary to ensure the efficient and high-quality delivery of medical services, necessitating a comprehensive review of strategies for the allocation and control of human resources, materials, and other resources within the hospital setting.

Such need for improvement for efficiency has become more significant since the recent decades. In EDs, overcrowding has become a widespread issue where the facilities are filled beyond capacity, leading to negative impacts on patient care, often characterised by long patient wait times, hallway placements, and full waiting rooms (McCabe, 2001). While it's difficult to give a definition of overcrowding, especially when there is not a clear threshold to declare an overcrowding, a common consensus is that when overcrowding happens, it causes longer wait times, delayed treatment, increased patient dissatisfaction, and potential harm to patients (Derlet & Richards, 2000). As indicated by existing studies, as a phenomenon of mismatch between supply and demand, overcrowding is not only caused by increased patient volumes, but a complex web of interrelated factors, such as limited facility capacity, human capacity shortage, and frequent flyer patients (Derlet & Richards, 2000; Lindner & Woitok, 2021; McCabe, 2001; Sartini et al., 2022). To address this challenge by improving the overall efficiency, one effective solution lies in the implementation of HISs in EDs.

A major challenge faced by physicians in making timely decisions in the ED arise from uncertainties about the stability of patients in observation units, an increasing number of patients with complex and rapidly deteriorating conditions, and the potential for concealed acutely serious conditions leading to sudden crises (Chang et al., 2004). Empirical research has underscored the ramifications of clinical uncertainty on patient care outcomes. Studies have indicated that patients characterised by clinical uncertainty tend to experience prolonged hospitalisation periods and heightened morbidity and mortality rates (Green et al., 2008). Interestingly, while research has suggested that more experienced physicians exhibit greater confidence with decision-making in the face of uncertainty, it does not conclusively establish a causal relationship between experience and the ability to manage uncertainty, translating into improved treatment outcomes (Lawton et al., 2019). Considering these challenges, emerging technological advancements offer promising avenues for mitigating uncertainties within the ED. It is proposed that decision support systems, leveraging ED data and innovative technologies, can be developed to address and alleviate the complexities associated with clinical decision-making in the ED setting (Graham et al., 2018).

Compassing a comprehensive set of technologies, processes, and tools designed to capture, manage, store, and exchange patient information, HISs play a pivotal role in facilitating the efficient and coordinated delivery of care within EDs (Landman et al., 2010). One of the key benefits observed in the integration of HISs is the improved accessibility of patient records (Handel & Hackman, 2010). Recent studies have highlighted the ability of HISs to provide healthcare providers with instant access to EHR not only expedites the diagnostic process but also improves patient safety by reducing medical errors (Patterson et al., 2019). Another benefit of HISs is that by facilitating computerised physician order entry to aid in CDS, practice variability can be decreased to ensure the quality and safety of healthcare in the Eds (Farley et al., 2013). For instance, at triage, HISs can streamline the registration process by capturing patient information electronically, reducing paperwork and minimising data entry errors to ensure that patients are quickly categorised based on their condition, allowing for faster allocation of resources to those in need of immediate care (Aronsky et al., 2008). Physicians can also take advantage of the accessibility to EHR data to make a more accurate diagnosis and admission decisions in a timely manner (Ben-Assuli et al., 2015).

However, there are studies which suggest the notable issue is the fragmentation of systems and the lack of a centralised data repository (Kuhn & Giuse, 2001). In other words, EDs struggle with insufficient integration among various HIS components, leading to information silos (Miller & Tucker, 2014). This fragmentation can hinder the seamless flow of information and create inefficiencies, potentially impacting patient care.

CDSSs are another HIS application with the expectation to improve patient care and decision-making processes in the EDs. Many studies have been conducted on employing CDSSs for triage.

Looking ahead, the future trend of CDSSs in the ED is poised for even more significant advancements. As technology continues to evolve, CDSSs are expected to become more sophisticated and seamlessly integrated into existing EHR data. They will increasingly incorporate ML and artificial intelligence to provide predictive analytics, enabling early identification of patients at risk for severe conditions and allowing for proactive interventions. Furthermore, CDSSs will likely expand its capabilities to support telemedicine and remote consultations, bridging geographical gaps and ensuring that patients receive timely, evidence-based care, even in underserved areas. While these developments hold great promise, ongoing attention to data security, system interoperability, and the effective training of healthcare providers in CDSS utilisation will be essential to ensure their successful implementation and continued impact on ED patient care.

ML, a subset of artificial intelligence, has emerged as a transformative technology widely adopted in healthcare sectors in various applications with the potential to enhance decision-making processes and improve patient outcomes in healthcare by enabling computers to learn and make predictions or decisions based on patterns and data, often with remarkable accuracy. Being capable to recognise complicated patterns from large amounts of data, ML algorithms have shown their potential to diagnose lifestyle diseases, such as diabetes in its early stages (Patil & Shah, 2022). For example, in Alghamdi et al. (2017) study, they demonstrated how ML algorithms can be used to predict incident diabetes at a significant accuracy using cardiorespiratory fitness data. Similarly, ML algorithms can also be used on early detection of abnormalities in heart conditions caused by heart disease, by processing of raw healthcare data of heart information (Mohan et al., 2019). With the capability of image processing, DNNs can be used to help diagnose diabetic retinopathy in regions lacking experts who are capable of detecting the disease (Gulshan et al., 2016). Another study suggests that DNNs can reduce the average time by up to 90% to diagnose small bowel diseases with capsule endoscopy, which usually takes a doctor one to two hours to analyse and diagnose the massive amount of image and video data for each patient (Ding et al., 2019).

Recent literature has shed light on the growing utilisation of ML in several crucial aspects in EDs.

Resource Allocation: Efficient resource allocation is crucial in emergency care. ML algorithms can assist in optimising resource allocation by predicting patient inflow, bed availability, and staffing requirements. This ensures that EDs are adequately prepared to handle patient loads, enhancing both efficiency and patient satisfaction. For instance, aiding in mitigating ED overcrowding issues, ML can be utilised in predicting hospital admission at the ED with the combination data of information collected at triage and historical patient data (Hong et al., 2018)

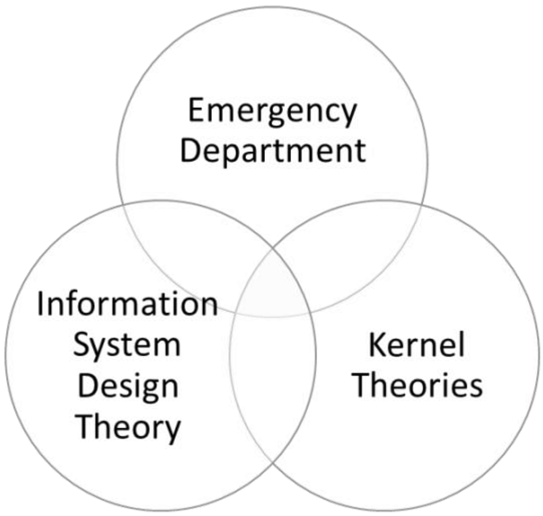
Diagnosis: ML models are trained on vast datasets of medical images, lab results, and patient histories. These models can aid physicians in diagnosing conditions such as strokes, heart attacks, and traumatic injuries more quickly and accurately. For example, ML algorithms can analyse radiological images to detect abnormalities or prioritise cases based on urgency. In a study by Horng et al. (2017), they demonstrated that incorporating free text data, in addition to vital signs and demographic information, significantly enhances the ability to identify patients with suspected infection as an early detection of sepsis in the ED. Another study suggests a ML approach using local big data outperformed existing clinical decision rules and traditional analytic methods in predicting in-hospital mortality of ED patients with sepsis (Taylor et al., 2016). And this study indicates another impact by ML on EDs, risk management.

Risk prediction: ML algorithms excel at predicting patient outcomes. They analyse historical data to identify risk factors and patterns that might not be apparent to human practitioners. In the ED, these models can help identify patients at higher risk of complications, enabling early intervention and personalised care plans.

2.6 Theoretical Framework

This section elucidates the foundational theoretical framework underpinning the design science research study related to HISs. As depicted in Figure 2-4, this theoretical framework of this study is constructed by synthesising principles from Information System Design Theory (ISDT) and core theories from diverse research disciplines, all tailored to the specific context of the hospital ED.

Figure 2-4: Theoretical framework



The ISDT forms the structural framework for this design science research, aimed at addressing complex challenges within the hospital ED context by designing a robust artefact. Complementing this, core theories including General Systems Theory, Information System Integration, and Enterprise Architecture provide substantial theoretical support for the design of the information system. These theoretical constructs serve as the foundational underpinning for this research, ensuring that the study is firmly grounded in established principles and methodologies. This, in turn, facilitates the generation of new knowledge and theoretical contributions within the scope of this research endeavour.

2.6.1 Information System Design Theory

This study falls within the discipline of information systems research, and this section provides a comprehensive review of theories pertaining to information systems design. Within the taxonomy established by Gregor (2006) , design theory is categorised as “theory for design and action”. This classification is distinguished by its capacity to offer explicit directives, encompassing methods, techniques, and principles that govern the development of artefacts. Walls et al. (1992) assert that design theories stand apart from natural and social science theories due to their primary focus on facilitating the attainment of goals. This contrasts with the latter, which either disregards goals entirely or analyses and predicts them. Gregor and Jones (2007) interpret design as a systematic method for conducting formative research and an iterative refinement process. This process entails creating an initial design based on theoretical principles, implementing it to assess its efficacy, and continually honing and revising the design based on real-world experience until all issues are resolved.

One of the foundational elements of design theory, as posited by Simon (1988) , involves the science of design, encompassing the theory of artefact structure, design, and evaluation. The concept of design science has been further developed into an information system research framework by March and Smith (1995). Within this framework, information system research is perceived as being driven by both design science activities—building and evaluating—and natural science activities—theorising and justifying. The output of design science encompasses constructs, models, methods, and instantiations. This concept has been expanded upon by Hevner et al. (2004), distinguishing design science from routine design or system building by its distinct focus on addressing wicked problems. These are complex and dynamic issues characterised by unstable requirements, intricate interactions among components, adaptability in design processes and artefacts, reliance on human creativity and teamwork, and dependence on ill-defined environmental contexts. In a separate study, Gregor and Jones (2007) outline an Information Systems Design Theory comprised of eight distinct components. At its core, the theory centres on six fundamental elements: "Purpose and Scope" defines the system's objectives and boundaries, setting the stage for design. "Constructs" are the building blocks representing core concepts. "Principle of Form and Function" outlines the abstract architecture of the information system artefact. "Artefact Mutability" anticipates and accommodates changes. "Testable Propositions" offer truth statements for validation. "Justificatory Knowledge" draws on foundational sciences for theoretical support. Additionally, two augmenting elements include "Principles of Implementation", providing practical guidance for applying the theory, and "Expository Instantiation", which creates tangible representations to aid understanding and adoption.

A longstanding debate within design science revolves around whether design can be considered a theory in itself. Some view design science as activities guided by natural science theories (March & Smith, 1995), while others believe that design theory can be broken down into several components, with natural science theory being just one of them (Gregor & Jones, 2007; Walls et al., 1992). Baskerville and Pries-Heje (2010) suggest that design theory can be decoupled into two categories: design practice theory, which prescribes practical methodologies for designing; and explanatory design theory, which prescribes principles that connect requirements to an incomplete description. The latter only requires requirements and solution components to be considered complete and is supported by logical and empirical arguments. Johannesson and Perjons (2021) emphasise that forming design theory necessitates adhering to three essential requirements, given the distinct purposes of design and design science research: the use of rigourous research methods to generate new knowledge of general interest, the connection of this knowledge to an existing knowledge base for a solid and innovative foundation, and effective communication of the new results to both practitioners and researchers.

Recognising the significance of design science for research and practice in information systems, A. R. Hevner and S. Chatterjee (2010) argue that an information system design theory is still a work in progress and little effort has been paid to date to the problem of specifying design theory. Hevner (2007) proposes a three-cycle framework to encapsulate design science research activities in the information system discipline. This three-cycle view delineates a systematic approach to creating and advancing information systems and technologies, consisting of three interrelated cycles: the relevance cycle, design cycle, and rigour cycle.

1. **Relevance Cycle:** The Relevance Cycle represents the initial phase in design science research, with a primary focus on identifying real-world problems and challenges that require innovative solutions. Its objective is to determine whether the designed artefact enhances the existing environment and how this enhancement can be quantified. Integral to this phase is field testing and evaluation within the application domain, with feedback from these processes potentially leading to subsequent iterations of the cycle.

2. **Design Cycle:** The Design Cycle constitutes the central component of design science research, encompassing iterative activities related to the creation, assessment, and refinement of the design artefact. It draws upon insights from the Relevance Cycle and leverages theories and methodologies from the Rigour Cycle. A crucial aspect of this cycle is the equilibrium between constructing and evaluating the evolving artefact. It is essential to emphasise that a robust argument for construction alone is insufficient if the evaluation component lacks rigour. Rigourous testing in controlled settings precedes field testing, necessitating multiple iterations before contributions are channelled back into the Relevance and Rigour Cycles.
3. **Rigour Cycle:** The Rigour Cycle functions to ensure that the designed artefacts adhere to rigourous research standards. Researchers are required to rigourously draw from the knowledge base of scientific theories and engineering methodologies to confirm that their designs are both innovative and conducive to advancing research, rather than relying on routine procedures. This cycle involves the selection and application of appropriate theories and methods for both constructing and evaluating the artefact. While grounding in theory holds significant value, the cycle also encourages the exploration of diverse sources of creative inspiration beyond merely descriptive theories.

ISDT and design science research play pivotal roles in the domains of HISs, CDS, and within the broader context of EDs. Numerous empirical studies have effectively applied ISDT in healthcare settings to demonstrate its practical validity. For instance, research by Ngai et al. (2009) utilised the ISDT as a guiding framework to design and develop a HIS artefact. Likewise, ISDT has served as the foundational framework in studies focused on CDS, as exemplified by Kasper (1996).

The study conducted by Kao et al. (2016) provides a compelling demonstration of how the design science research methodology can be effectively deployed within the healthcare sector. Their research showcases the application of design science principles in the development of a hospital-based business intelligence system. Furthermore, in the realm of CDS, there has been a growing utilisation of design science research methodologies in both producing CDS artefacts and refining the processes involved in developing these crucial artefacts, as illustrated by the work of Miah et al. (2020).

Within the healthcare context, design science research has also proven to be highly efficient in both the development and examination of artefact-based solutions aimed at addressing challenges within the ED setting (Alvarez et al., 2018; Martin et al., 2018; Mazor et al., 2016).

2.6.2 General Systems Theory

GST, also referred to as systems theory, serves as a foundational framework for the information systems discipline (Avgerou, 2000; Chatterjee et al., 2020; Fang et al., 2018; Matook & Brown, 2016; McBride & Draheim, 2020). Proposed by Bertalanffy (1968), GST is an interdisciplinary framework that emphasises the holistic examination of complex systems, highlighting their interconnectedness, hierarchical organisation, and shared principles. This approach stands in contrast to reductionist methodologies that fragment phenomena into isolated components.

GST advocates understanding systems holistically, emphasising their interdependence and the emergence of novel properties at higher organisational levels. The primary objective of GST is to promote integration among diverse scientific disciplines, constructing a unified framework rooted in the concept of systems, which Bertalanffy (1968, p. 38) defined as "sets of elements standing in interrelation".

In the field of information systems, GST plays a pivotal role. GST serves as the cornerstone upon which one can build an understanding of intricate systems, elucidate shifts in behaviour, and scrutinise the dynamics of communication and self-organisation within the intricate tapestry of information systems and socio-technical environments (Baskerville et al., 2014). Recognising the inherent complexity of information systems, Boell and Cecez-Kecmanovic (2015) assert that information system research typically adheres to an essentialist and dualist ontology. This perspective posits that both humans and technologies exist as discrete entities, each possessing intrinsic properties that define their essence. It further assumes a priori boundaries between these entities, wherein their interactions mutually influence one another, all while maintaining their essential characteristics without alteration. From a systemic standpoint, these entities can be viewed as subsystems embedded within an information system as a whole. Lee (2010) contends that to qualify as information systems research, one must meticulously account for the intricate interconnections permeating all facets of an information system. This underscores the paramount significance of employing systemic concepts as the bedrock upon which the information system discipline is built, thereby substantiating the distinct identity and scholarly relevance of information system research.

For instance, Porra et al. (2005) utilise GST to interpret the complex and evolving nature of information technology systems within organisations. They use GST as an interpretive lens to understand how misinterpretations of information technology performance, influenced by top management perceptions, can lead to long-term failures of information technology units within organisations. This highlights the need for enhanced alignment, standards, and environmental scanning for information technology success.

Garrity (2001) employs GST to propose an integrated approach to information systems development, combining designer-centred problem-solving, user-centred human considerations and business process alignment. They introduce a measurement and control system to enhance workplace quality and organisational effectiveness. Chatterjee et al. (2020) also apply GST to propose a theoretical conception of an information system artefact, offering a fresh perspective on the central artefact of the information system discipline.

The utilisation of GST extends beyond information systems to healthcare research, where it provides a comprehensive framework for understanding the complexities of healthcare systems. Its application underscores the necessity of viewing healthcare systems holistically, recognising the interplay between diverse factors, and shifting the focus from individual organ functions to a broader understanding of system dynamics, with an emphasis on identifying patterns and system failures to enhance healthcare quality and patient safety (Anderson, 2016). A systematic literature review conducted by Katrakazas et al. (2020) suggests that applying GST in healthcare holds promise for fostering a holistic perspective. However, it also underscores the need to address limitations and employ interdisciplinary data techniques for successful integration into the field.

2.6.3 Information System Integration

The definition of information system integration can vary depending on the context. According to Gartner (n.d.) information system integration is the process of developing a sophisticated information system by designing or constructing a tailored architecture or application, merging it with both new and existing hardware, as well as off-the-shelf and bespoke software, and establishing communication between these components. Based on existing studies, information system integration can be categorised into two distinct types: internal information system integration, which pertains to the connection and coordination of various information systems within an organisation; and external information system integration, which focuses on the integration of information systems with those of external partners or entities (Gu et al., 2017; Maiga et al., 2015; Mohamed et al., 2013). From an information system integration perspective, Hasselbring (2000) delineates the structure of an organisation into three distinct layers of architecture: the business architecture layer, which outlines organisational structures and workflows; the application architecture layer, responsible for implementing business concepts within enterprise applications; and the technology architecture layer, defining the information and communication infrastructure to meet business requirements, necessitating interdisciplinary collaboration between business and technology domains. Both external and internal integration can happen at all three layers.

In the context of enterprise systems, integration can be broadly categorised into two categories: "Big I" and "Little i". "Big I" integration involves aligning all relevant data within a unified data model and centralised storage, with the primary aim of reducing the overall cost of ownership. In contrast, "Little i" integration encompasses the interfacing of systems, often through point-to-point connections. However, this approach can lead to ongoing challenges related to data harmonisation, as well as potential complexities and costs associated with system changes (Gulledge, 2006). The discourse on integration models with a single data repository frequently pertains to the implementation of Enterprise Resource Planning (ERP) systems (Chapman & Kihn, 2009). Nevertheless, practical ERP implementations often take the form of integrated systems that interface with peripheral systems due to various practical considerations (Lynne Markus, 2001).

A majority of information system integration occurs at the technology architecture layer. Various technical approaches for information system integration can be identified within this layer, with the most prevalent ones being point-to-point integration, database-to-database integration, data warehouse integration, enterprise application integration, and application server integration (Gulledge, 2006). These practices are prominently featured in the integration approaches of HISs, which are typically categorised into message-oriented integration, application-oriented integration, coordinated-oriented integration, and middleware-oriented integration (Sabooniha et al., 2012).

Message-oriented integration, for instance, represents an implementation of point-to-point integration, facilitating data exchange among HISs through the transmission of messages in standardised protocols such as HL7. It's worth noting, as highlighted by Gulledge (2006), that point-to-point integration poses certain challenges, as it necessitates coding efforts on both the source and target systems. Furthermore, as the number of interconnected systems grow, interface maintenance costs increase dramatically due to the quadratic expansion in the number of interfaces, a limitation in scalability also acknowledged by Kuhn and Giuse (2001) in the context of HIS integration.

Application-oriented integration, distinct from enterprise application integration and application server integration as described by Gulledge (2006), is another form of message-based integration within the realm of HISs. Within this paradigm, disparate HISs communicate by transmitting messages through a dedicated application server. Rather than directly interconnecting various systems, this methodology is often referred to as an interface engine, communication server, or mediator service (Kuhn & Giuse, 2001). In this paradigm, the majority of the technological aspects related to data transfer and translation are consolidated within a single application server, streamlining both development and maintenance processes. However, it's important to note that this approach does have its limitations, particularly in addressing challenges related to semantic incompatibility and synchronisation. Consequently, it cannot effectively resolve issues such as data replication (Hasselbring, 1997).

Coordinated-oriented integration offers a cohesive front-end interface that harnesses information from disparate systems, fostering a unified user experience. A pivotal hallmark of this methodology lies in the establishment of unified access and identification, thereby granting users the ability to access all applications through a singular login (Gulledge, 2006; Kuhn & Giuse, 2001; Sabooniha et al., 2012). In practice, this integration approach is often centred around a pivotal system, which can assume the form of an administrative system, a billing platform, or an ERP system. Additionally, this approach facilitates the integration of processes within workflows across various scenarios.

Middleware-oriented integration involves the establishment of generic middleware components designed to provide services, interfaces, or shared facilities in support of the entire system. These services and functions operate independently of the context or state of other services and can be implemented using diverse technologies (Sabooniha et al., 2012). Essentially, this approach culminates in the creation of a centralised application capable of delivering a consistent array of services to multiple remote applications, thus facilitating the sharing and reusability of services across various enterprise applications (Gulledge, 2006). This approach closely aligns with the principles of Service-Oriented Architecture (SOA) which entails establishing generic middleware components to provide standardised services and interfaces, accommodating loosely coupled, standards-based, protocol-independent distributed computing (Papazoglou & van den Heuvel, 2007).

In addition to the four distinct HIS integration approaches identified by Sabooniha et al. (2012), a prevalent method for system integration involves database-level integration. This approach encompasses two primary variants: data replication across multiple databases or the establishment of a unified data repository, often referred to as a data warehouse (Gulledge, 2006). A widely adopted practice involves the consolidation and replication of data sourced from diverse HISs into a comprehensive database. This database can function as a standalone entity or serve as the database of a central system as discussed in coordinated-oriented integration (Kuhn & Giuse, 2001). Alternatively, another implementation strategy eschews the replication of data across multiple databases and, instead, leverages the creation of a virtual repository where data is aggregated from various data sources (Gulledge, 2006). It is imperative to note that this approach is rarely employed in systems intended for daily operational use. Its primary utility lies in applications such as data analysis, where the exclusive need is to extract and read data (Grimson et al., 2000). This is largely due to its inherent limitations, such as the inability to add or update data, which renders it unsuitable for more dynamic operational contexts.

2.6.4 Enterprise Architecture

In the realm of information systems, there is a prevailing consensus on the effectiveness of enterprise architecture in achieving information technology-business alignment (Gellweiler, 2022). Enterprise architecture is widely regarded as a framework that provides a structured approach to align enterprise management with the development of information systems within the organisation. Emphasising the crucial role of strategic alignment in harnessing information technology for digital transformation within organisations, Henderson and Venkatraman (1999) introduced the Strategic Alignment Model. This model identifies two types of integration between the business and information technology domains: strategic integration, which pertains to information technology's ability to support business strategy, and operational integration, which seeks to ensure coherence between organisational requirements and expectations and the capabilities delivered by the information system functionality. Achieving such strategic alignment in information system adoption necessitates a comprehensive approach that manages both business operations and information technology infrastructure.

The Zachman Framework stands as one of the pioneering examples of enterprise architecture. Rooted in information systems architecture framework by Zachman (1987), it underscores the need for architecture as a disciplined approach to enhance information system development's precision, which, in turn, influences business success. In his 1987 work, Zachman described the information systems architecture framework as a collection of various architectural representations that depict the same systems architecture at different stages of system development, from various perspectives, organised in a matrix, as illustrated in Table 2-1.

Table 2-1 Framework for Information Systems Architecture (adapted from Zachman (1987)

	Data Description	**Process Description**	**Network Description**
Scope Description (Contextual)	List of Entities	List of Processes	List of Locations
Model of the Business (Owner's View)	Entity/Relationship Diagram	Functional Flow Diagram	Logistic Network
Model of the System (Designer's View)	Data Model	Data Flow Diagram	Distributed Systems Architecture
Technology Model (Builder's View)	Data Design	Structure Chart	System Architecture
Detailed Description	Database Description	Program	Network Architecture
Actual System	Data	Function	Communications

Expanding upon the three-column model of the Zachman framework, which focuses on "what", "how", and "where", three additional columns were introduced by Sowa and Zachman (1992) to address "who", "when", and "why". This extension underscores the importance of interpersonal relationships, event-to-event relationships, and motivation in a comprehensive model.

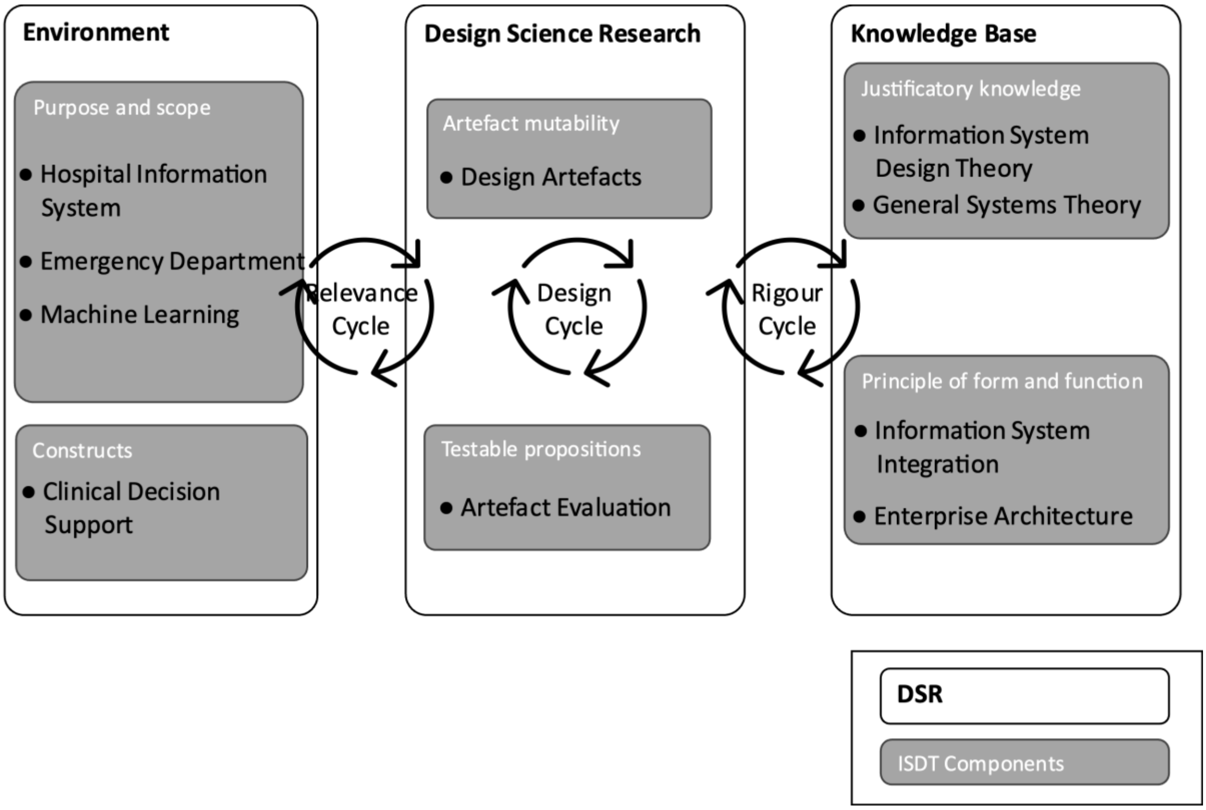
Another foundational concept of enterprise architecture can be traced back to a NIST (National Institute of Standards and Technology) report by Fong and Goldfine (1989), which presents enterprise architecture as a pyramid model comprising five separate yet interrelated architectures at different levels: business unit, information, information system, data, and delivery system. The NIST model also introduces the idea that an architecture can be used to describe either the current state ("AS-IS") or a representation of a future plan to be implemented ("TO-BE"), at any level. This concept has become a fundamental in many enterprise architecture methodologies (Bernard, 2012).

Numerous contemporary enterprise architecture frameworks draw inspiration from the aforementioned models. For instance, the Federal Enterprise Architecture Framework (FEAF) (Chief Information Officer Council, 2001), adopted by the U.S. federal government, combines elements from the NIST model with the first three columns of the Zachman framework, along with the enterprise architecture planning methodology proposed by Spewak and Hill (1993). The Open Group Architecture Framework (TOGAF), the industry's most widely used enterprise architecture framework, can also be mapped to the Zachman Framework (The Open Group, n.d.).

2.6.5 Research Framework

The research framework has been meticulously constructed by synthesising the theories expounded upon in this section. Central to this framework are the core theories, methodologies, and models seamlessly integrated within the ISDT framwork delineated by Gregor and Jones (2007). Additionally, all constituent components of this framework have been harmoniously converged with the three-cycle DSR framework introduced by Hevner (2007).

Figure 2-5 Research Framework adapted from Design Science Research Cycles (Hevner, 2007)

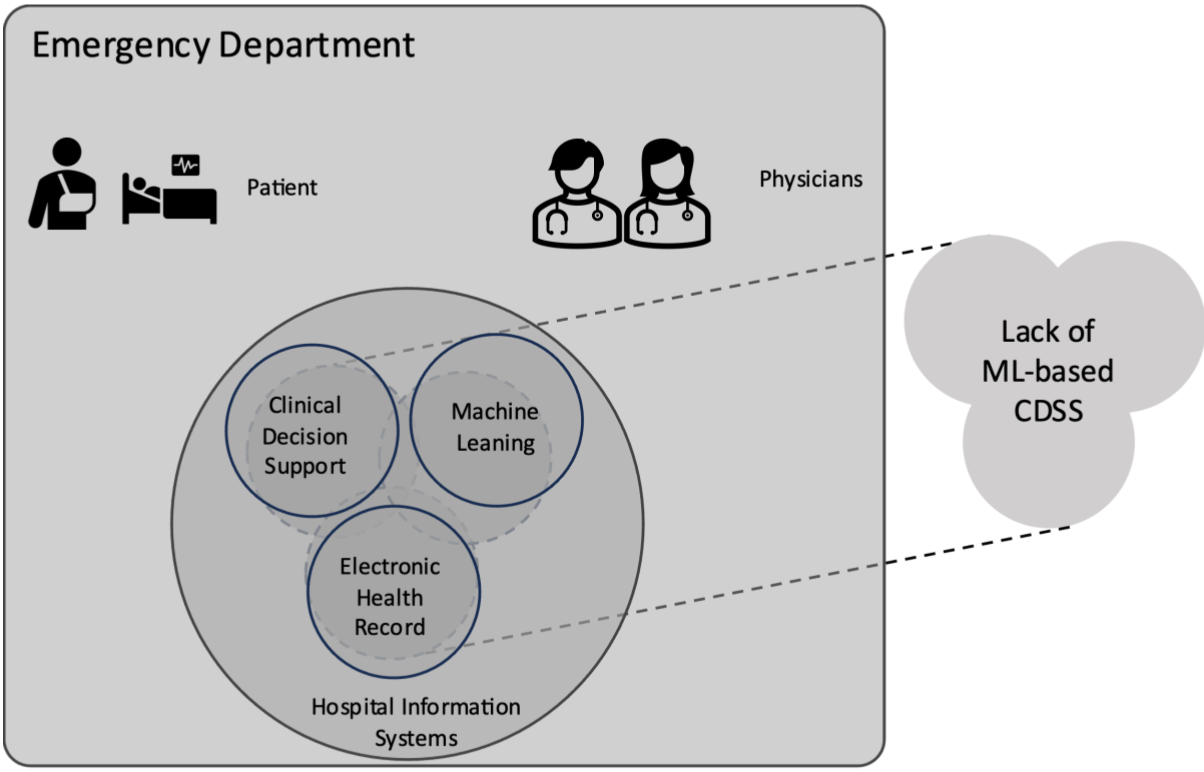


As illustrated in Figure 2-5, the research framework underpinning this study is firmly grounded in the three-cycle design science research framework. The development of artefact design is rooted in the contextual dynamics of the environment. Subsequently, the artefact undergoes a rigourous design, construction, and evaluation process within the design cycle. This design process is bolstered by a rigourous cycle, which in turn draws its strength from a robust theoretical foundation cultivated from the knowledge base.

Embedded within this three-cycle perspective are the ISDT components, intricately mapped to the insights gleaned from the literature review. Within the study, the environmental sphere HIS, ED, and ML, as these elements constitute the fundamental elements that define both purpose and scope. CDS, serving as the construct, signifies the overarching challenge and problem of interest in this study. The knowledge base, conversely, encapsulates ISDT and GST as the foundational knowledge and theories drawn from multidisciplinary sources, collectively serving as the cornerstone of this study. The information system integration methodologies for and enterprise architecture models, encompassed within this knowledge base, jointly function as the intellectual scaffold guiding the design process for addressing and resolving the challenges. At the epicentre of this framework lies the design science research activities. Here, design artefacts are built as representations of artefact mutability, propounding solutions to rectify the identified problems. Subsequently, these artefacts necessitate rigourous evaluation to establish testable propositions.

2.7 Knowledge Gap

Figure 2-6: Knowledge gap



In the dynamic and high-stakes environment of a hospital ED, physicians often face the daunting challenge of making timely clinical decisions for patients with unpredictable and critical conditions. The rapid evolution of medical knowledge and the increasing complexity of healthcare demand innovative solutions to assist healthcare providers. One such solution is the integration of HISs with ML-based CDSS. This integration has the potential to transform the way decisions are made in ED, providing informatic and action-led decision support to physicians. However, despite the promise of ML-based CDSS, a significant knowledge gap exists concerning how HISs can be effectively integrated to provide the necessary data inputs. This thesis aims to explore this knowledge gap in detail, emphasising the critical need for seamless data flow, the advantages of ML-based CDSS, and the empirical evidence required to demonstrate their impact on A&E efficiency.

The healthcare landscape has witnessed a transformation with the widespread adoption of HISs. These systems, particularly EHRs, have revolutionised the way patient information is collected, stored, and accessed. Compared to traditional paper-based medical records, EHRs are capable of storing a wide range of health data, including patient demographics, diagnoses, laboratory test results, prescriptions, radiological images, allergies, and more (Birkhead et al., 2015). This transition from paper to electronic records has improved data accessibility and reduced the risk of errors associated with manual record-keeping.

However, despite the advantages of EHRs, their implementation has not always led to significant efficiency gains within the ED. Access to electronic records is valuable, but it is not sufficient to address the complex and time-sensitive decision-making process that physicians in the ED must navigate across the various HISs. The literature emphasises the need to go beyond data storage and retrieval and focus on data quality and an “action-led” approach to leverage the potential of information systems (Sandiford et al., 1992).

Within the context of healthcare, adopting an “action-led” approach naturally leads to the consideration of CDSS. CDSSs are designed to assist healthcare providers, including ED physicians, in making timely and informed decisions. Knowledge-based CDSSs have played a valuable role in many healthcare settings by providing recommendations based on pre-defined rules and expert knowledge. However, these systems have limitations when applied in the dynamic and complex environment of an ED setting.

Knowledge-based CDSSs face challenges in adapting to rapidly evolving medical knowledge and capturing all relevant clinical expertise within the system. The healthcare landscape is constantly changing, with new research findings and treatment guidelines emerging regularly. Knowledge-based systems struggle to keep pace with these changes, which can result in outdated or inaccurate recommendations for ED physicians. Moreover, capturing the entirety of clinical expertise within a system is a monumental task, as medical knowledge is vast and continuously expanding.

In this context, the integration of ML technology with CDSS represents a significant advancement. ML-based CDSS offers the potential to overcome the shortcomings of knowledge-based systems. These systems can continuously learn and adapt to new data, providing healthcare providers with more accurate and up-to-date recommendations. ML algorithms excel in recognising patterns, which is particularly valuable in clinical tasks where patterns in patient data can be subtle indicators of disease or treatment efficacy.

While ML-based CDSS holds great promise for improving decision-making in ED, there is a critical knowledge gap concerning how HISs can be effectively integrated to provide the data required by ML algorithms. The seamless flow of data from EHRs and other sources to ML-based CDSSs is essential for their successful implementation.

2.8 Summary

This chapter presents a systematic literature review encompassing prior research on HISs within the context of hospital EDs, as well as the theoretical framework relevant to this domain. The review reveals that despite the widespread adoption of HIS, CDSS, and ML applications in the healthcare sector, there is a conspicuous gap in the literature concerning how these technologies can be optimally harnessed to enhance CDS for emergency physicians dealing with the challenges of making timely decisions within a dynamic and uncertain environment.

Notably, limited attention has been directed towards studies addressing the integration of existing technology and information sources to achieve this objective effectively. By integrating the ISDT and drawing upon theories from diverse disciplines, we have tailored a research framework that aligns with the DSR framework. This refined research framework provides a robust foundation for understanding how these theories can be pragmatically applied, guiding our research efforts towards the creation of information systems artefacts specifically tailored to the complex operational context of hospital EDs.

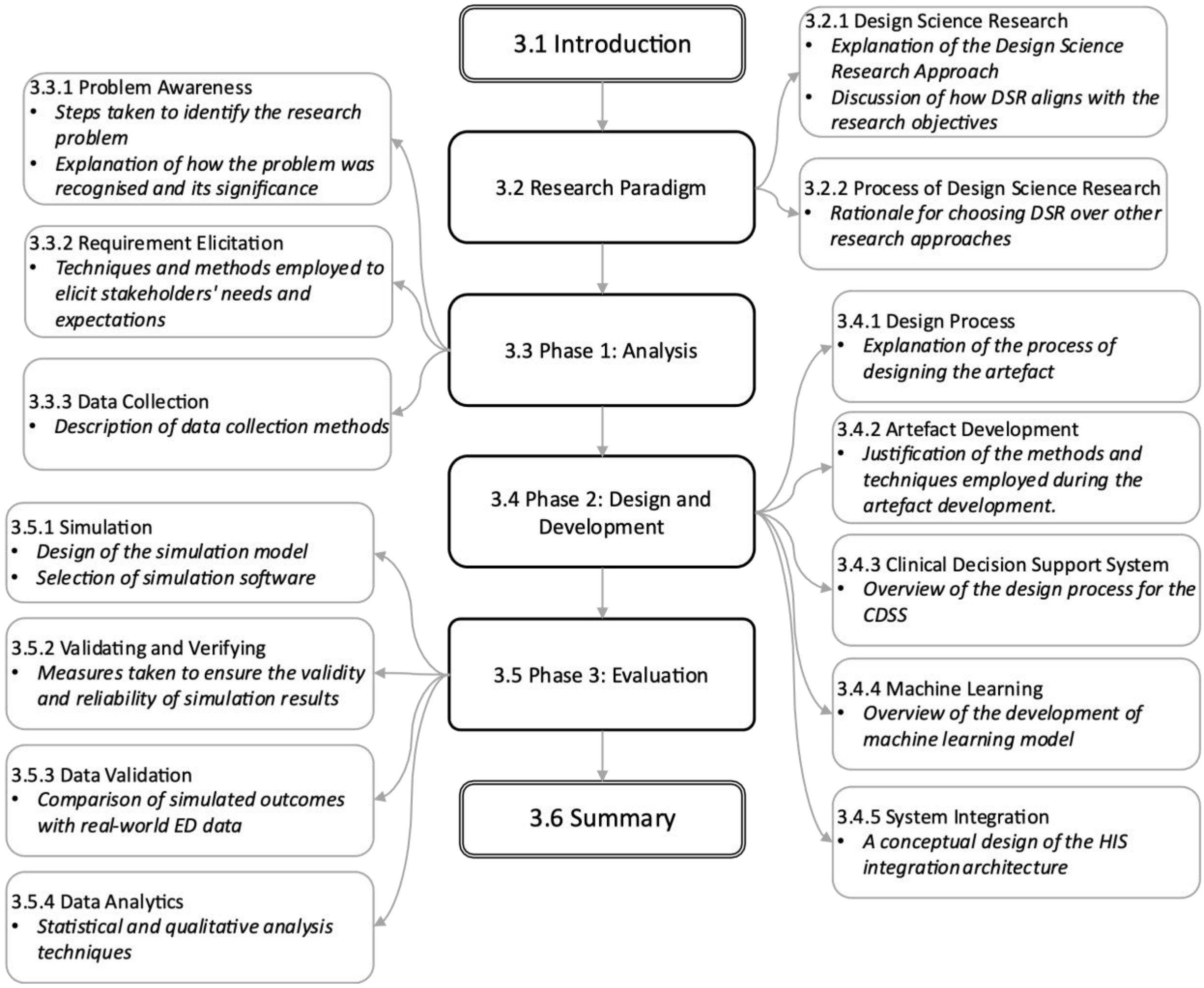
In the subsequent chapter of the Research Method, the research objectives and research questions will be formulated to address the knowledge gap identified in the preceding literature review. A comprehensive examination of the selected research methods will be conducted, elucidating the systematic approach employed in this study.

Chapter 3 Research Design

This chapter expounds upon the comprehensive framework that governs the present study. It initiates by elucidating the selected research paradigm, design science research, and its alignment with the research objectives. Subsequently, the chapter delves into the inaugural phase, Analysis, which encompasses problem identification, requirement elicitation, and data collection procedures. Following this, Phase 2, Design and Development, delineates the process of artefact design, clinical decision support system (CDSS) development, machine learning (ML) model implementation, and conceptualisation of the hospital information system (HIS) integration architecture. Concluding the discussion, Phase 3, Artefact Evaluation, employs simulation as the principal evaluation method, incorporating the design of the simulation model, measures to ascertain the validity and reliability of results, data validation techniques, and data analytics.

This chapter furnishes a structured approach that systematically guides the reader through the methodological underpinnings of the research process. Figure 3-1 illustrates the organisational structure of this chapter.

Figure 3-1: Chapter structure



3.1 Introduction

As established through the comprehensive literature review detailed in Chapter 2, a compelling imperative exists within emergency department (ED) contexts to augment the efficacy of decision support mechanisms. This exigency arises from the inherent intricacies associated with accessing pertinent information support. Furthermore, it is noteworthy that while ML algorithms have demonstrated significant potential within the healthcare domain and have gained widespread adoption across diverse clinical undertakings, a conspicuous dearth of research exists concerning their application in the enhancement of clinical decision support (CDS) and concomitant improvements in operational efficiency within the context of the ED. Collaboration with professionals specialising in hospital EDs has accentuated the formidable impediments encountered when endeavouring to access electronic health record (EHR) data from HIS precisely when physicians are tasked with rendering critical clinical determinations.

Hence, the overarching research inquiry that emerges is as follows:

"How can an integrated architectural framework for HISs be designed to provide ML-based CDS capabilities tailored to the exigencies of an ED setting?"

To effectively address this overarching research question, this study deconstructs it into two subsidiary research inquiries:

Sub-research question 1: " How to design a clinical decision support system imbued with machine learning capabilities?"

Sub-research question 2: “How can an integration architecture for hospital information systems be designed to accommodate the incorporation of machine learning-driven clinical decision support functionality?”

The objective of this research is to design a system integration architecture to enhance clinical decision support (CDS) in a hospital information system (HIS) with machine learning (ML) in an emergency department (ED) setting.

3.2 Research Paradigm

The selection of an appropriate research paradigm constitutes the foundational framework upon which the entirety of a study is constructed. This paradigm delineates the essential philosophical and methodological underpinnings that govern a researcher's approach to investigating a specific research question or problem (Guba & Lincoln, 1994). The three primary inquiries encapsulating this paradigmatic framework are as follows:

1. The Ontological Question: This pertains to the nature of reality itself.
2. The Epistemological Question: This concerns the relationship that exists between researchers and the acquisition of knowledge.
3. The Methodological Question: This addresses the methodologies employed in acquiring knowledge.

Within the realm of information systems research, the focus is primarily directed towards comprehending the interactions between system artefacts and the individuals who engage with these systems (Gregor, 2006). Predominantly, research in this field aligns with either the positivist or interpretivist paradigms, underpinned by distinct philosophical assumptions (Orlikowski & Baroudi, 1991). Positivism, as a paradigm, posits the existence of an objective, singular reality governed by universal laws, which can be ascertained through the empirical testing of hypotheses derived from general theories. In this perspective, researchers are expected to maintain objectivity and distance from the subjects under scrutiny (Shanks, 2002). Conversely, interpretivism asserts that reality is a construct shaped through human interactions, and the process of knowledge acquisition inherently involves researchers actively engaging and influencing the reality they study (Orlikowski & Baroudi, 1991; Weber, 2010).

To address the research question for this study, the adoption of a positivist paradigm within the framework of design science research is deemed congruent with the research objectives. Within this positivist paradigm, knowledge is garnered by observing and quantifying the extent to which problems can be ameliorated or resolved through the introduction of an artefact. The hypothesis in this context posits that the enhancement of clinical decision-making via the implementation of a CDSS artefact will result in improved operational performance within a hospital's ED. This necessitates the application of relevant metrics and analytical techniques to evaluate the artefact's performance, substantiated by empirical evidence or logical deduction (Peffers et al., 2007).

3.2.1 Design Science Research

The design science research paradigm serves as a framework aimed at addressing two prominent issues within the domain of information systems research. These issues revolve around the contentious role of information technology artefacts and the perceived lack of practical relevance in IS research endeavours (A. Hevner & S. Chatterjee, 2010b). Design science research, in its pursuit, amalgamates the creation of artefacts with a pronounced emphasis on their practical applicability, thereby seeking to bridge this gap.

In the context of the present study, the research embraces the design science (DS) paradigm as a complementary approach for tackling intricate problems identified within organisational contexts. This is accomplished through a systematic process involving the design, development, and evaluation of innovative IT artefacts (Hevner et al., 2004; March & Storey, 2008). In the words of A. Hevner and S. Chatterjee (2010c, p. 5):

> Design science research is a research paradigm in which a designer answers questions relevant to human problems via the creation of innovative artefacts, thereby contributing new knowledge to the body of scientific evidence. The designed artefacts are both useful and fundamental in understanding that problem.

As delineated in Table 3-1, Hevner et al. (2004) have laid down seven widely acknowledged guidelines for conducting and evaluating effective design science research in the realm of information systems.

Table 3-1 Design Science Research Guidelines adapted from Hevner et al. (2004)

Guideline	Description
Guideline 1	The core of design science research involves the creation of a workable artefact, which can take the form of a construct, model, method, or instantiation.
Guideline 2	The principal aim of design science research is to develop technology-based solutions for significant and relevant business problems.
Guideline 3	To substantiate the value of a design artefact, researchers must rigorously demonstrate its utility, quality, and effectiveness through well-executed evaluation methods.
Guideline 4	Effective design science research should provide clear and verifiable contributions in the areas encompassing the design artefact, design foundations, and/or design methodologies.
Guideline 5	The application of rigorous methods is essential in both constructing and evaluating the design artefact within design science research.
Guideline 6	The pursuit of an effective artefact involves utilising available resources to achieve desired outcomes while adhering to the constraints within the problem environment.
Guideline 7	Successful design science research necessitates effective communication that caters to both technology-oriented and management-oriented audiences.

These guidelines have been adapted to align with the research activities conducted across the three phases of this study.

3.2.2 Process of Design Science Research

As stated by A. Hevner and S. Chatterjee (2010a), multiple research methodologies exist within design science research in the IS discipline.

One of the early and well-established conceptual methodologies in design science is the system development research methodology proposed by Nunamaker Jr et al. (1990). They argue that due to the central role of systems development in information systems research, a multimethodological approach is necessary, consisting of four research strategies: theory building, experimentation, observation, and systems development. The system development research methodology comprises five components: constructing a conceptual framework, developing system architecture, analysing and designing the system, building the system or a prototype, and observing and evaluating the system.

Compared to the system development research methodology, which focuses on development, the design science research cycle serves as an alternative framework in design science research that emphasises knowledge contribution (Vaishnavi & Kuechler, 2015b). The cycle begins with problem awareness, where research problems, stemming from various sources, such as literature reviews, practical experience, or related disciplines, need to be identified and defined. This phase involves abduction, where a tentative design is established based on existing knowledge or theory (Takeda et al., 1990; Vaishnavi & Kuechler, 2015b). Subsequently, an artefact is created during the development stage, which encompasses most of the design activities. Once implemented, the artefact undergoes evaluation using appropriate methods and techniques (March & Smith, 1995) based on the functional specifications implicit or explicit in the suggestion (Vaishnavi & Kuechler, 2015a). Iterations can be triggered by feedback and new knowledge acquired during development or evaluation, allowing for further refinement of the artefact through problem awareness and suggestions. The design science research cycle concludes by producing knowledge contribution.

The design science research methodology, developed by Peffers et al. (2007) is a widely accepted framework that provides a reference process for effectively conducting design science research in information systems.

Given the numerous choices of design science research methodologies in the information systems discipline, a framework for comparing information systems methodologies established by Avison and Fitzgerald (2003) is employed to select an appropriate methodology for this research. This framework compares methodologies based on different elements, including philosophy, model, techniques, scope, outputs, practice, and products.

Through a comparison of the three methodologies, system development research methodology, design science research cycle, and design science research methodology, the flexibility in the evaluation activity makes design science research methodology the suitable methodology to serve as a guideline for this research. System development research methodology evaluates artefacts based on the conceptual framework and system requirements defined at the outset (Nunamaker Jr et al., 1990). The design science research methodology evaluates prototypes according to functional specifications implicit or explicit in the suggestion (Vaishnavi & Kuechler, 2015a). In design science research methodology, evaluation can incorporate any relevant empirical evidence or logical proof, such as a comparison of the artefact's functionality with the solution objectives; objective quantitative performance measures, like budgets or produced items; and results from satisfaction surveys, client feedback, or simulations. The six activities in design science research methodology also satisfy all seven guidelines outlined by Hevner et al. (2004) for conducting high-quality design science research.

This research follows the design science research methodology process developed by Peffers et al. (2007). for conducting design science research. The design science research methodology process consists of six activities:

- Activity 1: Problem identification and motivation
- Activity 2: Define the objectives for a solution
- Activity 3: Design and development
- Activity 4: Demonstration
- Activity 5: Evaluation
- Activity 6: Communication

The entry point for different activities may vary depending on the research approach in a design science study (Peffers et al., 2007). As this research is motivated by observed problems and a literature review, it falls under the problem-centred approach. Therefore, this study proceeds with the design science research methodology process, starting with activity 1. This section introduces the research process in this study by aligning the thesis structure with the design science research methodology activities.

Table 3-2: Thesis Structure Mapped to Design Science Research Methodology Activities

Phases	Activities	Chapters
Phase 1: Analysis	Problem identification and motivation	Chapter 1 Introduction
		Chapter 2 Literature Review
	Define the objectives for a solution	
Phase 2: Design and development	Design and development	Chapter 3 Research Method
		Chapter 4 Situation Awareness
		Chapter 5 System Development
	Demonstration	
Phase 3: Evaluation	Evaluation	Chapter 6 System Simulation
	Communication	Chapter 7 Discussion

3.3 Phase 1: Analysis

3.3.1 Problem Awareness

The activity of problem awareness defines the specific research problem and justifies the value of a solution (Peffers et al., 2007). According to Hevner et al. (2004), in the guidelines for design science research in the field of information systems, the objective is to address significant business problems through the development of a technical artefact that enhances the current situation. Researchers must possess a thorough understanding of the existing problem and substantiate the significance of its solution in order to create an effectively designed artefact (Peffers et al., 2007). The primary task of problem identification and motivation in this study is achieved through a comprehensive literature review and consultation with professionals working in hospital EDs.

The literature review encompasses various topics including emergency departments (EDs), clinical decision support (CDS), machine learning (ML), hospital information system (HIS), and system integration.

The literature in Chapter 2 demonstrates that inadequate operational efficiency is a pervasive issue in the EDs of most hospitals. The predominant problem is overcrowding, which adversely affects the performance of the ED in terms of length of stay, patient throughput, and service quality. Further investigation reveals that healthcare practitioners in EDs, including physicians and nurses, lack sufficient clinical decision support and face challenges accessing EHR data from the HIS. This issue remains largely unresolved due to the fragmentation of data and the existence of information silos within the HIS. Consequently, this research is motivated to design a system integration architecture for the HIS, aimed at developing a CDSS specifically designed for an ED setting.

The primary objective of conducting design science research in information systems is to acquire knowledge for the development and implementation of technology-based solutions aimed at addressing business problems. These problems can be defined as the disparities between the current state of a system and its desired goal state (Hevner et al., 2004). Following the problem relevance guidelines for design science research, the design artefact should possess the ability to address real-world problems in an actual application environment.

To identify the issues that exist in EDs, this research project engaged with professionals working at EDs in two university-affiliated hospitals located in different regions of the Asia-Pacific area. The

National Cheng Kung University Hospital, situated in Tainan, is a renowned university-affiliated teaching hospital and medical centre. It offers a comprehensive range of specialities and high-quality emergency, inpatient, outpatient, and health examination services. Similarly, the Sun Yat-sen Memorial Hospital, also known as the Second Affiliated Hospital of Sun Yat-sen University, is a prominent medical institution in Guangzhou. It operates as a hospital dedicated to medical care, education, research, disease prevention, and healthcare services. Both modern general hospitals, situated in well-developed cities, have implemented and utilised HIS to support their daily workflows.

The relevance of this design science research can be substantiated by consulting professionals from these two hospitals. Firstly, the identified issues regarding the interactions between practitioners and HISs in EDs correspond to the concerns addressed in the existing literature. Secondly, the similarity of the system integration problems encountered in two distinct hospitals located in different cities illustrates the widespread nature of these challenges.

The disintegration of data and information silos within HISs has emerged as a persistently unsolved issue, posing a significant challenge in the routine workflow (Jee & Kim, 2013; Parks et al., 2019). Professionals working in the EDs of both hospitals have confirmed that the deployment of HISs by different vendors separately has a detrimental impact on the performance of hospital EDs. Physicians and nurses are required to log in to various interfaces and manually reconcile data across multiple systems to access the necessary information. The inherent complexity of a HIS adds further challenges to the common extract, transform, load approach for data integration, often resulting in failures (Marchildon, 2019; Reichertz, 2006).

To gain a deeper understanding of the challenges associated with system integration in a HIS, experts from the Business Intelligence team at Te Whatu Ora Health New Zealand Waikato (HNZW), previously known as Waikato District Health Board (WDHB), were also consulted regarding the current state of system integration in the healthcare sector. HNZW oversees multiple hospitals, clinics, and other healthcare services, most of which utilise HISs within the Waikato Region. Information technology experts from WDHB reaffirmed the problem of disintegration and emphasised the pressing need for improvement in this area.

3.3.2 Requirement Elicitation

Once the problem has been defined, the subsequent step involves establishing performance objectives for a solution based on the problem delineation and understanding what is possible and feasible (Peffers et al., 2007).

In accordance with the design science research guidelines, the present research employs the observation method to examine the interaction between physicians and the existing HISs within the ED setting. The observation method involves systematically recording observable phenomena or behaviour in a natural setting to study and understand people within their natural environment, often leading to an ethnographic description and providing an insider's view of reality (Baker, 2006). Observation is widely adopted within the field of information systems studies to acquire insights, experience, and research results more relevant to the practical application environment (Nunamaker Jr et al., 1990).

The integration of observation as a constituent of the design science research activity serves multiple purposes in establishing performance objectives for the design artefact. Firstly, it engenders a more precise and contextually grounded comprehension of the problem at hand, as observations capture genuine behavioural patterns, interactions, and environmental factors that might otherwise elude detection. Consequently, in this study, it aids in the exploration of the user interface of prevailing HISs and elucidates how physicians interact with these systems in the ED. Furthermore, observations play a crucial role in validating the research objectives established within the conceptual framework. Through direct observation of the problem domain, researchers can corroborate whether the theoretical knowledge aligns with actuality and subsequently make necessary refinements to the research objectives. Moreover, observations serve to unearth latent patterns, routines, and challenges that may not be fully articulated by the users themselves.

In addition to observation, this study undertakes a comprehensive examination of the issues by engaging in consultations with various stakeholders, including healthcare practitioners and information technology professionals affiliated with the collaborating institutions. Considered as a complementary approach to observation, consultation facilitates the exploration of multiple stakeholder perspectives. The involvement of stakeholders in the consultation process also serves to validate the identified phenomena and problems derived from the initial observation.

Through consultations conducted with healthcare experts affiliated with two hospital EDs and information technology professionals associated with a district health board, it has been ascertained that the fragmentation of systems has emerged as the main obstacle for physicians seeking to access relevant information from EHR data to aid in their decision-making during the clinical workflow. Prior research has extensively presented compelling evidence to support the proposition that improved accessibility to EHRs play a crucial role in enhancing performance and cost-effectiveness through facilitating CDS within EDs (Everson et al., 2017; Knepper et al., 2018).

However, simply enhancing access to EHRs alone does not suffice to augment patient throughput within Eds (Knepper et al., 2018). Within the context of an ED, a substantial volume of information must be taken into account in order to determine the appropriate course of action for each patient within a restricted timeframe (Kadri et al., 2014). The adoption of a CDSS within the ED environment presents a prospective resolution to tackle this challenge (Fernandes et al., 2020). In order to leverage EHR data for the enhancement of operational efficiency in EDs, researchers have been exploring the potential of ML techniques to reduce patient length of stay and unnecessary resource utilisation (Grant et al., 2020; Hunter-Zinck et al., 2019). Consequently, this has led to the proposition of a ML-based CDSS as a feasible solution to enhance decision-making in the ED setting.

Upon conducting an analysis of the existing HIS in the collaborating hospital, it has been ascertained that the hospital possesses EHR data that is essential for training a ML model to facilitate CDS. However, a notable challenge arises from the fact that the data is not consolidated within a single database. Rather, different components of the EHR data are managed and stored by distinct systems across various locations. Although it is possible to manually extract, transform, and load the data from these systems for model training, the primary concern lies in acquiring all pertinent information at the point of care in the ED. The implementation of a CDSS in the ED necessitates real-time access to relevant data from various HISs, allowing for the generation of timely suggestions to physicians. However, due to insufficient system integration, the problem persists in accessing EHR data within the ED environment.

3.3.3 Data Collection

In this research, data are collected from a collaborating hospital ED for two purposes: training the ML model and simulation.

The dataset from this hospital is chosen for the reason that it meets the requirement for completeness, accuracy, and consistency, which are the three common metrics in EHR data quality assessment (Johnson et al., 2015; Weiskopf & Weng, 2013). The completeness of the dataset can be assessed by whether the data gives enough information about the patients for the study. Accuracy refers to whether the data is true or not (Weiskopf et al., 2017). Consistency requires data to be coded and stored in a unified format or standard and sometimes must satisfy syntactic and semantic rules in the domain (Johnson et al., 2015).

The collaborating hospital is a teaching hospital which also serves as a medical centre in a major Asian city with a population of nearly two million. Most departments, including the ED in this hospital, have been operating with information systems for many years. Thus, patients visiting the

ED could have relevant information recorded in the EHR systems from triage to leaving the ED. The dataset acquired for this study consists of a combination of EHR data from various systems in the hospital, which also validate the data consistency across different systems in the hospital. Thus, the dataset satisfies the requirements of completeness, accuracy, and consistency to support the data analytics in this research.

To train the ML model as part of the CDSS, this study uses EHR data from the collaborating hospital ED. In the area of ML, it is difficult to determine the minimum sample size for data collection. In a recent article by Balki et al. (2019), among 167 articles, only four studies mentioned the sample-size determination methodologies and 18 studies compared model performance on different sample sizes. For structured data like the EHR data used in this study, a rough rule of thumb is that the dataset should contain "at least an order of magnitude more examples than trainable parameters" (Google Developers, 2022). Alwosheel et al. (2018, pp. 9 - 11) advised a "factor 50" rule of thumb that a sufficient dataset should have a minimum sample size of 50 times the number of parameters.

In addition to the rule of thumb, to determine the sample size for this study, an analogy approach is also applied by reviewing other articles using machine learning with EHR data.

Table 3-3 Ratio of Record to Variables in EHR Machine Learning Dataset

Article Title	**Number of Records**	**Number of Variables**
"A Machine Learning-Based Framework to Identify Type 2 Diabetes Through Electronic Health Records" (Zheng et al., 2017)	300	110
"Learning to Predict Post-Hospitalization VTE Risk from EHR Data" (Kawaler et al., 2012)	720	119
"Prediction Modeling Using EHR Data: Challenges, Strategies, and a Comparison of Machine Learning Approaches" (Wu et al., 2010)	536	35
"Predicting Hospital Admission at Emergency Department Triage Using Machine Learning" (Hong et al., 2018)	560486	972

To match the rule of thumb and record to variable ratios in similar studies, this study acquires a dataset including a total of 471,182 records of patient visits from 2015 to 2019 at an ED of a collaborating hospital. The dataset includes 71 variables identified by working with professionals from the collaborating hospital. The size of this data is believed to be sufficient for this study considering the ratio of records to variables is about 6636.37 to 1, which is much higher than the requirement of the "factor 50" rule of thumb and higher than similar studies in Table 3-3.

3.3.3.1 Ethical Considerations

This study places significant emphasis on ethical considerations due to the utilisation of EHR data. Rigorous ethical protocols were diligently adhered to throughout the research activities, including data collection. Ethical approval (ethical application: HREC(Health)2020#01) has been duly obtained from the University of Waikato Human Research Ethics Committee, ensuring the study's strict adherence to ethical principles and guidelines.

In alignment with these ethical principles and guidelines, permission to conduct research and access Sun Yat-Sen Memorial Hospital has been secured with the support of the emergency department. A formal letter of authorisation has been issued by the Chief Physician of the Emergency Department.

Access to and utilisation of EHR data are facilitated by the Institutional Review Board at the National Cheng Kung University Hospital (IRB number: --/A-ER-108-451). This further guarantees that patient data is handled with the utmost security and ethical integrity, in strict accordance with principles of privacy and confidentiality.

3.4 Phase 2: Design and Development

Design and development is the process of designing an artefact embedded with a research contribution (Peffers et al., 2007). The artefact's desired functionality and its architecture need to be determined to create the actual artefact.

3.4.1 Design Process

The artefact design process is a crucial stage in design science research methodology. It involves translating the identified requirements and problem understanding into a tangible artefact that addresses the specified needs. This section explains the process of designing the artefact and how the conceptualisation of the artefact was carried out. In accordance with the design science research methodology and the design science research guidelines, the design process follows the Agile methodology to guide the design process.

Agile methodology is an iterative and incremental approach to software development that emphasises flexibility, collaboration, and continuous improvement (Chan & Thong, 2009). It prioritises the delivery of working software in short, time-boxed iterations called sprints, allowing for frequent feedback and adaptation (Lindstrom & Jeffries, 2004).

Agile was chosen over other design approaches due to its focus on iterative development, stakeholder collaboration, and adaptability, which match the guidelines of design science research. In this study, particularly, the iterative nature of Agile enables researchers to quickly develop and refine the artefact, incorporating stakeholder feedback. It also promotes close collaboration between researchers, and stakeholders, during the process of designing the artefact.

The artefact design process using Agile involves the following steps:

1. Plan and break down the artefact design into small, manageable tasks.
2. Conduct iterative development cycles. Being able to work together as a whole solution, the design and development of each component are iterative individually without affecting other components.
3. Regularly review and evaluate the design artefact to assess its performance. The design artefacts are tested in a simulation environment to evaluate the functionality and measure the performance of the artefact.
4. Results from the evaluation are incorporated into the subsequent development cycles.
5. Conduct frequent retrospectives to reflect on the development process and identify areas for improvement.
6. Continuously iterate and refine the artefact based on evaluation and evolving requirements until the desired solution is achieved.

This study focuses on the design of an integrated architecture for HISs that incorporates ML-based CDSS within an ED setting. This solution can be broken down into three components, each of which can be designed and developed separately as sub-artefacts.

The first sub-artefact involves designing a system integration architecture. The goal of this architecture is to merge EHR data from different HISs, creating a unified data repository for training ML models and accessing EHR data in real time.

The second sub-artefact centres on creating an ML-based CDSS that utilises EHR data to enhance clinical decision support in EDs.

The third sub-artefact outlines a process model for integrating the ML-based CDSS into the workflow of an ED. It focuses on ensuring the incorporation of the CDSS into the existing clinical processes.

The design of the three components needs to be conducted in parallel to make sure they align with each other. The system integration design needs to be able to provide EHR data in a way that can meet the requirements for ML. When designing the ML-based CDSS, the development of the ML model is constrained by the available EHR data and how it can be integrated with the clinical process in the ED. And the functionality of the ML-based CDSS will affect how the process model is designed.

3.4.2 Artefact Development

The development phase of the artefact involves utilising various techniques, tools, and frameworks to implement the design and bring it to fruition. This section describes the resources employed during the artefact development and highlights any specialised tools or frameworks used.

The system integration artefact is designed and described using the ArchiMate Enterprise Architecture modelling language (Josey et al., 2016). ArchiMate is a visual language specifically designed for describing, analysing, and communicating various aspects of enterprise architecture. It offers a standardised set of entities, relationships, and corresponding iconography that enables the representation of architectural descriptions.

The ArchiMate language is developed by The Open Group and aligned with their widely adopted Open Group Architecture Framework (TOGAF) (Josey, 2018). TOGAF is a framework for enterprise architecture that offers a comprehensive methodology for developing, delivering, and governing enterprise architectures. The structure of the ArchiMate modelling language closely corresponds with the development phases for three main architectures: business architecture, system architecture, and technology architecture, as addressed in the TOGAF Architecture Development Method (ADM).

The standardisation of modelling language ensures the attainment of consistency and compatibility in the representations of artefact designs, thereby facilitating effective communication and fostering collaboration among stakeholders. By adhering to the default iconography, the modelling language ensures that artefact designs can be comprehended and utilised by diverse participants coherently. This visual aspect of the language serves as a powerful tool for communication, allowing for the effective conveyance of complex ideas and concepts.

The language offers a comprehensive repertoire of entities and relationships that have been purposefully designed to cater specifically to architecture descriptions, enabling the capture of various concerns, including interfaces, services, data flows, and integration patterns. Consequently, the resulting artefact design representation achieves a holistic and intricate level of detail, providing a comprehensive understanding of the artefact's structure and function.

In this study, the software "Archi", an open-source visual modelling and design tool for creating ArchiMate models, is utilised to design the system architecture artefact. Despite its cost-free availability, Archi offers a wide array of features to effectively create and manage ArchiMate models. Notably, it is listed on The Open Group website as the reference open-source implementation of the ArchiMate standard, ensuring its adherence to the most current ArchiMate features.

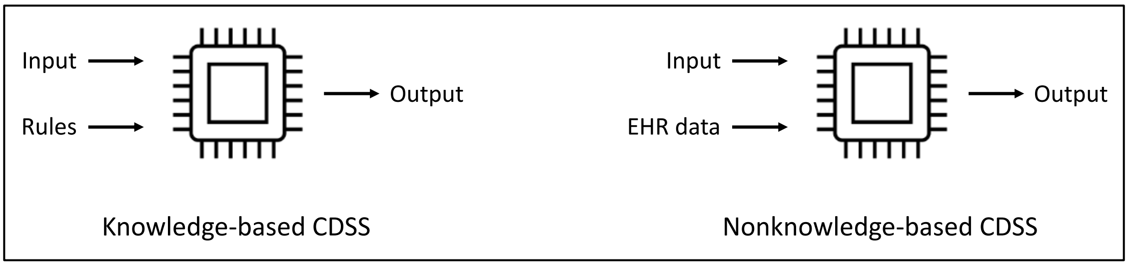
With its user-friendly interface and comprehensive feature set, Archi enables efficient documentation, analysis, and communication of software architectures. Consequently, it proves to be a suitable and pertinent choice for this study, where robust and reliable modelling and design tools are essential for investigating system architecture artefacts.

3.4.3 Clinical Decision Support System

CDSSs are computer applications that are designed to improve patient outcomes and reduce operating costs in hospitals by providing useful information on clinical decisions to physicians (Berner & La Lande, 2007). Some major motivations for the adoption of CDSSs in the healthcare sector include dealing with the challenge of knowledge management, making meaningful use of EHR data, and providing personalised healthcare services (Musen et al., 2021).

Most CDSSs can be categorised as knowledge-based systems, or non-knowledge-based systems (Berner & La Lande, 2007). A general knowledge-based CDSS consists of the following components: the knowledge base, an inference engine, and an interface to handle input and output (Spooner, 2016). The knowledge base contains pre-set rules or formulas which are often in the form of IF-THEN rules. The system receives patient data and relevant data from manual entry, EHRs, or both as input. The inference engine is where the system processes patient data with the pre-set rules and generates output information. The output may contain information which needs to be cautious about or suggestions on possible interventions.

Figure 3-2: Knowledge-based and non-knowledge-based clinical decision support systems



A knowledge-based CDSS relies on existing knowledge of the relationship between patient data and diagnosis that can be described and encoded in a programming language to solve a problem (Spooner, 2016). For example, Arden Syntax is the markup language to maintain medical acknowledge as part of the widely adopted Health Level 7 (HL7) standard (Samwald et al., 2012). In the Arden Syntax, each rule is coded as a medical logic module (MLM) with predefined variables, IF-THEN rules, and output information (Musen et al., 2021).

A non-knowledge-based CDSS does not require any rules to be maintained. Instead, ML is adopted to recognise unexpected patterns from historical data in EHRs. Non-knowledge-based CDSS can detect disease with significant accuracy by extracting information from imaging and laboratory tests (Sutton et al., 2020).

To explore how EHR data can be used to enhance CDS in EDs, this study chooses to design a CDSS artefact in the non-knowledge-based approach for the following reasons:

CDSS can improve operating efficiency in EDs; the previous study suggests that CDSS can improve the performance of an ED in triage, admission, length of stay, and mortality rate (Fernandes et al., 2020); and ED is a highly complex and dynamic environment where unexpected patients could arrive with an unforeseeable situation which all need specific treatment (Kadri et al., 2014). The existing study also suggests a knowledge-based CDSS which performs well in other departments might not be suitable for individual cases in an ED setting where most information might not be available in the first place (Graber & VanScoy, 2003). Non-knowledge-based CDSS can provide more accurate decision support for each case instead of for a category of patients (Frize et al., 2001).

Hence, it is imperative that the ML-based CDSS artefact is designed to align with the architectural characteristic of a non-knowledge-based CDSS. This paradigm comprises constituents including the training dataset, ML models, input interface, and output interface.

The training dataset assumes the critical role of historical EHR data procured from diverse HISs. This repository of data serves as the foundation upon which the ML models are nurtured through training processes. These ML models, developed and trained utilising the EHR data, undertake the pivotal role of serving as the inference engine.

The input interface operates by receiving patient-specific data instances, which subsequently undergo processing by the trained ML models. This process entails the manipulation of varied data variants within a coherent framework, thus capitalising on the sophisticated learning embedded within the models. The outcomes generated by the ML models, encapsulating their assessments, are subsequently channelled to ED physicians through the dedicated output interface.

3.4.4 Machine Learning

A non-knowledge-based CDSS employs ML to learn patterns within EHR data (Berner & La Lande, 2007). Consequently, the formulation and construction of a ML model constitute pivotal facets within the development of the ML-based CDSS for this study.

Echoing established paradigms in ML inquiry, the present study adheres to a comprehensive approach, characterised by a sequence of discrete phases (Kamiri & Mariga, 2021):

1. Data collection: The initial phase entails the meticulous accumulation of pertinent data.
2. Data pre-processing: After data procurement, a phase of data pre-processing is enacted, wherein raw data is refined, normalised, and purged of redundancies and outliers.
3. Model training and testing: The phase encompasses the training of the ML model through exposure to the processed data. This phase is complemented by rigorous testing and validation procedures to ensure the competency and robustness of the model.
4. Model evaluation: Lastly, the performance of the model is subjected to meticulous evaluation, often involving metrics and benchmarks to quantify its predictive accuracy and generalisation capabilities.

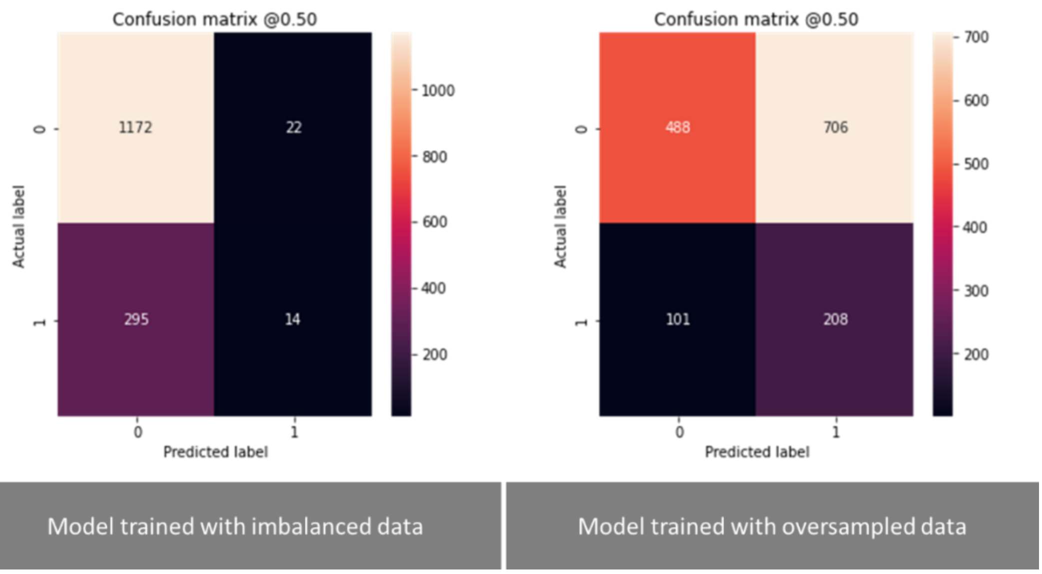
As introduced in Section 3.3.3, this study acquires an EHR dataset from a collaborating hospital. The dataset encompasses comprehensive patient visitation records to the ED spanning the temporal interval of 2015 to 2019. The retrieval of EHR data is derived from a confluence of diverse HISs and shared by collaborating researchers affiliated with the hospital.

Data pre-processing constitutes a pivotal undertaking within the realm of ML research, given its substantial ramifications upon the efficacy of ML models (Kamiri & Mariga, 2021; Kotsiantis et al., 2006). The present study encompasses a spectrum of customary data pre-processing endeavours, entailing the resolution of intricate issues such as data imbalance, missing values, and data normalisation.

The concept of imbalanced data pertains to datasets characterised by an unequal distribution of data across distinct categories. In the realm of healthcare, this disparity may manifest as certain medical conditions being infrequently observed within a significantly expansive patient cohort. The ramifications of training models on such imbalanced datasets are underscored by a proclivity for these models to disregard the underrepresented minority categories. A panoply of strategies exists to mitigate this concern, spanning data-level interventions, algorithmic adaptations, and composite methodologies (Krawczyk, 2016). In this study, a hybrid approach is embraced, wherein random sampling is implemented at the data level, concomitant with the introduction of augmented weights for minority classes at the algorithmic level.

Illustratively, the dataset under scrutiny comprises 112,847 records of blood culture tests, where 100,510 yield negative outcomes and 12,337 yield positive outcomes. To gauge the potential ramifications of imbalanced data on the efficacy of model training, a rudimentary neural network model is trained employing both the original, imbalanced dataset and a rectified, balanced dataset. Subsequent to this training phase, the models are subjected to evaluation through an independent dataset that remains extraneous to the training process. As evidenced in Figure 3-3, the model trained on imbalanced data evinces a predilection for affording positive predictions, whilst neglecting to identify over 90% of actual positive outcomes. In stark contrast, the model trained on oversampled data evidenced a capacity to accurately identify upwards of 60% of positive outcomes. This juxtaposition between models underscores the exigency of addressing the underlying dataset imbalance, as inferred from this comparative analysis.

Figure 3-3: Confusion matrix for models trained on imbalanced and oversampled data

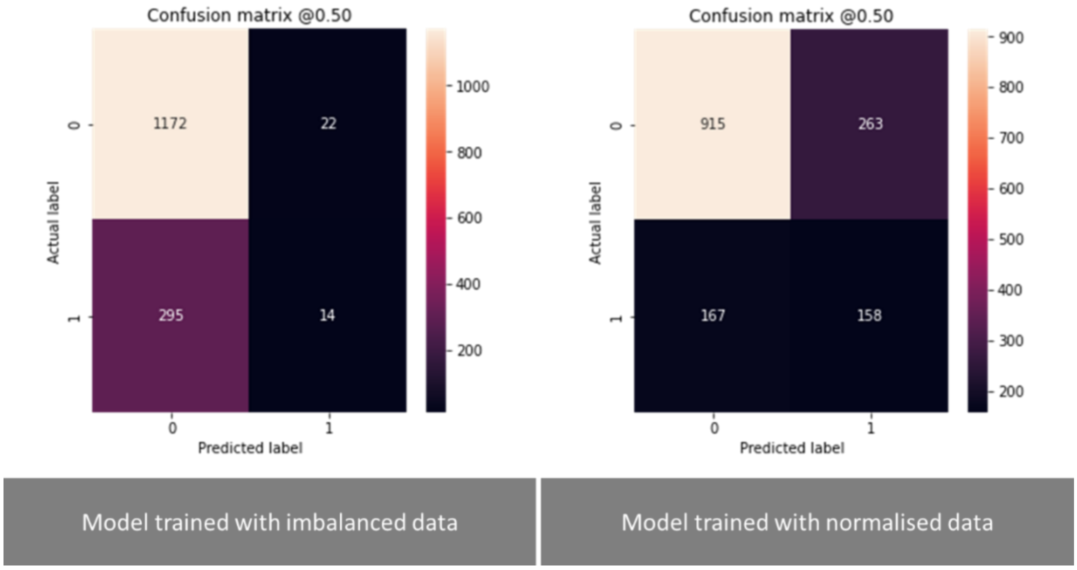


The issue of omitted values constitutes a recurring complication within EHR data. In the context of this study, it has come to light that a substantial number of EHR entries encompass vacant data fields. This absence of information predominantly emanates from instances where patients have foregone certain medical examinations. To address this concern, a spectrum of prospective remedies for handling the issue of omitted values has been postulated. These encompass 1) a high frequency or mean value in the whole dataset, 2) a high frequency or mean value in the same class, 3) a predicted value by another model trained on completed data, or 4) one specific value for all missing data (Donders et al., 2006; Lakshminarayan et al., 1999). For a comprehensive exploration of these strategies, further elaboration is provided in Chapter 5, dedicated to the system development.

Data normalisation encompasses the process of rescaling a variable's magnitude, as articulated by Kotsiantis et al. (2006). The rationale for data normalisation arises from two distinct scenarios. Firstly, instances where a substantial divergence prevails between the maximum and minimum values of a given variable within a sample set. This dissonance bears the potential to compromise model accuracy analogous to the deleterious effects incurred by imbalanced data. Addressing this issue entails rectification of outliers, if their influence is discerned, or necessitates the undertaking of data normalisation procedures. Secondly, when certain attributes are characterised by magnitudes of significantly dissimilar proportions, resulting in an undue predisposition towards features of greater magnitude in predictive modelling. Data normalisation, in this context, serves to mitigate the predisposed bias towards attributes with higher magnitudes by standardising all features onto a unified scale.

Within the context of the EHR dataset at hand, the dataset comprises diverse attributes encompassing laboratory test results with binary positive and negative values represented as 1 and 0, respectively. Additionally, quantitative vital signs such as body temperature and pulse, are presented on disparate scales. To assess the potential impact of value range on model performance, an experimental framework is devised wherein a model is trained and evaluated both on the original value dataset and a normalised value variant. Notably, as depicted in Figure 3-4, discernible advantages are observable in the performance of the model trained on the normalised dataset. This advantageous performance manifests particularly in its heightened ability to accurately identify positive results while concurrently maintaining a controlled rate of false positives. Consequently, the explication of these results underscores the imperative of embracing data normalisation as an indispensable facet for optimising model performance.

Figure 3-4: Confusion matrix for models trained on original data and normalised data



In the context of model training, the dataset is partitioned into three distinct segments: the training dataset, the validation dataset, and the test dataset. A typical practice involves training candidate models using the training dataset and then determining the best-performing model through performance evaluation on previously unseen data from the test dataset. The introduction of a validation dataset within the iterative training process serves to mitigate the likelihood of overfitting, a phenomenon characterised by the model excessively tailoring itself to the training data to the detriment of its generalisation capability to new instances (Google, 2020).

This study employs the receiver operating characteristics graph as a methodological apparatus for assessing model performance. The adoption of the receiver operating characteristics graph is motivated by its pervasive utilisation as a benchmark for evaluating the efficacy of models within the domains of ML research and diagnostic tests within healthcare contexts (K. Hajian-Tilaki, 2013; Kannan & Vasanthi, 2019). The receiver operating characteristics graph serves as a visual representation that delineates the classification prowess of a model, wherein a two-dimensional Cartesian plane is employed. Within this graph, the ordinate axis encapsulates the true positive rate, while the abscissa axis represents the false positive rate (Kannan & Vasanthi, 2019).

3.4.5 System Integration

The primary objective of this study revolves around creating a system integration architecture that aims at effectively integrating heterogeneous systems utilised in the ED of a hospital. In practical application, system integration can be executed through diverse approaches, as outlined in Table 3-4.

Table 3-4 Approaches for hospital information system integration

Integration Approach	**Description**	**Strength**	**Weakness**
Message	Systems exchange data in a standard format such as HL7 (Grimson et al., 2000; Sabooniha et al., 2012).	It allows message exchange between different systems (Sabooniha et al., 2012).	The implementation could still be various across vendors (Grimson et al., 2000; Sabooniha et al., 2012).
Data Warehouse	Data from different systems is collected, replicated and stored in a dedicated database (Grimson et al., 2000).	It supports a single access point to an integrated database (Grimson et al., 2000).	Data conflict might happen between different data sources (Grimson et al., 2000; Kuhn & Giuse, 2001).
Middleware	A set of service components are built to access data from distributed systems (Grimson et al., 2000).	It provides a system-wide general interface to access data across different systems (Grimson et al., 2000; Sabooniha et al., 2012).	The required number of interfaces grows with the square of the number of systems to be interconnected (Kuhn & Giuse, 2001).

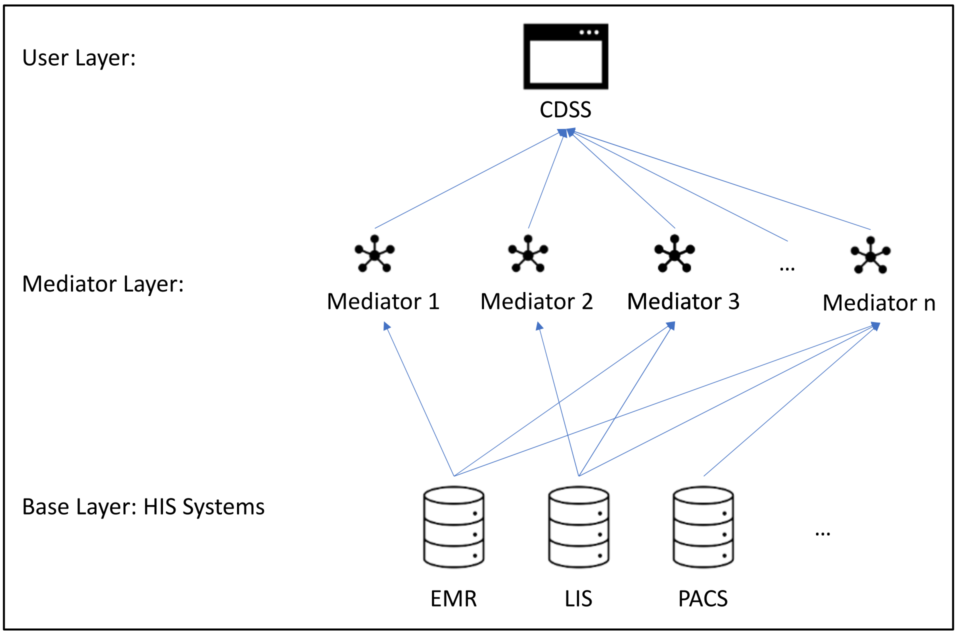
In the context of integrating information systems, a pivotal undertaking resides in the discernment of the fitting technological apparatus to be assimilated into and fortify the operational contours of the business process (Grimson et al., 2000). This study is principally motivated by the imperative to address the exigency articulated by medical practitioners for enhanced CDS within the dynamic milieu of the ED setting. The chosen approach to integration must evince the capacity to seamlessly retrieve data in heterogeneous formats from disparate systems, in real time, thereby affording a dependable foundation for this concerted undertaking.

Upon analysing the distinct approaches in Table 3-4, the adoption of a middleware approach emerges as a judicious selection for this study, substantiated by the subsequent rationales:

1. Proficiency in integrating diverse systems: The middleware approach has demonstrated its capacity to adeptly amalgamate both contemporary and legacy systems within the heterogeneous milieu of HISs (Blobel & Holena, 1997)
2. Technology neutrality and versatility: An inherent advantage lies in the middleware's amenability to implementation across a spectrum of extant technologies, disentangled from the dependencies on the preexisting systems (Sabooniha et al., 2012).
3. Mitigation of semantic heterogeneity: The middleware approach efficaciously addresses the intricate quandary of semantic heterogeneity that arises from disparate autonomous systems coalescing within HISs (Kuhn & Giuse, 2001; Liu et al., 2010)

Illustrated in Figure 3-5, a middleware approach constitutes an organisational framework within information systems, delineating three distinct strata: the user layer, the mediator layer, and the base layer. This architecture is specifically designed to facilitate the automated information-acquisition processes for decision-making endeavours (Wiederhold, 1992). The user layer encompasses applications devised to furnish both information and decision-support functionalities to human users. Positioned within the base layer are the underlying backend systems responsible for housing assorted data repositories. Within the intermediary stratum, mediators are instantiated with the purpose of effecting data retrieval from one or multiple distinct data sources. Subsequent to retrieval, these mediators engage in data preprocessing operations, culminating in the provisioning of tailored data outputs through a comprehensive interface (Xu et al., 2000).

Figure 3-5: A Mediator Integration Architecture adapted from the three-layer architecture by Wiederhold (1992)



This study adopts the Lambda Architecture to implement the middleware approach for designing an integration framework aims at providing EHR data to the CDSS artefact. The CDSS can access EHR data through a standardised interface provided by mediators. The mediators function to retrieve and pre-process EHR data sourced from one or multiple HISs. Further elaboration on this matter is provided in Chapter 5, which is exclusively dedicated to the exposition of the system's developmental process.

3.5 Phase 3: Evaluation

During the evaluative phase within the design science research process, the resolution through which the design artefact addresses the initial predicament is subjected to observation and quantification (Peffers et al., 2007). The assessment of the artefact necessitates adherence to the criteria unveiled during the problem recognition phase (Vaishnavi & Kuechler, 2015b). In design science research, the evaluation of the artefact may be made evident in diverse manifestations, accompanied by suitable empirical substantiation or logical substantiation. The outcome of this evaluation may potentially trigger a regression to the design and development phase, with the aim of refining the artefact, subsequently demanding a renewed assessment of the enhanced iteration. This study designs a system integration architecture, dedicated to the enhancement of CDS in a HIS with ML, thereby augmenting operational efficacy within the EDs. In the context of assessing an information system within the confines of an ED setting, simulation emerges as a judicious approach.

3.5.1 Simulation

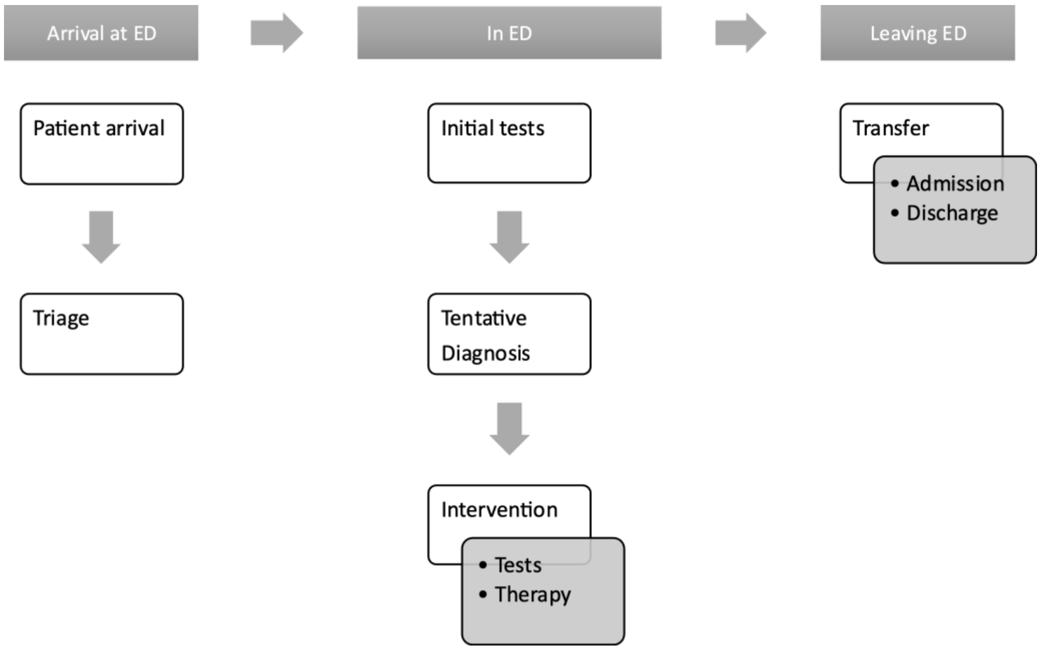
A simulation of a system refers to the execution of a model representing that system, affording the ability to reconfigure and conduct experiments under circumstances where direct manipulation of the actual system is unfeasible (Maria, 1997). In this study, the focal point pertains to the HISs within the ED of hospitals. Previous studies have established simulation as a potent methodology for evaluating decision-support interventions aimed at enhancing ED management. For instance, Kadri et al. (2014) developed a discrete-event model, which replicated scenarios of strain, corresponding states, and subsequent remedial actions within an ED of a hospital. Within this model, a CDSS was devised to furnish decision support by analysing said strain-related scenarios.

To assess the efficacy of the proposed design artefact via simulation, this study adopts a methodological framework synthesised from the work of Maria (1997), involving the following sequential steps:

1. Formulation of a comprehensive simulation model.
2. Construction of a meticulously structured simulation experiment.
3. Rigorous analysis of simulation-generated outcomes.

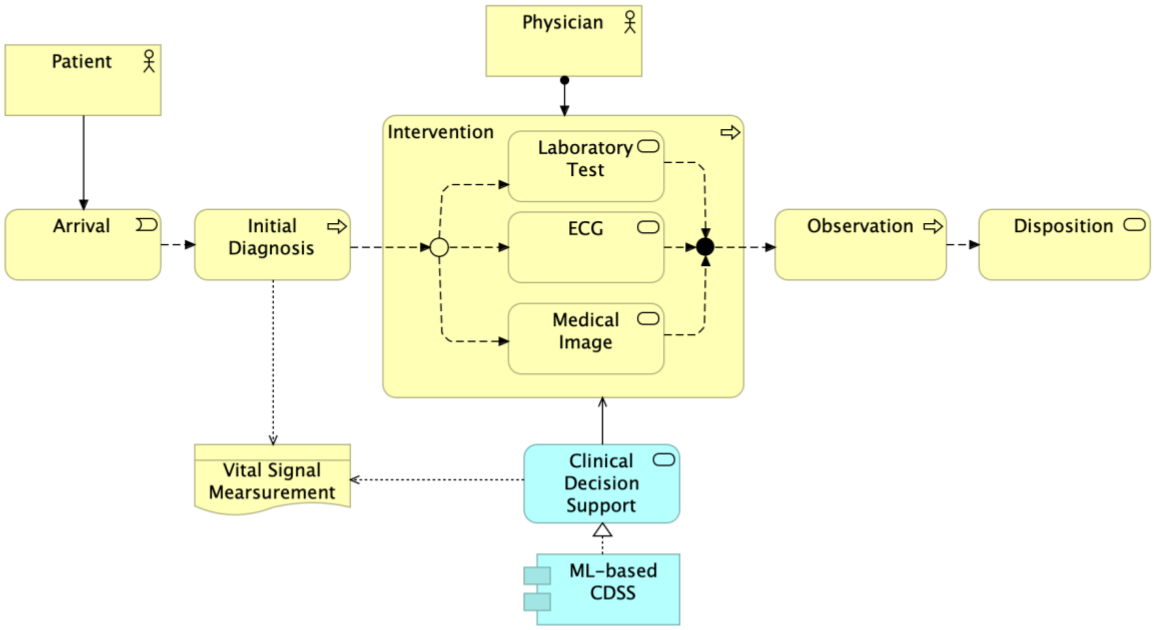
A simulation model comprises the formulation of the problem to be addressed and the contextual parameters of the environment. In the context of the present study, the primary objective entails the enhancement of operational efficiency within EDs through the augmentation of decision support. Consequently, a comprehensive comprehension of the performance metrics pertinent to EDs and the underlying clinical judgements is imperative. The established protocol within an ED encompasses a sequential progression, initiated by the application of triage protocols to both self-presenting patients and those conveyed by emergency medical services. This is succeeded by an initial diagnosis, potentially followed by diagnostic tests, requisite medical interventions, and culminating in the determination of either discharge or transfer to inpatient units (Roessler & Zuzan, 2006). These procedural stages entail a multitude of associated determinations. The existing body of literature germane to healthcare administration within emergency settings has predominantly concentrated on quality benchmarks, factors influencing clinical outcomes, and certain investigations concerning resource allocation dynamics (Sugrue et al., 2017). Illustratively, parameters, such as length of stay, temporal intervals, and instances of patients leaving the premises prior to medical evaluation (referred to as "Left Without Being Seen" or LWBS) represent the prevailing yardsticks when evaluating the efficacy of an ED (Di Laura et al., 2021). With knowledge from pertinent literature and insights from subject matter experts, this study has devised a schematic representation, presented in Figure 3-6, encapsulating the flow of patients within EDs.

Figure 3-6: Model of patient flow in an emergency department



The process of designing a simulation experiment entails the introduction of alterations, encompassing novel systems or revised workflows, into a model. This procedural approach facilitates the observation and quantification of performance enhancements resulting from these modifications, as elucidated by Maria (1997). In the context of assessing the efficacy of the CDSS in enhancing operational performance within EDs, a simulation experiment is meticulously formulated, as visually depicted in Figure 3-7.

Figure 3-7: Simulation design



3.5.2 Validating and Verifying

The validation and verification processes represent essential components of simulation methodology, ensuring the precision and dependability of simulated outcomes when employing simulation as an evaluation method (Kleijnen, 1995; R. G. Sargent, 2004). The validation process primarily revolves around ascertaining the alignment between the conceptual simulation model and the real-world system it aims to replicate. This entails scrutinising whether the model effectively captures the essential characteristics and dynamics of the system under investigation. In contrast, verification pertains to confirming the accurate functioning of the simulation computer program in accordance with its intended design. To ensure that a program accurately simulates the behaviours and responses of a targeted system, it must undergo an evaluation of its coding, algorithms, and mathematical representations. Both validation and verification processes are employed to rigorously assess the reliability and precision of the simulation model in this study.

The selection of face validation as the preferred validation technique in this context is substantiated by its appropriateness for the initial stages of simulation model development. Face validation is a particularly valuable technique to assess the plausibility and relevance of the structure and assumptions of the model (Klügl, 2008). Face validation, as a qualitative and expert-driven approach, is well-suited for this purpose. This process entails seeking input from subject matter experts, in this case, clinical practitioners working within the EDs of the collaborating hospital. Their subjective judgements are gathered to assess the representational fidelity of the simulation model (R. G.

Sargent, 2004). These experts provide valuable insights into whether the key parameters, assumptions, and logical constructs of the model correspond with their professional understanding of ED operations.

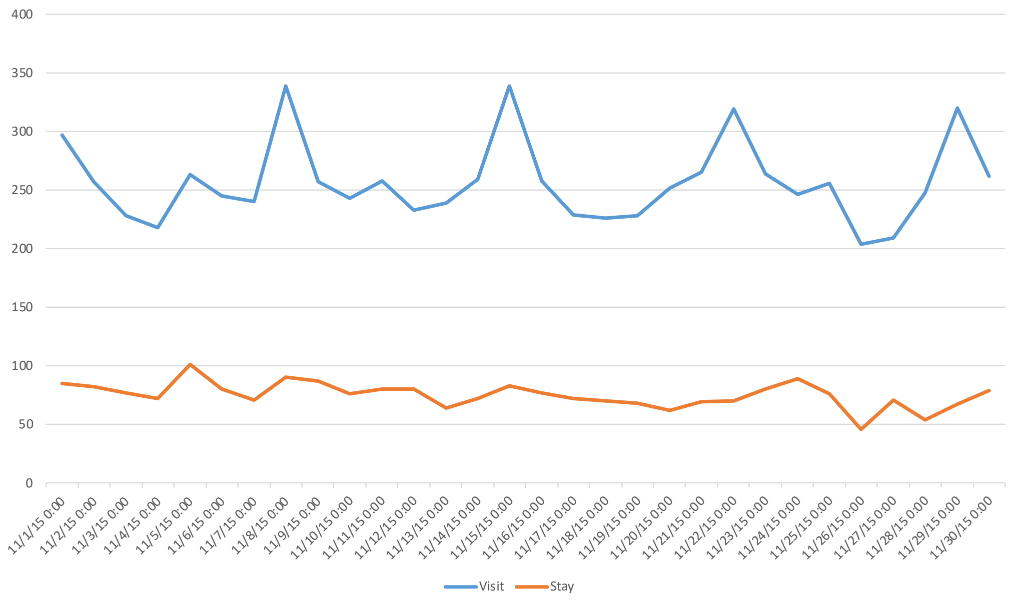
To ensure the accurate implementation of the simulation model within a computer program, a combination of both static and dynamic analyses is employed to validate its correctness and reliability (Whitner & Balci, 1989). Static analysis entails a meticulous examination of the code, equations, and algorithms without their execution, with the primary objective of identifying logical errors, inconsistencies, or potential issues. Conversely, dynamic analysis involves the execution of the model under various input conditions and scenarios, facilitating an assessment of its behaviour and performance over time.

The utilisation of these verification techniques is well-justified due to their complementary nature. In this study, static analysis is conducted through the adoption of a well-established simulation software tool, AnyLogic (The AnyLogic Company, 2023), which offers robust capabilities for scrutinising model logic and structure. Concurrently, dynamic analysis is executed by conducting simulation experiments using input derived from historical data. Subsequently, the outcomes of these simulations are compared with the actual historical data to verify the model's ability to accurately replicate past events.

3.5.3 Data Validation

Empirical data plays a pivotal role in ensuring the fidelity of simulations conducted within a given environment (Oh et al., 2016). In an ED setting, the distribution of patient visits across time is often non-uniform. To emulate real-world conditions accurately, this study leverages EHR data spanning five years, encompassing the period from 2015 to 2019. Within this dataset, distinct temporal patterns of ED patient visits emerge, discernible at various temporal scales. For instance, Figure 3-8 graphically illustrates the weekly fluctuations in patient visits over the course of a month. Analogously, the dataset unveils monthly and seasonal visitation patterns. Moreover, temporal peaks in patient visits manifest at particular times of day and during specific months of the year.

Figure 3-8: Patient visits in the emergency department



Simulating an ED environment mandates a comprehensive understanding of its system specifications (Maria, 1997). These specifications encompass factors profoundly influencing healthcare service capacity, including medical personnel, equipment, treatment areas, and beds (Gul & Guneri, 2012; Kadri et al., 2014). In this study, the requisite environmental parameters are derived from the identical ED facility collaborating in the provision of historical EHR data.

To validate the structural integrity and parameter validity of the model, a series of simulations have been conducted across various scenarios and situations, leveraging the historical EHR data. These simulations serve as a means of evaluating the robustness of the model and its capacity to effectively accommodate diverse conditions.

3.5.4 Data Analytics

The designed artefact is subjected to rigorous assessment employing key performance metrics derived from the outcomes of a simulated experiment. To facilitate a comprehensive evaluation, a series of simulations have been conducted, each utilising identical patient data, staff shifting schedules, and resource capacity. Two distinct simulation scenarios are executed: one with the integration of an ML-based CDSS and one without. The latter simulation, performed without the ML-based CDSS, serves the dual purpose of validating the accuracy of the simulation model and establishing a performance baseline for comparative analysis.

Conversely, the results obtained from the simulation conducted with the ML-based CDSS are meticulously collected and subsequently subjected to a rigorous comparative analysis. This analysis aims to assess the performance enhancement offered by the design artefact within the clinical decision-making process.

3.6 Summary

This chapter presents a comprehensive research methodology for conducting a design science research study aimed at addressing the overarching research question, which seeks to enhance clinical decision-making in EDs by designing an integrated architect for HISs to provide ML-based CDS. The chapter establishes the fundamental concept of design science research and its salient characteristics, thus substantiating its applicability in addressing the research objectives. Aligned with the guidelines of design science research, this chapter delineates a systematic approach derived from the design science research methodology. This approach commences with the identification of impediments to the adoption of ML-based CDSS, a theme that will be further expounded upon in Chapter 4, titled “Problem Awareness”. Subsequently, it delves into the phases of artefact design and development, employing the Agile methodology to facilitate iterative progress, foster stakeholder engagement, and ensure adaptability. A comprehensive discussion of this aspect is reserved for Chapter 5, titled “System Development”. This methodological framework encompasses the process of requirements elicitation, integration of specialised tools and frameworks, and adherence to an iterative and participatory design approach. Furthermore, this chapter outlines the subsequent stages of artefact evaluation, data analysis, and the measures taken to ensure both the validity and reliability of the research outcomes. These aspects will be expounded upon in detail in Chapter 6, titled “System Simulation”.

Chapter 4 Situation Awareness

4.1 Introduction

The present study, through a comprehensive analysis of relevant literature in Chapter 2, identifies a significant knowledge gap pertaining to the integration of machine learning (ML) within a system architecture to enhance clinical decision support (CDS) in the emergency department (ED) setting. Furthermore, the literature review highlights the challenge of system integration as a major barrier hindering the implementation of ML-based clinical decision support in the ED. The goal of this study is to design a system integration framework that leverages machine learning (ML) to improve clinical decision support (CDS) within a hospital information system (HIS), specifically within the context of an emergency department (ED).

In Chapter 3, the selection of an appropriate research methodology is discussed, and design science research is justified as the suitable approach to achieve the research objective. Building upon the rationale provided in Chapter 3, the subsequent step in the research process entails analysing the current application environment to ascertain the specific research problems, with a particular focus on situation awareness.

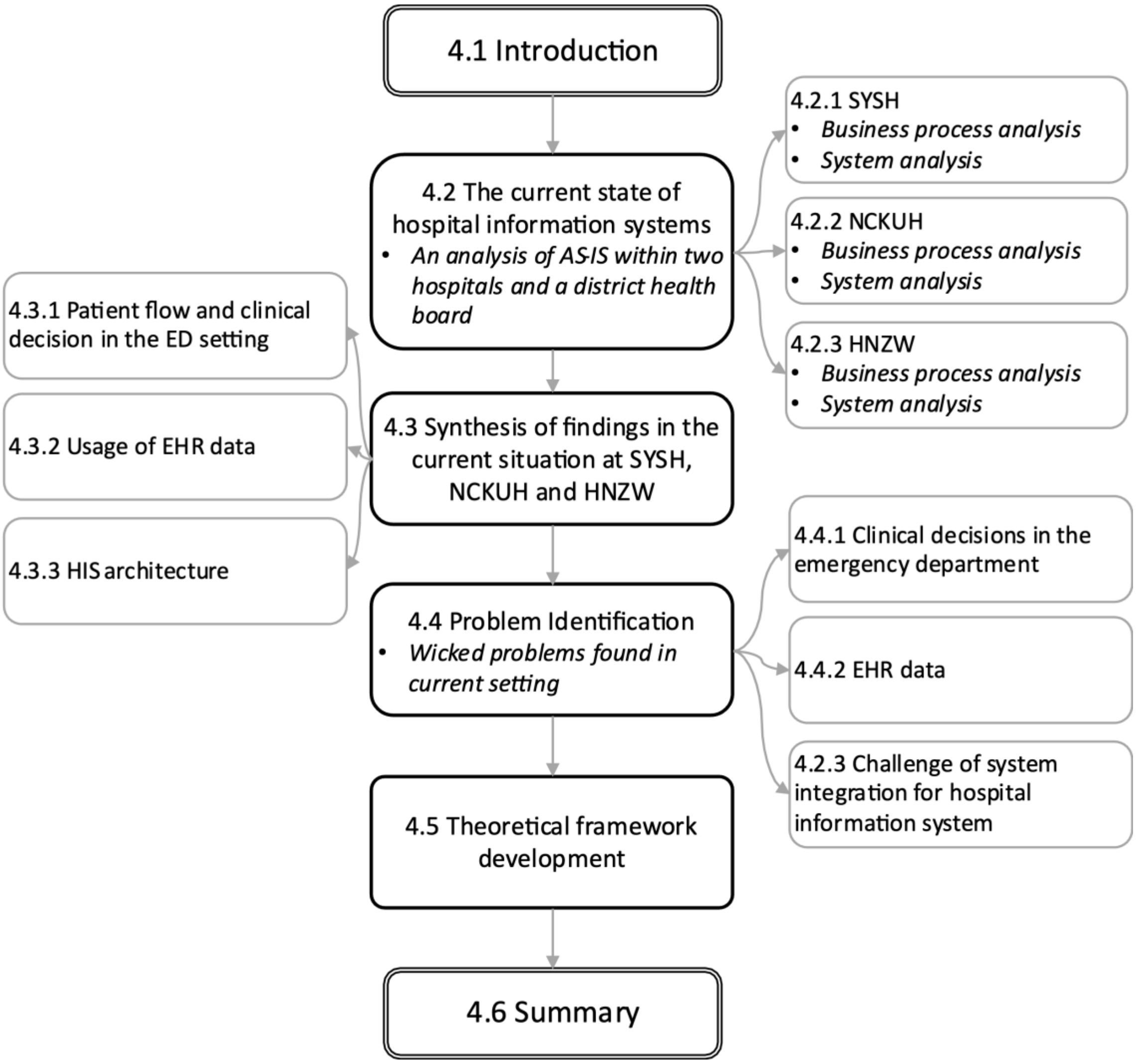
The structure of this chapter adheres to the design science research process, as depicted in Figure 4-1. Section 4.2 presents an analysis of the problem identification tasks conducted through visits to the ED of two hospitals and a district health board. The purpose of these visits is to gain a comprehensive understanding of the current situation, encompassing clinical workflow, hospital information systems (HIS), and electronic health record (EHR) data within the EDs of the respective hospitals.

Subsequently, in Section 4.3, the findings from the three application environments are compared and synthesised to establish a robust theoretical foundation. This synthesis process entails integrating and harmonising the insights derived from the diverse ED contexts explored in Section 4.2.

To exemplify the identification of research problems, Section 4.4 examines National Cheng Kung University Hospital (NCKUH) as a real-world application environment. Through a comprehensive examination of NCKUH, this section aims to shed light on the research challenges and issues that arise when applying the theoretical foundation established in Section 4.3.

To address the knowledge gap identified during the literature review, Section 4.5 establishes a theoretical framework. This framework serves as a reflective representation of the aforementioned knowledge gap, incorporating insights from the existing body of literature.

Figure 4-1: Chapter structure



4.2 The Current State of HISs

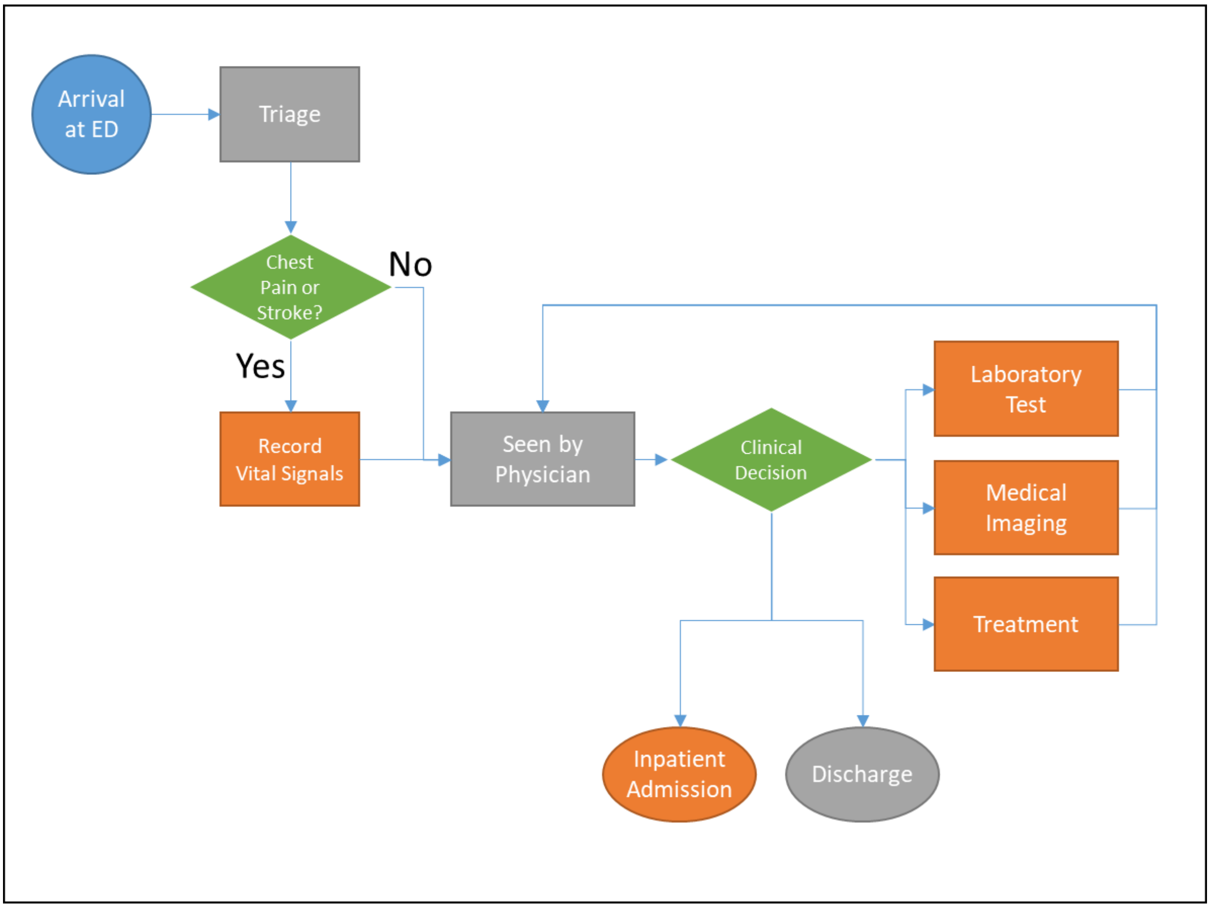
In accordance with the design science research process, the researcher undertook a comprehensive situation awareness activity by visiting two hospitals, as well as a district health board. This section aims to present a meticulous account of the clinical workflow and the HISs from the viewpoint of physicians in the aforementioned hospitals. Furthermore, a thorough examination of the system structure within the district health board offers intricate technical insights into the current state of HIS integration. The assimilation of common issues derived from these three real-world application environments serves to encapsulate the research problems and the improvement requirements identified in the literature review.

4.2.1 Sun Yat-Sen Memorial Hospital

The current situation of the HISs at the ED of Sun Yat-Sen Memorial Hospital (SYSH) has been evaluated from three key perspectives: business process, user experience, and system structure. The business process within the ED can be defined as the sequential flow of patients from their arrival until their departure. To gain a deeper understanding of the patient flow within the ED of SYSH, the researcher has sought the guidance of physicians who possess extensive familiarity with the process.

The flowchart presented in Figure 4-2 has been formulated based on the insights provided by the ED physicians at SYSH. Upon arrival at the ED, patients undergo a triage process, where their priority for receiving medical attention is determined according to the severity of their condition. In instances where patients present with specific medical conditions, such as chest pain or stroke, their vital signs are recorded on a paper report. Alternatively, if the patient has been transported to the hospital via an ambulance, their vital signs are measured and recorded during the transportation. Subsequently, when the patient is examined by a doctor, the aforementioned report is made available for the doctor's reference and consideration.

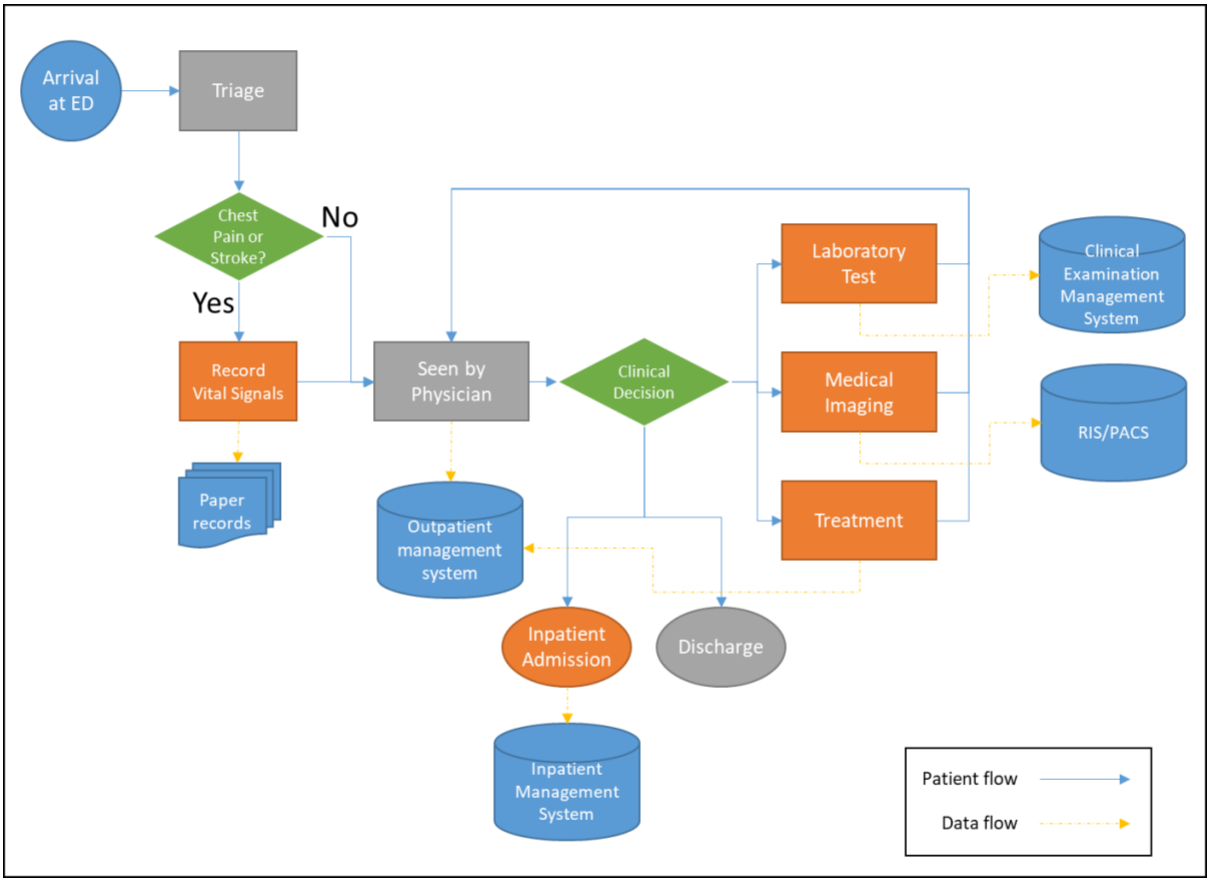
Figure 4-2: The patient flow in the emergency department of Sun Yat-Sen Memorial Hospital



During the patient's consultation with a physician, the physician undertakes a series of clinical assessments, which form the basis for subsequent clinical decisions. Should further diagnostic procedures be deemed necessary, the patient is referred for laboratory tests, medical imaging, or both. In emergency cases, the physician administers immediate treatment to stabilise the patient while awaiting the results of the diagnostic tests. Patients who do not require immediate intervention are required to wait until the completion of the diagnostic imaging or test reports before being reassessed by the physician. Subsequently, the physician administers the appropriate treatment as required. It is important to acknowledge that there may be an iterative process involving repeated diagnostics and treatments within the ED. Upon the conclusion of the intervention at the ED, the patient is either admitted to the inpatient department or discharged from the ED.

To understand the role of HISs in the workflow, the researcher undertook consultations with physicians and conducted observations regarding their utilisation of the systems within the ED. It is found that four primary systems have been implemented at the ED of SYSH. One of the systems is an outpatient management system designed to oversee the electronic medical records encompassing personal information, visitation history, diagnostic records, prescription records, test request records, treatment records, and clinical notes. It was observed that physicians do not possess access privileges to laboratory test reports or medical images within the outpatient system. Another system in place is the clinical examination management system (CEMS), which facilitates the organisation and management of all laboratory test results. For the storage of medical images, either a radiology information system (RIS) or a picture archive and communication system (PACS) is employed. Conversely, at the ED of SYSH, a singular RIS/PACS system has been implemented to effectively handle medical image data. Subsequently, upon a patient's admission, medical records generated during their inpatient period are directed to the inpatient management system for data management and accessibility.

Figure 4-3: Hospital information systems at Sun Yat-Sen Memorial Hospital

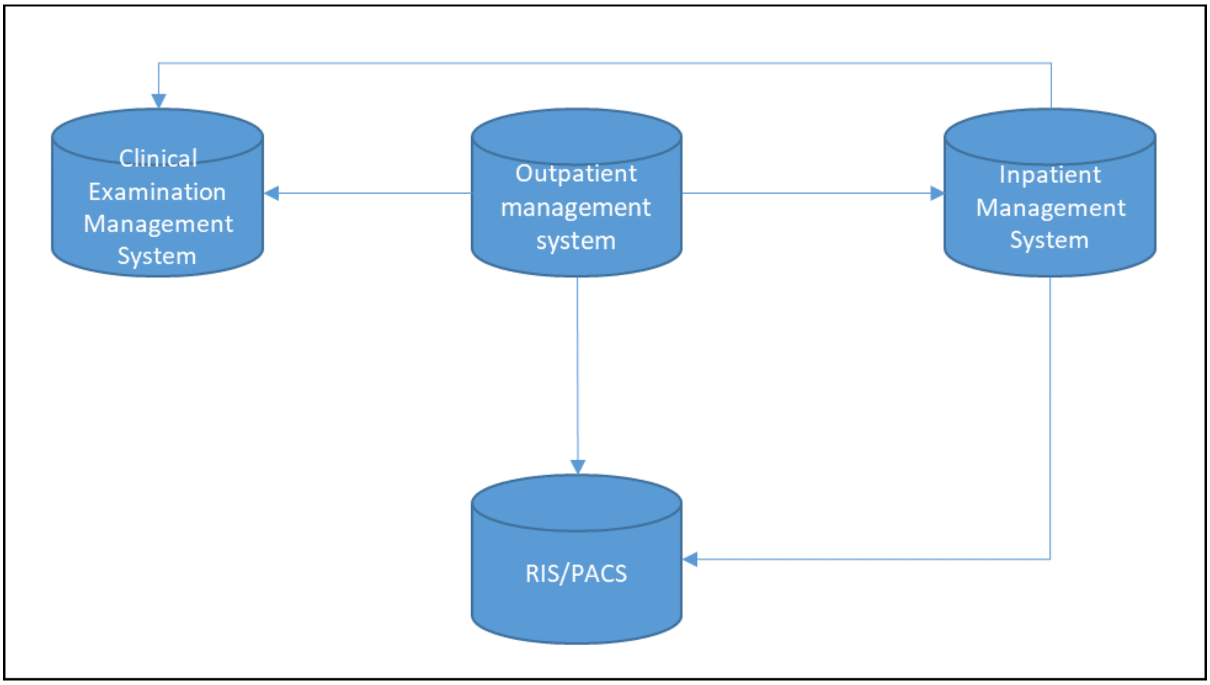


When physicians require access to the test reports or images, they need to log into distinct systems using separate credentials. No automated processes or bidirectional communication have been observed between these systems. Physicians working in the ED have substantiated that they must manually retrieve data from multiple systems, as there is a notable absence of integration.

Through consultation with physicians, who are regarded as system users, and a thorough review of the system interfaces, it has been determined that the current implementation of data exchange between the systems is rather limited. Upon a patient's arrival and subsequent check-in at the ED, a unique outpatient series number is assigned to their visit record within the outpatient management system. When a physician requests a laboratory test or medical imaging, the same outpatient series number is assigned to the corresponding records within either the CEMS or the RIS/PACS. This outpatient series number serves as a search criterion on the interfaces of the CEMS and RIS/PACS. Additionally, the outpatient series number is also visible on the interface of the inpatient management system, where it can be employed as a search criterion as well. Consequently, this shared attribute acts as a crucial link between the inpatient management system and either the CEMS or the RIS/PACS.

Despite limited data exchange, each of the aforementioned four systems exhibits a significant degree of autonomy. To obtain access to the data administered by a particular system, users are required to authenticate themselves within the said system and subsequently navigate the system's interface to access the desired data.

Figure 4-4: Data exchange among Hospital information systems at Sun Yat-Sen Memorial Hospital



4.2.2 National Cheng Kung University Hospital

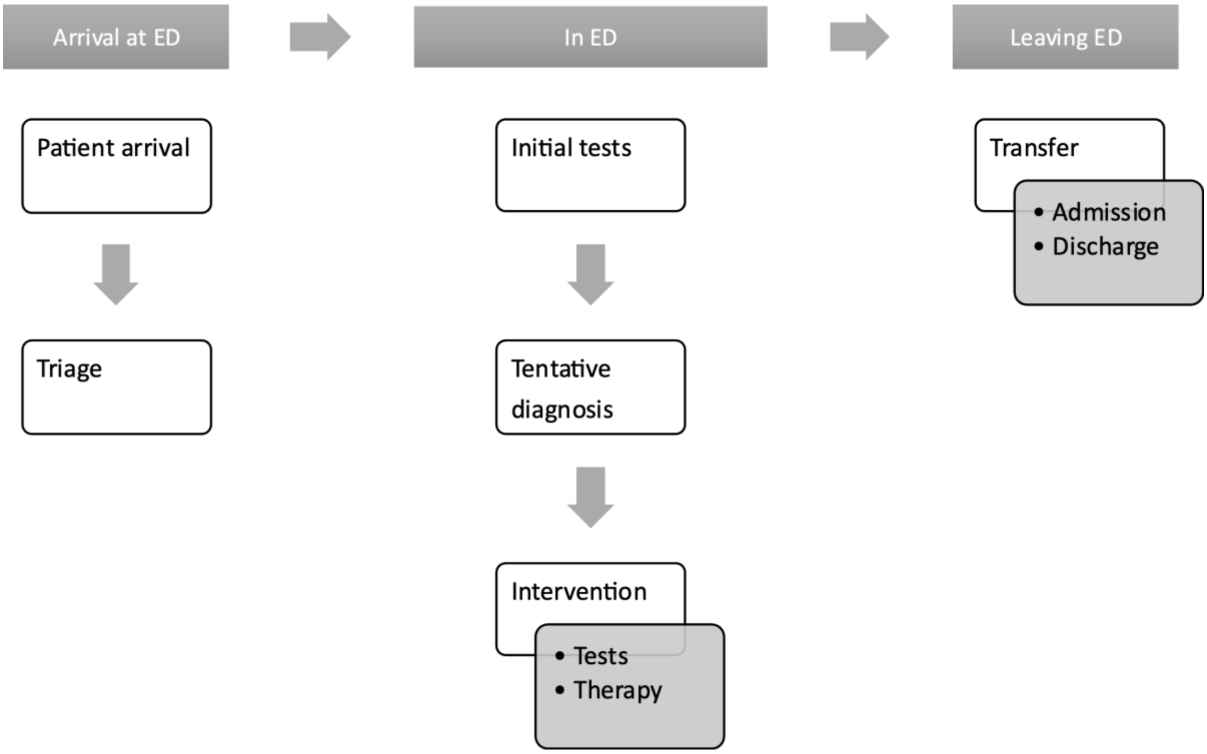
In parallel with the examination of the case of SYSH, an evaluation is undertaken to assess the prevailing state of the HIS implemented in the ED of NCKUH. To comprehend the business process within the ED of NCKUH, consultations have been conducted with physicians who provide first-hand insights into the patient flow within this department. In addition, consultations with physicians help to gain knowledge about the integration within the HISs, thereby improving the understanding of the user experience. Moreover, to discern the operational synergy between the various HISs within NCKUH, the researcher is granted access to a subset of EHR data extracted from these systems. This access aids in comprehending the interplay and collaborative functionality of these systems.

As depicted in Figure 4-5, the patient flow process at NCKUH encompasses three distinct phases. Phase 1 encompasses the initial activities carried out upon the patient's arrival. During this phase, patients undergo triage to determine the priority of their medical attention to a physician. Subsequently, in the following phase, once patients are situated in the ED, nurses conduct preliminary tests to assess vital signs and input the corresponding data into the HIS. This data is made available to the physician, aiding them in formulating a provisional diagnosis.

Following the initial assessments, the intervention phase commences, during which the physician prescribes laboratory tests, medical imaging procedures, or suitable therapies for the patient's treatment. In cases where specific laboratory tests are required, the physician may opt to retain the patient in the inpatient division within the ED to monitor their condition until the test results are obtained. It is not uncommon for patients to endure prolonged stays in the intervention phase when multiple tests or treatments are deemed necessary.

Upon the completion of the intervention phase within the ED, the attending physician evaluates whether the patient is eligible for discharge or necessitates admission to the inpatient department.

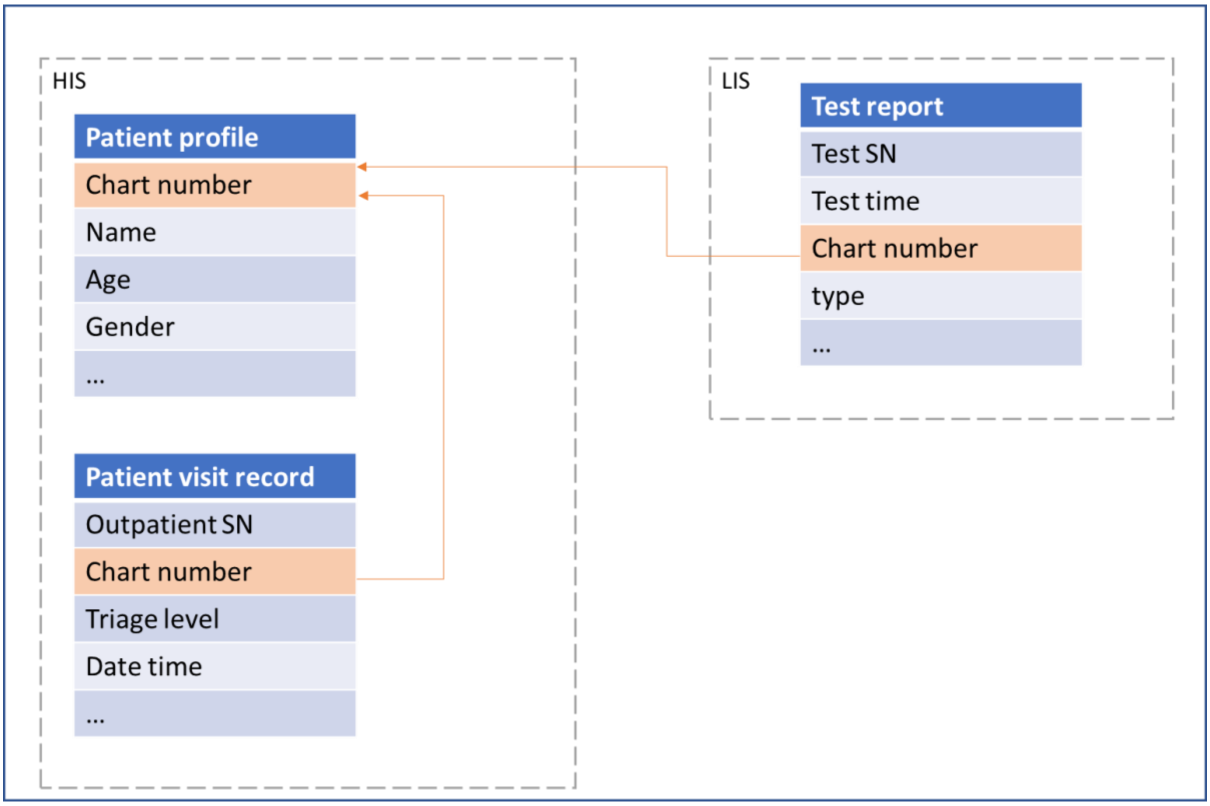
Figure 4-5: Patient flow at National Cheng Kung University Hospital



It is acknowledged that several HISs predominantly employed throughout the healthcare process exist. One of these systems encompasses an information management system dedicated to the handling of electronic medical records (EMR). The EMR encompasses a comprehensive array of data, such as general patient information, records of past visits, prescription details, initial test outcomes, and diagnostic records. Additionally, a laboratory information system (LIS) serves the purpose of overseeing laboratory tests and their associated data. To facilitate the management of medical imaging, a PACS has been implemented, allowing for seamless operation and storage of all image-related data.

Through a comprehensive analysis of the EMR data derived from multiple HISs, along with consultations with the medical practitioners at the ED of NCKUH, a significant observation has emerged. It has been determined that the disparate fragments of EHR data, existing within the diverse systems, are intricately linked through a distinctive attribute referred to as the chart number.

Figure 4-6: Partial data scheme at National Cheng Kung University Hospital



As illustrated in Figure 4-6, patients who are registered at NCKUH are assigned a distinct chart number, which serves as their unique identifier within the HIS. This chart number is used to establish a connection between each patient record and their corresponding patient profile. Consequently, when a physician requests a laboratory test, the resulting test report within the LIS is also associated with the patient profile by referencing the chart number.

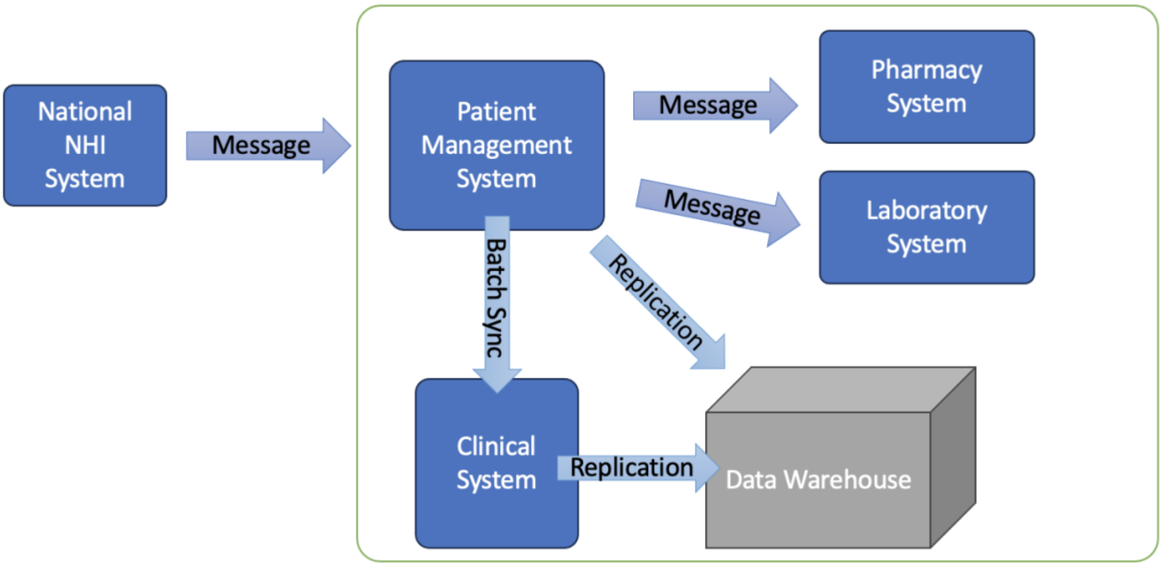
4.2.3 Health New Zealand Waikato

In the case of SYSH and NCKUH, an examination of the system structure has been undertaken by analysing the system interface and data. To gain comprehensive insights into the integration of HISs in a real-world application environment, consultations have been sought from experts within the business intelligence team at Health New Zealand Waikato (HNZW), formerly recognised as the Waikato District Health Board (WDHB), during the inception of this study. HNZW is the governing body responsible for overseeing numerous hospitals, clinics, and other healthcare services, as well as the majority of the HISs operating within the Waikato region.

The primary role of the business intelligence team at HNZW is to extract data from multiple HISs to conduct data analytics. Consequently, they possess a wealth of knowledge about the health information processing among HISs, particularly from a technical standpoint.

Figure 4-7 illustrates the exchange of health data for a patient among major HISs in a healthcare institution. The conceptual diagram of health information processing is delineated through consultation with professionals at HNZW. Due to significant variations in the implementation of these systems, different approaches to system communication are observed. Among the four types of data exchange, only data replication occurs in real time. However, the data warehouse does not serve clinical purposes. Most data exchanges within the clinical workflow experience delays, and the data flow is unidirectional.

Figure 4-7 Health information processing among hospital information systems



Within the structure of the HNZW system, the linkage of various EHR data components for a specific patient relies on the national health index (NHI) number. Every patient utilising health services in New Zealand possesses a patient profile managed by the National NHI system. The NHI number is assigned as a unique identifier to each patient profile within the national NHI system. The patient management system retrieves patient profiles by establishing a connection with the NHI system through messages. This approach is also employed by HNZW to transmit data from the patient management system to the pharmacy system and the laboratory system.

The business intelligence team at HNZW extracts data from these systems to fulfil requests from other teams within the organisation. These tasks encompass a range of activities, including generating one-time reports and constructing data visualisation platforms. Currently, the business intelligence team must develop a new programming script for each task to extract data from the relevant databases and convert it into the appropriate format. Unfortunately, most of these scripts are not reusable for subsequent tasks.

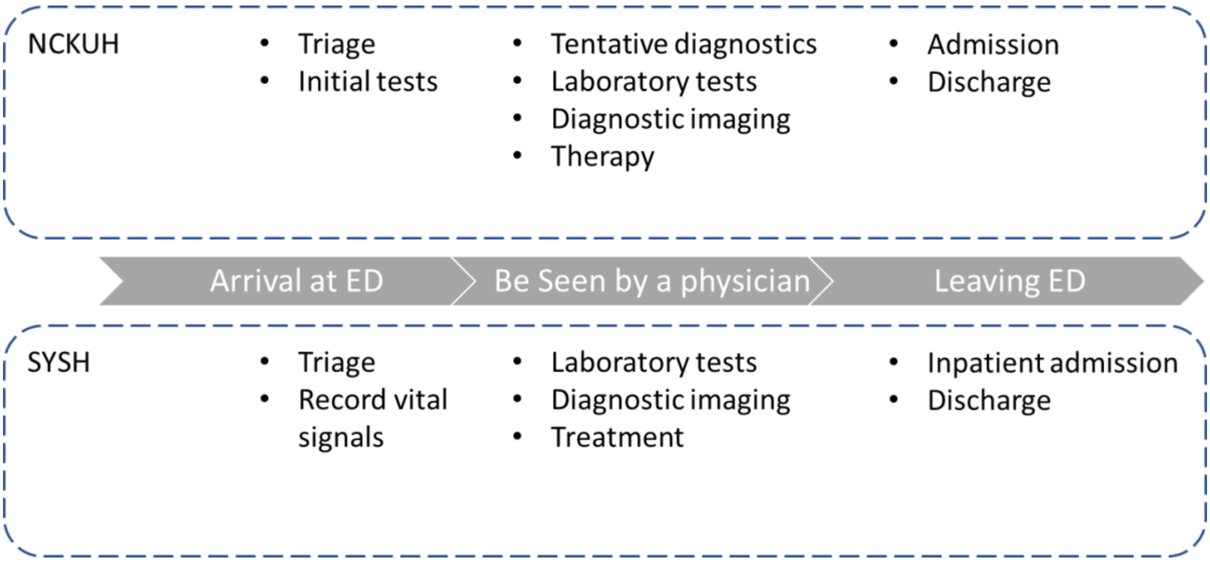
4.3 Synthesis of Findings from SYSH, NCKUH, and HNZW

Through a comparative analysis of the workflow and system structures at SYSH, NCKUH, and HNZW, discernible patterns in business processes and system architectures have emerged, indicating shared characteristics among hospitals and healthcare service providers. These identified commonalities hold significant relevance in the context of various ED settings, warranting widespread applicability. This section explores the above observations by comparing findings across three key dimensions: patient flow, system structure, and EHR data.

4.3.1 Patient Flow and Clinical Decision in the ED Setting

The patient flow at the ED of NCKUH exhibits similarities to that of the ED at SYSH. The workflow in one hospital closely mirrors the sequence of steps in the other hospital's workflow. To consolidate the steps involved in the patient flow at the ED of NCKUH and the ED of SYSH, a three-stage patient flow model has been devised. Figure 4-8 illustrates the positioning of clinical tasks derived from the processes of NCKUH and SYSH within the three distinct stages of the patient flow model.

Figure 4-8: 3-stage patient flow at emergency department setting



In the initial phase, upon the patient's arrival at the ED, demographic information such as their name, age, gender, and contact details will be gathered to establish a comprehensive patient profile within the HIS, if one does not already exist in the database. The patients will then undergo triage based on the severity of their condition upon arrival. An initial assessment will be conducted by a nurse to examine and record vital signs, including body temperature, blood pressure, pulse rate, and respiratory rate. The data collected during this initial stage serves as the primary input for the subsequent stage.

During the subsequent stage, when the patient is seen by a physician for intervention, the data obtained in the initial stage is presented to the physician who conducts preliminary diagnostics. Depending on the outcomes of these preliminary diagnostics, the physician may prescribe laboratory tests, diagnostic imaging procedures, or initiate treatment for the patient. The rationale behind grouping these clinical decisions within the same stage lies in the fact that they are all contingent upon the initial assessment conducted in the first stage. Once the necessary medical intervention is concluded, the patient proceeds to the subsequent stage, which involves their departure from the ED.

During the departure phase from the ED, the physician will decide whether the patient should be discharged or admitted to the inpatient department for further care and treatment.

4.3.2 Usage of EHR Data

Thanks to the well-established HIS covering most of the steps in the patient flow, both the hospitals and HNZW possess a repository of EHR data of exceptional quality. The recognition of potential benefits offered by EHR data has already been acknowledged by hospitals and healthcare providers. In both NCKUH and SYSH, physicians have engaged in studying the EHR data and disseminating their research findings through academic publications. Furthermore, at HNZW, data analysts have utilised EHR data to enhance operational efficiency and service quality at the strategic level.

However, literature review and consultations conducted with physicians in the ED revealed that the clinical tasks carried out in the ED have not yet exploited the potential of EHR data to improve operational efficiency and service quality. Although it is feasible to trace laboratory test results or images in the respective systems using a unique identification number of a patient, such as the series number, chart number, or NHI number, the process remains disjointed as physicians are required to switch between different systems without a cohesive workflow.

ED physicians at both NCKUH and SYSH have verified that the present HISs exhibit an improvement in the documentation and tracing of medical history for patients. These systems offer a uniform interface and format for entering data. Nevertheless, the incorporation of EHR data into CDS at the point of care remains underutilised.

4.3.3 HIS Architecture

Within the ED of a present-day hospital, it becomes evident that the management of numerous tasks has substantially shifted towards the utilisation of HISs. These systems, procured from separate vendors for SYSH, NCKUH, and HNZW, exhibit conspicuous resemblances in their architectural compositions, thereby suggesting a shared underlying structure.

At each stage of the patient flow, an information system is in place to document and oversee the clinical activities. Among the diverse range of systems implemented, a patient management system assumes responsibility for handling patient profile data as well as serving as the central repository for electronic medical record data. In addition to the patient management system, separate systems are employed to oversee clinical tasks and store data about laboratory tests and diagnostic imaging. These systems are designed to deliver highly specialised functionalities tailored to specific purposes. Moreover, it is worth noting that within the HIS structures of SYSH, NCKUH, and HNZW, HISs exist that are externally owned and shared across multiple hospitals or other health service providers.

Table 4-1 illustrates the predicament of data fragmentation within the HIS, specifically in relation to the storage of EHR data across disparate systems. The HISs at NCKUH, SYSH, and HNZW are compared to illuminate the issue.

At NCKUH, the primary repository for EHR data is the EMR system. This system encompasses the main body of health information for patients. However, it should be noted that laboratory test results are stored in the LIS, while diagnostic images are stored in the PACS.

In contrast, SYSH utilises separate systems for managing EHR data about outpatients and inpatients. The outpatient management system is responsible for handling EHR data related to outpatient care, whereas the inpatient system serves the same purpose for inpatient care. Furthermore, the management of laboratory test results is facilitated by the CEMS. Notably, SYSH employs a RIS/PACS, which is owned by the local government. This system allows for access to medical images across multiple participant hospitals.

At HNZW, patient profile management is overseen by the NHI system, which operates nationwide under the authority of the Ministry of Health. In this setup, the local patient management system, clinical system, and pharmacy system all rely on the NHI code assigned to each patient as a reference for accessing pertinent information.

Table 4-1: EHR Data and Hospital information systems at NCKUH, SYSH and HNZW

EHR data	NCKUH	SYSH	HNZW
Patient profile Personal statistics Medication history Prescription history Vital signals	Electronic medical record (EMR)	Outpatient management system Inpatient management system	National health index (NHI) system Patient management system Clinical system Pharmacy system
Laboratory test results	Laboratory information system (LIS)	Clinical examination management system (CEMS)	Laboratory system
Diagnostics images	Picture archive and communication system (PACS)	Radiology information system (RIS)/Picture archive and communication system (PACS)	Picture archive and communication system (PACS)

4.4 Problem Identification

This section addresses the sub-research question of identifying the challenges associated with the development of an integrated architecture for HISs that facilitate ML-based CDS within the context of an emergency department. It accomplishes this by thoroughly examining the problems and challenges prevalent in the ED setting.

4.4.1 Clinical Decisions in the ED

After consulting with physicians at the ED of NCKUH, it is revealed that the current system lacks decision support. Clinical decisions in the ED of a hospital must consider both clinical outcomes and cost efficiency. At NCKUH, patients' medical expenses are largely covered by the universal health care programme, which introduced the diagnosis-related group system to control expenditures. This system classifies patient cases and restricts the amount a hospital can be reimbursed by the health insurer for services provided to each patient. The reimbursement should not exceed the reference cost set for the patient's diagnostic-related group category.

In the context of ED settings, where challenges related to overcrowding and cost constraints prevail, physicians often encounter situations necessitating clinical decisions under conditions of inadequate information. These decisions frequently entail resource-intensive and time-consuming services, including laboratory tests and diagnostic imaging. In such instances, clinicians in the ED environment are compelled to rely solely on their professional expertise when determining whether a patient should undergo a specific test. To optimise healthcare outcomes, they tend to opt for the most pertinent test, albeit some of these tests could have been potentially avoidable.

An illustrative case arises from an analysis of outpatient data gathered from the ED of NCKUH between 2015 and 2019. It is observed that during this period, over 20,000 patients underwent blood culture tests, yielding an approximately 10% positive rate. Consequently, a significant number of these patients were required to remain within the confines of the ED for hours on end, solely to await a negative test report. A closer examination of the results for other laboratory tests within this dataset reveals that a considerable proportion of the outcomes fell within the normal range.

Thus, there is a need for a CDSS at the point of care to help physicians make clinical decisions more efficiently in the ED setting.

4.4.2 EHR Data

The identified issue lies in the fact that hospitals possess a considerable quantity of high-quality EHR data and acknowledge the advantages associated with such data. However, the utilisation of EHR data for facilitating clinical decisions has been lacking. Despite the abundance and significance of EHR data, its potential as a tool to aid clinical decision-making remains untapped. The available EHR data, which encapsulates a wealth of patient-specific details, has not been effectively leveraged to inform and guide physicians in their clinical judgements at the point of care.

The ML-based CDSS does not require any rules to be maintained. Instead, ML is adopted to recognise unknown patterns from historical data in EHR. Non-knowledge-based CDSS can detect disease with significant accuracy by extracting information from imaging and laboratory tests (Sutton et al., 2020). The accuracy and quality of an ML-based CDSS rely on the quality and volume of the EHR data.

Compared to traditional paper-based medical records, EHR is capable of storing more types of health data, including demographics, diagnoses, laboratory test results, prescriptions, radiological images, allergies, etc. Over recent decades, significant growth in the adoption of EHRs in hospitals has been seen worldwide.

In this research, the sample data collected for training and evaluating ML models for CDS is from the ED of NCKUH. The data set includes deidentified patient visit records at the ED of NCKUH between 2015 and 2019.

In 2015, the Ministry of Health of New Zealand commissioned an independent review conducted by Deloitte to assess the nation's EHR strategy. The ensuing report presents a comprehensive model of the Maturity Staircase, which outlines four distinct stages of EHR development and delineates the corresponding advantages of each stage. Based on meticulous observations and consultations with medical practitioners at the ED, it has been determined that NCKUH is currently situated at stage 1 of EHR implementation, as indicated in Table 4-2.

Table 4-2 EHR Maturity Staircase adapted from Deloitte (2015)

EHR stage	**Description**	**Benefits**
Stage 1. Common Identifiers & Information Exchange	Practitioner-level ability to exchange patient information and track service delivery	Administrative benefits: Core service utilisation and management information become available Resource allocation and service configuration can be optimised Billing, revenue, and costing visibility Scheduling and appointment efficiency
Stage 2. Clinical Information Access	Transactional patient information with data entry and display	Visibility & Turnaround Times: Improved clinical staff efficiency Improved patient experience and satisfaction Faster turnaround times through information sharing
Stage 3. Service Management & Collaboration	Information is shared and services are coordinated in real-time to trigger tasks for other healthcare workers in a collaborative process	Care Coordination & Collaboration: Improved efficiency of services with reduced error rates Improved productivity through workflow automation and straight-through processing Basic real-time decision-support and event alerts Patient engagement and participation in their health/wellness plan
Stage 4. Decision Support & Risk Management	Information is used to generate insights that alert practitioners to specific issues or generate workflow tasks automatically based on agreed rules	Continuous Learning: Management of outliers to reduce the risk of patients' slipping through the cracks Population risk and needs analysis based on comprehensive data sets and business intelligence capabilities Improve clinical care from evidence-based decision support that reduces adverse event Pro-active intervention and risk management carried out consistently Analytics-driven research opportunities

NCKUH has implemented HISs to manage and store EHR data for their patients. Within the premises of NCKUH, the primary EMR system encompasses personal demographic information, requests, and categories for laboratory examinations and diagnostic imaging, prescriptions, and medical charges. Notably, the outcomes of laboratory tests and radiological images can solely be retrieved from the LIS and PACS respectively.

The EHR data that has been recorded within the HISs within the ED setting holds considerable potential to enhance the provision of healthcare services. However, the present HISs at NCKUH have yet to furnish evidence indicating the active utilisation of EHR data in clinical decision-making processes within the ED setting. Consequently, it is imperative to formulate an ML-based CDSS with the aim of augmenting CDS within the confines of the ED setting.

4.4.3 Challenge of System Integration for HIS

The utilisation of EHR data for an ML-based CDSS in an ED presents a formidable challenge due to the dispersed nature of EHR data across multiple HISs. The primary factor contributing to the fragmentation of EHR data is the lack of integration and information silo within the HIS. Within the ED environment, the persistence of system disintegration and information silos within the HIS has been identified as an unresolved predicament, consequently emerging as a significant obstacle in the routine workflow (Jee & Kim, 2013; Parks et al., 2019).

The HIS architecture comprises multiple sub-systems driven by distinct purposes in various domains. For instance, within the ED of NCKUH, alongside the EMR system, the LIS and PACS are employed for the management and storage of laboratory test results and diagnostic images, respectively. Most HISs exhibit a high level of autonomy, with limited workflow integration. To facilitate the tracing of disparate segments of EMR data for a given patient across multiple systems, a unique identifier known as the chart number is assigned to the patients' records within each system.

The existence of diverse HISs responsible for managing different aspects of EHR data often leads to inconsistencies within the data. This issue is also apparent in the sample data obtained from NCKUH. The EHR data originating from NCKUH encompasses records from the primary EMR system, as well as records from the LIS. One of the identified challenges involves merging certain records from the LIS with those from the EMR system. Although it is feasible to establish a link between the records from the LIS and the EMR system using the chart number, the task of associating each test result with its corresponding patient visit becomes arduous when multiple visit records exist for the same patient. This difficulty arises due to variations in the standards used to record the timing of tests within the EMR system and the LIS. While a human observer may recognise equivalent timestamps presented in different formats, manually conducting the matching process for a dataset comprising hundreds of thousands of records proves impractical. Employing programming techniques offers a viable solution for handling large volumes of data; nevertheless, significant efforts are required to overcome the challenge of format inconsistency.

As the number of involved HISs increases, the complexity of the problem intensifies. The heterogeneity in data formats and the autonomous nature of workflow across different HISs persist as formidable obstacles to achieving system integration. Furthermore, it has been observed that certain data exchanges between HISs are not conducted in real time, potentially resulting in data conflicts when attempting to merge data from a source that has not yet been updated.

4.5 Theoretical Framework Development

By establishing a connection between the observed issues and existing literature, this section lays the theoretical groundwork necessary for the design and development of the artefact discussed in the subsequent chapter.

In contrast to conventional paper-based medical records, EHRs possess the capability to store a wider range of health data, encompassing demographics, diagnoses, laboratory test results, prescriptions, radiological images, allergies, and more. Over the past few decades, there has been a significant global increase in the adoption of EHR in hospitals. Previous studies indicate that EHR data can be effectively utilised in conjunction with ML techniques for various clinical tasks, such as disease diagnosis, prediction of emergency visits, length of stay, and unexpected readmission (Miotto et al., 2016; Rajkomar et al., 2018; Shickel et al., 2018; Xiao et al., 2018).

Through consultation with ED physicians, the patient flow can be generalised as a three-phase process, which includes arrival at the ED, intervention by a physician, and departure from the ED. Discussions with ED physicians highlight the necessity for CDS during the intervention phase, where crucial clinical decisions regarding diagnostic tests and treatment are made. However, existing research primarily focuses on the arrival and departure phases of ED.

This study aims to address this issue by designing an ML-based CDSS. CDSSs are computer applications specifically designed to enhance patient outcomes and reduce operational costs in hospitals by providing valuable information to physicians regarding clinical decision-making (Berner & La Lande, 2007). CDSS can generally be categorised into knowledge-based systems and non-knowledge-based systems. There are two primary justifications for selecting an ML-based CDSS in this study. Firstly, by leveraging EHR data to learn rather than relying on pre-established rules, ML-based CDSS exhibits greater flexibility in adapting to the dynamic nature of the ED setting. Secondly, hospitals already possess high-quality EHR data, rendering it feasible to train ML models.

The ML-based CDSS eliminates the requirement for maintaining explicit rules. Instead, it adopts ML techniques to identify previously unknown patterns from historical EHR data (Sutton et al., 2020). The accuracy and efficacy of an ML-based CDSS hinge on the quality and quantity of the EHR data.

However, the utilisation of EHR data from the HIS poses challenges in implementing an ML-based CDSS at the point of care in the ED setting. Analysis of the systems at two hospitals and a district health board reveals that the main obstacle to constructing an ML-based CDSS lies in the fragmented nature of the HISs. This issue has been substantiated through the literature review and consultations with medical practitioners. Although there are studies on system integration for HISs, there is a lack of research on a system integration framework specifically tailored to support ML-based CDSSs.

Therefore, it is imperative to design a system integration architecture to integrate the existing HISs with a unified data repository.

4.6 Summary

In accordance with the research methodology outlined in Chapter 3, this chapter presents the research activities and outcomes pertaining to the phase of situation awareness. The objective of this phase is to identify and depict the issues that can be defined as disparities between the desired goal state and the current state of the HIS in the ED, which serves as an authentic application environment.

By engaging in consultations with physicians from two hospitals' EDs, a general patient flow has been discovered and implemented within the ED setting. The clinical tasks involved in this patient flow have been categorised into three stages based on the sequence of clinical data and decisions. These three stages of patient flow delineate the input data and clinical decisions at each stage. Upon examining the clinical workflow in the EDs of the two hospitals, it has been observed that their routine operations integrate the HIS for recording EHR data. Nevertheless, physicians from both hospitals have expressed that the current HIS fails to enhance clinical efficiency in the ED. The crux of the problem lies in the inadequate provision of decision support features within the current HISs when ED physicians are confronted with a surge in demand for emergency care, despite having limited resources. Consequently, this discovery forms the foundation for the design of a CDSS artefact to be integrated into the ED workflow.

Upon investigating the HISs and EHR data at the two hospitals, it becomes apparent that these hospitals possess EHR data of high quality. The data already offers some level of visibility for administrative tasks, such as the reports generated by the business intelligence team at the district health board. Furthermore, EHR data from these hospitals has been utilised for research purposes. The abundant and high-quality nature of the EHR data satisfies the prerequisite for designing an ML-based CDSS.

However, a notable challenge in employing EHR data for an ML-based CDSS within the ED setting is the distribution of such data across various HISs. The fragmentation of EHR data arises due to the issues of system disintegration and information silos. The structure of the HIS comprises multiple subsystems driven by distinct purposes in different domains. Frequently, these subsystems are deployed as separate applications that are highly optimised for specific departments, without considering integration with a centralised data repository. The heterogeneity and autonomy of information systems across the HISs present an enduring obstacle to the integration of EHR data for CDS. To bridge this gap, there is a necessity to devise a system integration artefact specifically tailored for HISs.

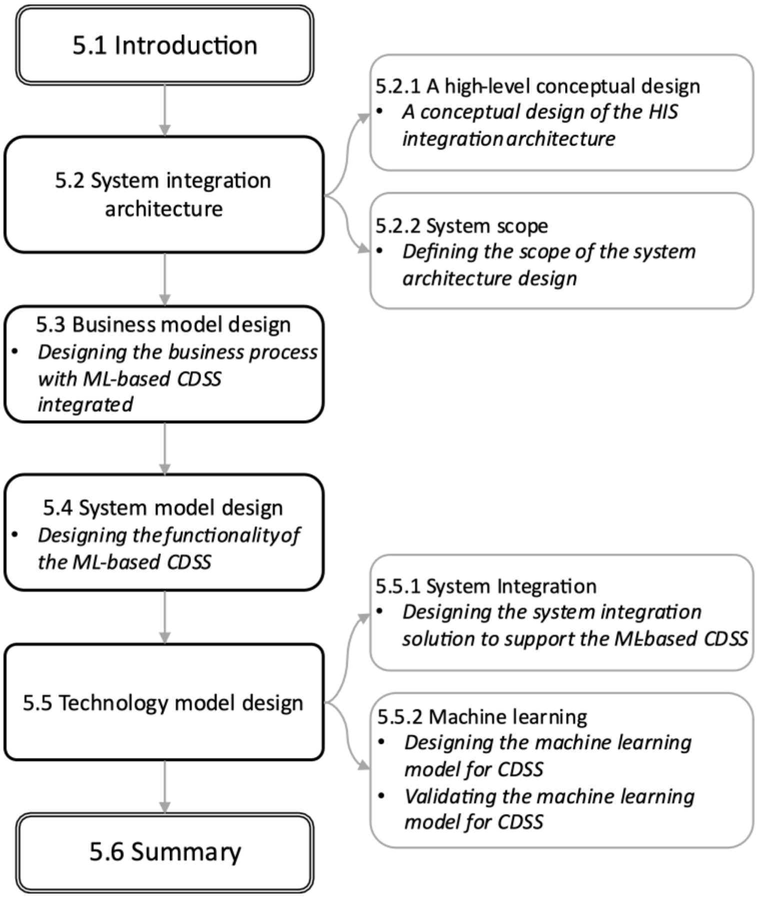
Chapter 5 System Development

5.1 Introduction

In accordance with the design science research methodology outlined in Chapter 3, this chapter presents the design and development activities undertaken to address the issues identified in Chapter 4 and to answer the research question: "How can an integrated architecture for hospital information systems (HIS) be designed, incorporating machine learning techniques to enhance percent within the context of an emergency department?"

As identified in Chapter 4, physicians in the emergency department (ED) of a hospital require clinical decision support systems (CDSS) based on Machine Learning (ML) to improve their efficiency at the point of care. Upon analysing the existing system architecture, it becomes apparent that the primary obstacle to implementing ML-based CDSS is the lack of system integration and the presence of information silos within the HIS. To adhere to the design science research methodology, a proposed system integration architecture for the HIS is designed to enhance clinical decision support (CDS) in the ED setting through the utilisation of ML-based CDSS.

Figure 5-1: Chapter structure



To accomplish this objective, a systematic design process is being pursued, entailing a comprehensive analysis of the requirements, identification of the key components, and formulation of an architectural framework. This chapter adheres to the structure depicted in Figure 5-1. Section 5.2 presents the system integration architecture in a high-level conceptual design, while also defining the system scope through a three-layer system architecture. Subsequently, the business model design for the business layer addresses the integration of the ML-based CDSS with the patient flow in the ED setting. The system model design at the application layer focuses on the features of the ML-based CDSS that cater to the needs of physicians in the ED. Additionally, the technology model design at the technology layer encompasses the technology solution for system integration, and a ML model is constructed and trained to validate the feasibility of an ML-based CDSS using Electronic Health Record (EHR) data obtained from the National Cheng Kung University Hospital (NCKUH).

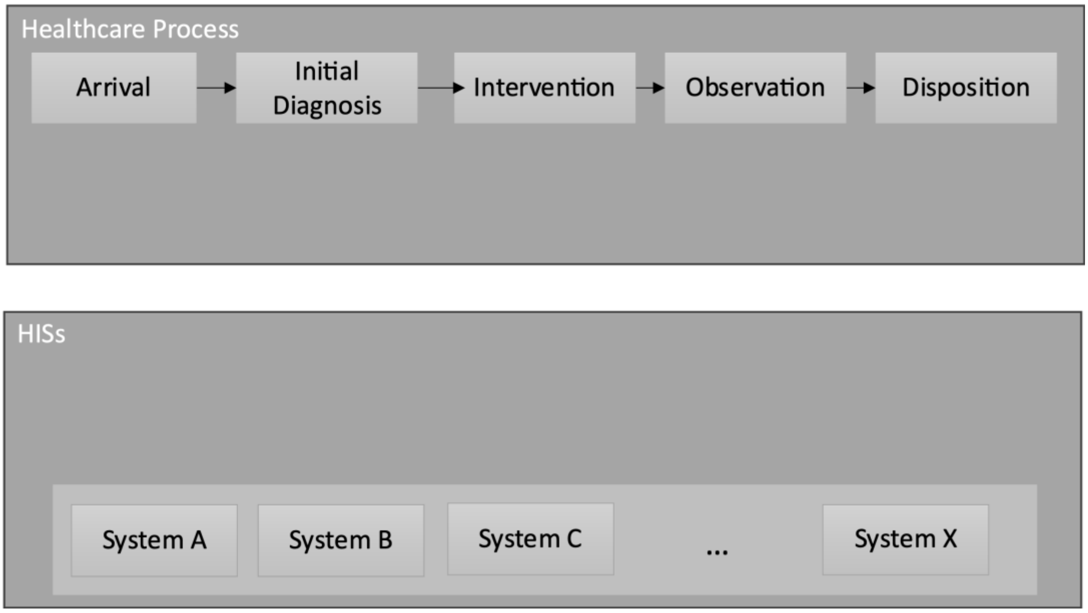
5.2 System Integration Architecture

This section presents the design of the system integration architecture for the HIS as a design artefact. In the context of this study, the focus is on designing a system integration architecture that enables the provision of an ML-based CDSS for physicians, aiming to enhance clinical efficiency within the ED of a hospital. The system design follows an approach adapted from the Framework for Information Systems Architecture (ISA) by Sowa and Zachman (1992). The system architecture design is defined and described in the dimension of scope, business model, system model, and technology model. This design approach aligns with the principle that encompasses user activities and design artefacts, necessitating the inclusion of specific features within the system to support users in their respective activities (Gregor et al., 2020).

5.2.1 A High-Level Conceptual Design

Based on the literature reviewed in Chapter 2 and the analysis of the existing HISs employed by the collaborating hospitals as discussed in Chapter 4, it is evident that the majority of current HISs deployed in hospital EDs exhibit limited integration with the overall healthcare process. These systems primarily serve the purpose of facilitating clinical tasks such as ordering prescriptions, treatments, and laboratory tests, as well as documenting clinical activities and patient information within the EHR data.

Figure 5-2: Current system architecture at emergency department of the hospitals

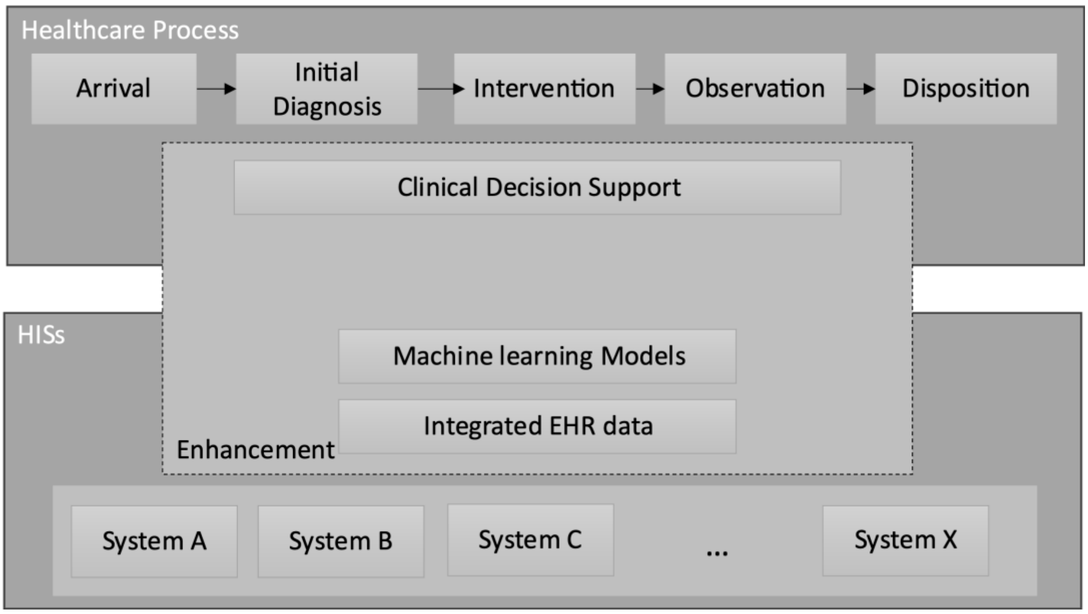


As outlined in Chapter 4, the current system architecture exhibits several disadvantages. Primarily, the existing decision support system predominantly focuses on the diagnosis, employing a knowledge-based CDSS driven by predefined rules that rely on established knowledge regarding the correlation between patient data and diagnosis, often expressed through mathematical constructs (Spooner, 2016). However, this approach fails to offer comprehensive recommendations to physicians when faced with the need to optimise clinical outcomes and cost efficiency for specific clinical decisions, such as determining the necessity of particular laboratory tests or the appropriate duration of patient observation in the ED.

Additionally, another challenge encountered by physicians in the ED pertains to the accessibility of EHR data. Extensive research and literature have demonstrated the potential of EHR data in improving healthcare outcomes and cost efficiency within hospital settings (Patterson et al., 2019). Nevertheless, translating this potential into practice presents considerable difficulties. During the researcher's visits to hospitals, it was observed that patient EHR data is distributed across multiple HISs, with limited workflow integration. Physicians and nurses must navigate between disparate systems and logins to enter or retrieve data for a given patient. Conversations with ED physicians revealed that within the demanding and fast-paced ED environment, time constraints often prohibit manual searching of EHR data from diverse HISs. Consequently, physicians heavily rely on their experience and observations when making clinical decisions.

To address these issues, the proposed integration architecture combines the integration of clinical processes, CDS, and HISs to enable ML-based CDS. This approach aims to provide physicians with improved decision-making capabilities that take into account a wider range of factors beyond diagnosis and to facilitate seamless access to patient data by integrating different HISs.

Figure 5-3: Framework of data integration architecture for hospital information systems



As depicted in Figure 5-3, the framework introduces a data integration architecture that seamlessly incorporates ML-based CDSS into the current ED workflow, utilising EHR data from HISs. This CDSS provides real-time recommendations at the point of care, enhancing healthcare outcomes and cost efficiency. By integrating the CDSS with the existing HISs and leveraging ML algorithms, the proposed architecture offers a solution to the limitations of the current system design. It empowers physicians with timely and data-driven recommendations, enabling them to make informed clinical decisions, leading to improved patient outcomes and cost efficiency in the ED setting.

5.2.2 System Scope

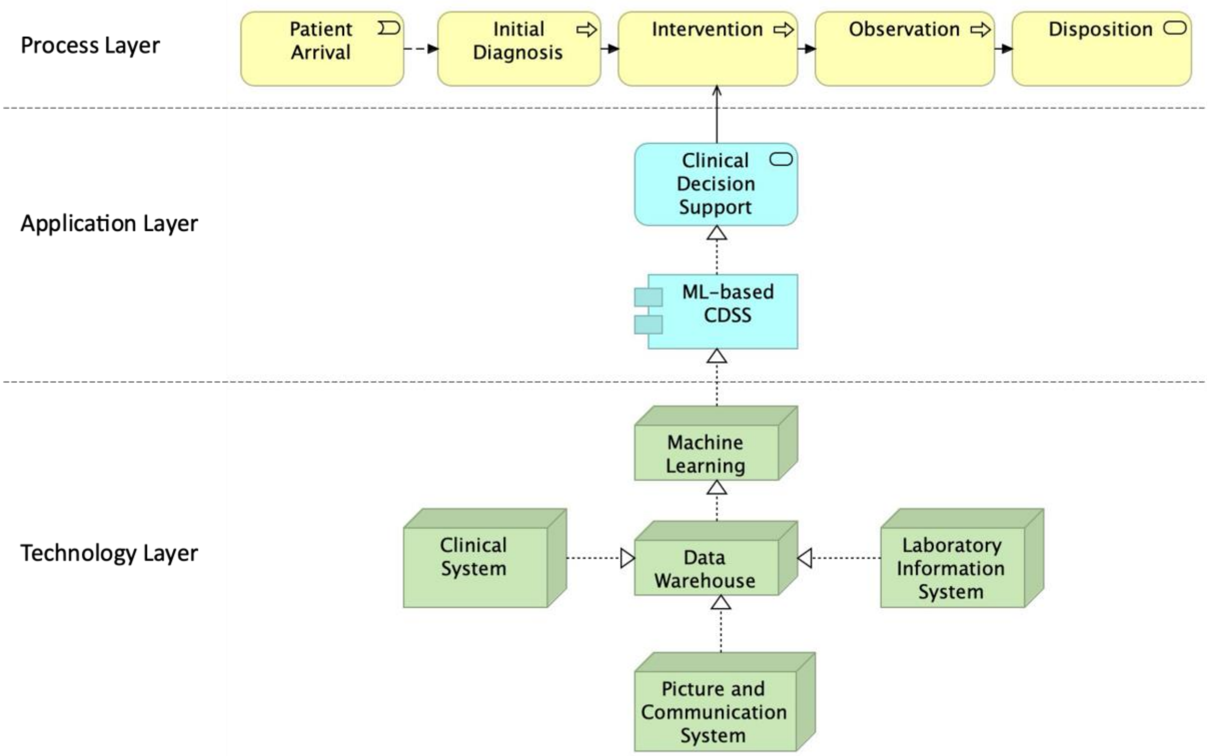
From an information system perspective, the HISs serve as the supporting infrastructure for hospital operations. In the context of design science research, the development of an artefact aims to address a specific business problem. The ArchiMate Core Framework is utilised to present the design of the system architecture. It is worth noting that the ArchiMate Standard has gained significant adoption in the field of information systems research, particularly within the healthcare domain (Júnior et al., 2020). The ArchiMate Specification provides a standardised language for visualising the relationships within and between various domains, including processes, data, applications, and technical infrastructure.

Figure 5-4 depicts the system integration architecture that has been developed based on the conceptual design to facilitate the implementation of an ML-based CDSS in the ED setting. This system architecture combines elements of the business model, system model, and technology model, forming a three-layered structure.

The business layer emphasises business processes, ensuring that the architecture aligns with the organisation's operational goals. The process layer delineates the primary stages a patient undergoes within the ED. In the intervention stage of the business layer, physicians can receive recommendations from the CDSS regarding resource-intensive diagnostic tasks, such as the necessity of ordering blood tests, CT scans, or X-rays for a patient.

The application layer focuses on information systems and software applications supporting business processes, encompassing data flow and application functionalities. Within this layer, a dedicated CDSS application component, based on ML, is designed to provide CDS. This component includes the program responsible for implementing the CDSS's inference engine. Additionally, the CDS function serves as the user interface for interaction with the system.

Figure 5-4: System architecture



Lastly, the technology layer addresses the underlying technological infrastructure essential for supporting information systems, including hardware, networks, databases, and other components. At the technology layer, data integration is implemented to establish a unified data repository that supports the training of the ML model. This integration module seamlessly merges EHR data from diverse sources, such as laboratory information systems (LISs), clinical systems, and picture archive and communication systems (PACSs). As a result, the ML models are trained using the integrated EHR data.

5.3 Business Model Design

To mitigate the challenges identified in Chapter 4, an ML-based CDSS is proposed as the solution to enhance efficiency within the ED. This section elucidates the integration of an ML-based CDSS into the patient flow at the ED of NCKUH. Drawing upon existing research, the study underscores four key elements crucial to the success of CDSS: integration with the clinical process, point-of-care delivery, automatic provision, and recommendation-oriented outputs rather than mere suggestions (Kawamoto et al., 2005).

Figure 5-5: Patient flow in the emergency department setting

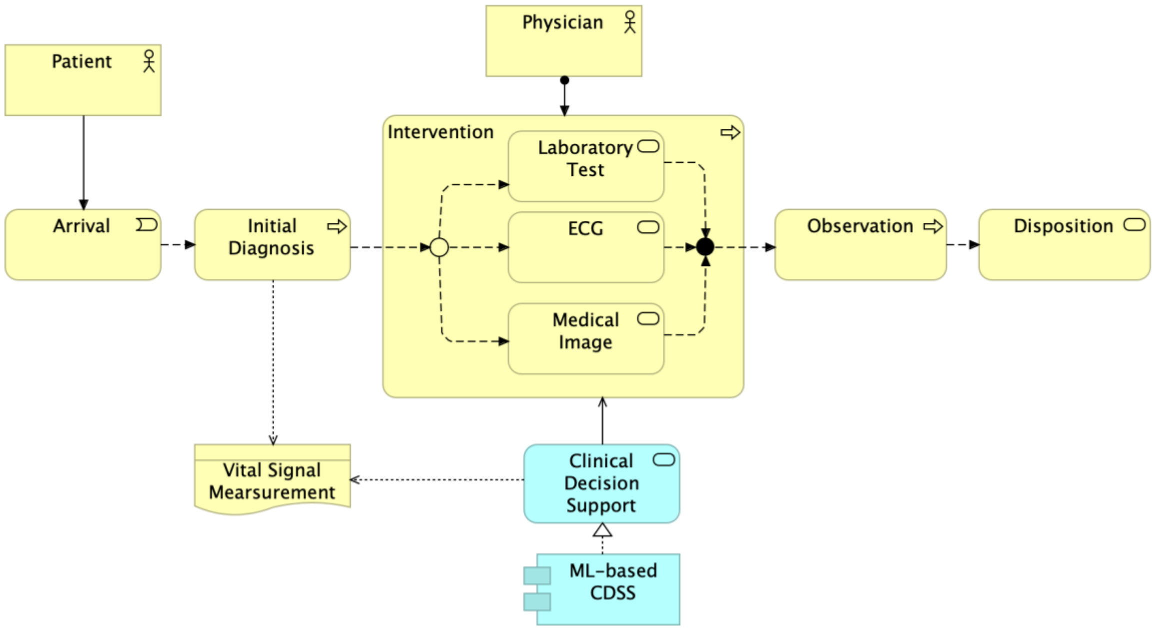


Figure 5-5 presents the business model design artefact of patient flow in the ED setting, incorporating the integration of an ML-based CDSS. At the arrival of the patient, demographic data such as name, age, gender, and medical history are collected. Patients are triaged at this stage based on their arrival condition. As part of the triage process, vital signal data are collected, for example, body temperature, pulse rate, respiratory rate, blood pressure, and SpO2 (oxygen saturation). Then, at the initial diagnosis stage, a tentative diagnosis is made regarding the patient's condition, considering the available information collected at previous stages. Most important clinical decisions are identified during the intervention stage of the process, encompassing diagnostic tasks, such as laboratory tests, CTs, medical imaging, and patient disposition, which significantly impact the efficiency of the ED. These clinical decisions are made depending on the available information at the point of care. Following the intervention, patients need to undergo the observation stage for a period before they leave the ED.

In Chapter 4, it was identified that a major issue in the decision-making process within the healthcare setting is the lack of consistent high confidence among physicians when making clinical decisions. These decisions involve determining the necessity of certain laboratory tests and the appropriate duration of patient observation. Physicians make these critical decisions at the point of care following the initial diagnosis. In a publicly funded hospital like NCKUH, the ED operates under the dual goals of cost efficiency and optimal healthcare outcomes. The overuse or unnecessary utilisation of resources can result in increased costs without significant clinical benefits. This places strain on the hospital's budget and potentially limits the availability of services for other patients.

For instance, when a patient who could have been discharged remains in the observation zone, they occupy a bed that could have been allocated to a patient in greater need. Physicians aim to avoid such situations in their decision-making process. However, discharging a patient prematurely, before their condition has stabilised, can lead to worsening conditions and unplanned readmissions. Thus, physicians face the challenge of prioritising patient safety while ensuring comprehensive evaluations through appropriate diagnostic procedures. Consequently, there is a growing demand for CDSS to provide recommendations in these clinical decision-making scenarios. The primary objective of a CDSS is to assist physicians in avoiding unnecessary laboratory tests, imaging procedures, and inpatient admissions, while simultaneously ensuring that each patient receives the essential tests for accurate diagnosis and effective treatment. To achieve this, the CDSS must seamlessly integrate patient-specific information and medical knowledge to deliver timely and appropriate recommendations pertaining to diagnostic procedures, including laboratory testing and patient observation duration. In order to provide tailored suggestions, the CDSS must take into account factors such as the patient's medical history, symptoms, and risk factors.

To address this challenge of balancing cost efficiency and optimal healthcare outcomes in the ED, the primary objective of the integrated CDSS application is to enhance ED efficiency by providing recommendations aimed at reducing unnecessary laboratory tests, CTs, and medical imaging at the stage of intervention.

As presented in Figure 5-5, the patient flow model in the ED consists of the stage of arrival, initial diagnosis, intervention, observation, and disposition.

At the stage of arrival, it is the beginning of the patient data entering the system. Including demographic data, such as name, age, gender, and vital signal data, such as body temperature, pulse rate, respiratory rate, blood pressure, and SpO2. These are the data crucial to the tentative diagnosis at the initial diagnosis stage. Medical historical data might also be retrieved from the HISs for registered patients. These data are also the input to the ML-based CDSS for generating personalised recommendations for each patient.

At the stage of initial diagnosis, a tentative diagnosis was made by the physician. A tentative diagnosis, also known as a working diagnosis or provisional diagnosis, is a preliminary or initial diagnosis made by a healthcare professional based on the available information and assessment at a particular point in time. It represents the healthcare provider’s best judgement or hypothesis regarding the patient’s condition, and the information collected at the arrival stage. A tentative diagnosis is not considered definitive or final. It serves as a starting point for further investigation, additional tests, and monitoring to confirm or refine the diagnosis.

However, the current HIS often necessitates launching multiple windows from various systems to retrieve additional information. Consequently, seamless integration of the ML-based CDSS with the existing HISs and clinical process, requiring minimal manual interaction, becomes crucial. To address this requirement, the ML-based CDSS captures vital signal data from the corresponding interface and automatically provides applicable recommendations to physicians. For instance, the CDSS can interpret a patient's vital signal data and predict potential laboratory test outcomes, subsequently delivering the results to physicians along with suggestions regarding the necessity of specific tests. Moreover, patient throughput can be improved during the observation stage through appropriate patient disposition, including admission to the inpatient department, transfer to another department, or early discharge (Grant et al., 2020).

Overall, the integration of the ML-based CDSS into the clinical process within the ED setting holds the potential to enhance efficiency, optimise decision-making, and streamline patient care by providing relevant recommendations seamlessly and accurately.

5.4 System Model Design

This section focuses on the system model design of the ML-based CDSS that supports clinical decision-making processes. CDSSs are computer applications designed to enhance patient outcomes and reduce hospital operating costs by furnishing physicians with relevant clinical decision information (Berner & La Lande, 2007). Typically, a CDSS comprises a user interface to manage input and output, an inference engine, and a knowledge base (Spooner, 2016).

Figure 5-6: Knowledge-based and non-knowledge-based clinical decision support systems

The user interface serves as the interactive platform between the user and the CDSS. It allows users to input relevant clinical data, access system outputs, and interact with the CDSS functionalities. The user interface can manifest as a web-based application, a standalone software, or integrated within a HIS. The inference engine is the core component responsible for processing the input data and generating appropriate recommendations or suggestions. The knowledge base provides a foundation for the CDSS to reason and make informed decisions.

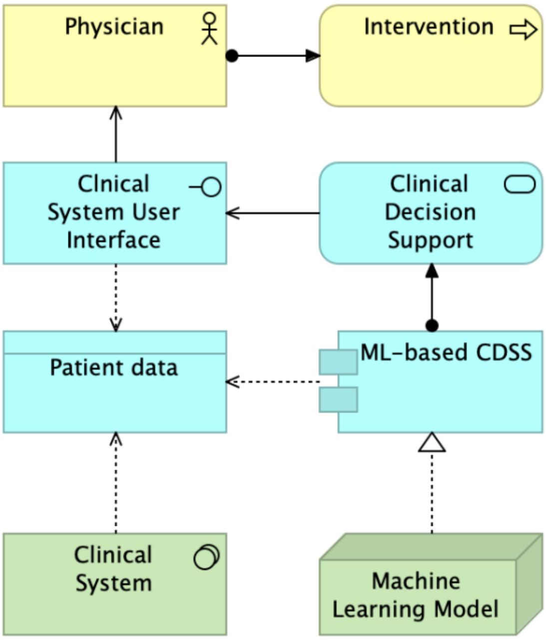
A knowledge-based CDSS may possess several limitations. The maintenance of the knowledge base can prove to be arduous. Research indicates that one of the primary challenges lies in the acquisition of knowledge, which is a time-consuming process. Collecting, verifying, and codifying the requisite knowledge for constructing a knowledge-based CDSS can be a meticulous and time-intensive task (Ash et al., 2007). Furthermore, the inflexibility inherent in knowledge-based systems presents another concern, as they are designed to adhere strictly to predefined rules. Additionally, a knowledge-based CDSS is susceptible to bias. Since the rules are devised by humans, the knowledge obtained from one population may not be applicable or suitable for another population (Bright et al., 2012).

In an ML-based CDSS, the conventional knowledge base is replaced with artificial neural network (ANN) models, enabling the generation of recommendations based on the analysis and learning from EHR data (Berner & La Lande, 2007). The ANN models are trained using large datasets of EHR information, allowing the CDSS to leverage the patterns and relationships within the data to provide accurate and contextually relevant recommendations.

The system model design is based on what has been learned from consultation with the physicians and from the collaborating hospitals. Currently, physicians primarily rely on an outpatient clinical system to access patient information and order tests and pharmaceuticals. Through the consultations, a comprehensive understanding of the current interaction between users in the ED and their HISs has been gained. An identified issue revolves around the insufficiency of information available to physicians in supporting their clinical decisions regarding diagnostic tests. Physicians express the desire for a CDSS that can provide them with insights into possible test results and their respective probabilities, thereby enhancing their confidence in decision-making. Such a CDSS would need to consider the constraints of cost-efficiency while ensuring optimal healthcare outcomes. However, it is noteworthy that physicians currently base their decisions predominantly on their expertise and experience.

To tackle this matter, it is imperative that the system design bridges the gap between the informational requirements of physicians and the current capabilities of the HIS. The design ought to empower physicians by equipping them with advanced decision-making tools, which should include evidence-based recommendations. Furthermore, it should make effective use of the abundant EHR data that is accessible within the HIS.

Figure 5-7: Clinical decision support system architecture



The system architecture model, depicted in Figure 5-7, describes how physicians interact with the CDSS system to get CDS from the CDSS during the intervention stage of the ED patient flow. When a physician reaches the intervention stage, they decide on administering diagnostic tests for a patient. The physician accesses the patient data through the clinical system, utilising the familiar interface that is already a part of their existing workflow. Simultaneously, the CDSS, situated at the backend, captures patient data from the same backend system to serve as input for generating CDS. In this process, the CDSS may utilise a ML model that can be loaded and employed as the inference engine to generate suggestions based on patient data. Ultimately, the recommendations or suggestions generated by the CDSS are presented to the physician on the same user interface they are accustomed to within the clinical system. This integration allows the physician to seamlessly review and consider the additional insights provided by the ML-based CDSS, thereby facilitating informed decision-making in the clinical setting.

With this system design, the HIS utilises EHR data, which is subsequently employed by the ML-based CDSS to provide evidence-based suggestions for clinical decisions in the ED. By employing ML algorithms that assimilate large volumes of EHR data, an ML-based CDSS can adapt to evolving data patterns. Consequently, it enables greater flexibility in cases that have not been encountered previously. Moreover, by learning from the EHR data present within the HIS of the hospital, the CDSS can generate patient-specific recommendations that are optimised for individual cases. The CDSS automates the input of data by retrieving patient information in real time from various HISs. Furthermore, the output is presented to physicians on the same screen, eliminating the need for them to navigate away from their current system or launch a new window. This design is intended to furnish physicians with the desired supporting information without disrupting the existing workflow in the ED.

5.5 Technology Model Design

Providing the CDSS at the application layer requires system integration at the technology layer. The technology layer is where existing and future technology components are deployed to enable the required functionalities to implement the architecture (Spewak & Tiemann, 2006).

5.5.1 System Integration

As discussed in Chapter 4, the implementation of ML-based CDSS at ED faces a significant challenge in terms of system integration. Specifically, there is a lack of integrated data sources for EHR, which are essential for training ML models and utilising them to generate predictions. Within the realm of ML, the process of model training necessitates the acquisition of substantial data quantities. In line with many hospitals that have already implemented HISs, the two hospitals visited by the researcher have amassed substantial volumes of EHR data. However, a predicament arises as the EHR data is regulated and dispersed across heterogeneous HISs. The primary obstacle encountered in integrating these HISs pertains to the divergent formats utilised by distinct systems (Kuhn & Giuse, 2001).

As highlighted in Section 5.2.4, ML-based CDSS heavily relies on ML models trained with historical EHR data, and the efficacy of model training is heavily contingent upon the quality of the data (Cortes et al., 1994). The lack of system integration poses difficulties in achieving data synchronisation among autonomous systems, consequently resulting in data inconsistencies (Kuhn & Giuse, 2001).

Moreover, the ML-based CDSS necessitates input data for analysis and decision support. These data are collected or generated in real-time during patient visits, entered by various practitioners, stored in disparate systems, and require comprehensive integration into the CDSS. Ideally, the CDSS should automatically collect this data with minimal manual input, with a continuous data stream serving as an updated clinical data source.

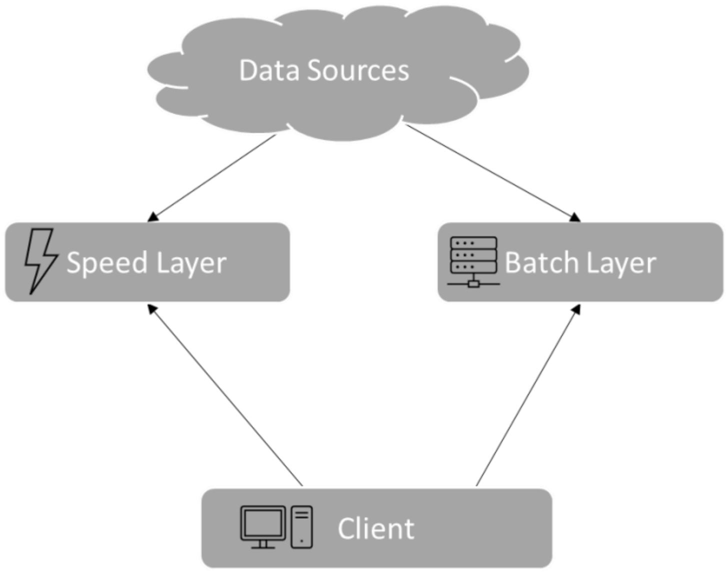
To address this challenge, the development of an architecture is imperative to tackle the data integration issue. The integration architecture must possess the capability to communicate effectively with the heterogeneous HISs, accommodating diverse data formats and protocols. Furthermore, this architecture needs to facilitate the provisioning of large-scale, high-quality EHR datasets for model training purposes and ensure the real-time availability of data as input to the CDSS, enabling it to offer timely suggestions for decision-making.

Following the principles of design science research, the process of system integration design undergoes iterative stages. During these stages, design artefacts are presented to domain experts, including physicians in the ED and technologists specialising in HISs. The design artefacts are subsequently revised, taking into consideration the prevailing business environment and feedback received from the aforementioned experts. This iterative approach ensures a comprehensive and robust integration design, aligning with the relevance and rigour cycle of DSR.

5.5.1.1 The Lambda Architecture

Considering the aforementioned challenges, Lambda Architecture emerges as a potential solution. Originally proposed by Marz (2011) the Lambda Architecture aims to achieve high consistency and high availability within a distributed data system. It serves as a comprehensive and timely framework for capturing and analysing heterogeneous datasets (Marz & Warren, 2015). The architecture consists of two primary layers: the batch layer and the real-time layer. The batch layer is responsible for processing large volumes of historical data, involving the pre-processing and integration of EHR data from diverse sources. Its main objective is to provide a comprehensive EHR dataset for training ML models, ensuring the availability of accurate and high-quality predictive models. On the other hand, the real-time layer addresses the need for immediate data processing and analysis. It captures and processes streaming data from ongoing patient visits, allowing for real-time insights and decision support. The Lambda Architecture is designed for applications requiring low-latency processing of complex asynchronous transformations. It achieves this by capturing an immutable sequence of records and simultaneously processing them with both a batch layer and a stream processing layer. Criticism has been directed towards the Lambda Architecture, primarily regarding code maintenance and operational burden, as it requires maintaining code for both the batch and real-time layers (Kreps, 2014). When considering its application within HISs in hospitals, the existence of two parallel processing layers aligns seamlessly with the legacy system infrastructure. As highlighted in Chapter 4, through consultation with the business intelligence team at Health New Zealand Waikato (HNZW), formerly known as Waikato District Health Board (WDHB), it was discovered that the HIS infrastructure already comprises these two parallel data processing layers. Specifically, a batch processing layer exists, responsible for periodically synchronising data in batch form into a relational database, functioning as a data warehouse. Moreover, interconnected systems are operating on an additional data exchange layer, utilising the Health Level Seven standard (Dolin et al., 2001).

Figure 5-8: 8 Lambda Architecture diagram adapted from Marz and Warren (2015)



Considering the factors discussed earlier and the presence of parallel data processing layers within the HIS infrastructure, the adoption of a system integration architecture design based on the Lambda Architecture presents itself as a viable option. This design approach aims to leverage the strengths offered by both the batch and real-time layers. By integrating the existing batch processing layer, responsible for periodically synchronising data into a relational database, with the Health Level Seven standard-driven data exchange layer, a comprehensive system integration architecture can be established. This integration facilitates seamless data flow, enabling efficient processing and analysis of historical and real-time data among HISs in the ED.

The stream layer within the system integration architecture serves as an interface that enables the CDSS to access relevant clinical data for individual patients and generate recommendations for physicians. By leveraging the real-time layer, the CDSS can retrieve up-to-date information about a patient's medical condition, treatment history, and other relevant factors. This real-time data interface facilitates the CDSS in generating timely and contextually appropriate suggestions to assist physicians in making informed decisions. On the other hand, the batch-processing layer synchronises and consolidates data periodically into a relational database, serving as a data warehouse. This curated historical data can be utilised for training ML models. By incorporating the batch layer, the system ensures that the ML models receive comprehensive and reliable data, enhancing their effectiveness and enabling them to make informed predictions and recommendations.

Figure 5-9: Integration Architecture for hospital information systems

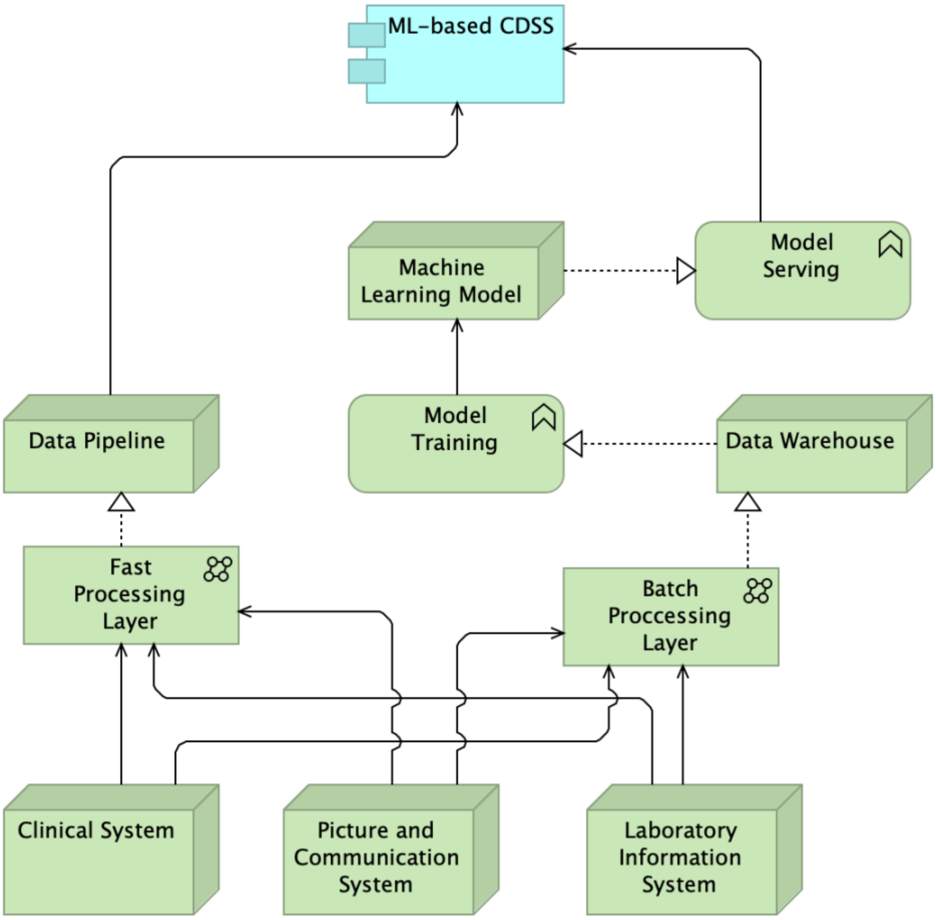


Figure 5-9 presents the technology model design of the integration architecture for HIS. To support the functionality of the ML-based CDSS, the system architecture needs to provide data in both batch and stream methods. To provide a system-wide general interface to access data across different systems, adapted from the Lambda Architecture, a stream processing layer and a batch processing layer are added to the current system architecture.

The batch processing layer focuses on handling large volumes of historical data and performing offline analytics. Techniques such as extract, transform, and load can be employed to cleanse and prepare the data (Dhanda & Sharma, 2016). Data is extracted from various heterogeneous sources, such as clinical systems, LISs, PACSs, and other healthcare data repositories. The extracted data undergoes transformation and fusion processes to integrate and reconcile information from different sources. Data cleansing, normalisation, and standardisation techniques are applied to ensure consistency and accuracy. This step involves merging and resolving any conflicts or inconsistencies within the data. The merged data is then stored in a central data warehouse or a data lake. The data warehouse acts as a unified repository, facilitating efficient data access for model training in ML.

The stream processing layer of the Lambda Architecture handles real-time data streaming and provides low-latency processing for ongoing patient visits. It deals with data that arrives in real-time or near real-time from heterogeneous sources, such as clinical systems, LISs, PACSs, and other healthcare data repositories. Streaming data is ingested continuously into a data pipeline. The ingested streaming data is processed in real-time to match the data format required for the input interface of the CDSS.

This system architecture design reduces implementation complexities and allows for seamless integration leveraging existing practices and standards in hospitals. The utilisation of batch extract, transform, and load processes and a data warehouse aligns which the practice widely adopted in many hospitals. By leveraging the widely adopted Health Level Seven standards, the speed layer facilitates smooth integration and enables healthcare professionals to harness real-time or near-real-time data processing capabilities.

5.5.2 Machine Learning

This section outlines the research activities undertaken to devise the artefact aimed at augmenting clinical decision-making through the integration of a ML component within the technology model design. This encompasses the development of the ML model, which serves as the fundamental element of the proposed ML-based CDSS. As discussed in Section 5.5.1, within the system design, the ML model accesses EHR data through a data warehouse as the batch process layer of the system integration architecture. To ascertain the viability of the design artefact, this study employs the EHR data obtained from the ED of NCKUH to construct the ML model. The initial segment of this section emphasises framing CDS tasks in the context of the ED as ML problems. Subsequently, the procedure and tools employed for processing the NCKUH dataset in preparation for ML analysis will be elucidated. Furthermore, it presents the construction and training process of artificial neural network models utilising the authentic dataset.

5.5.2.1 The ML problem

This section presents the analysis of the process of ML problem framing, which involves the translation of real-world problems into ML solutions. This step holds significant importance in effectively addressing problems using ML approaches.

Based on the desired outcome, an ML problem can be classified either as a classification problem or a regression problem (Ray, 2019). A classification model aims to assign a label from a predefined set of labels, while a regression model predicts a numeric value within a continuous range.

Insights obtained from physicians at the ED revealed that when they order a diagnostic test for a patient at the ED, they seek a suggestion regarding the potential outcome of the test. Some tests yield a positive or negative result, while others provide a numeric result.

For tests generating positive or negative reports, an ML model is expected to predict two distinct outcomes based on the available input data. For instance, a blood culture test is a laboratory procedure conducted to identify the presence of bacteria or fungi in the bloodstream. It is employed for diagnosing bloodstream infections, also known as bacteraemia or septicaemia, which occur when microorganisms enter the bloodstream and spread throughout the body. The potential results of a blood culture test comprise a positive outcome, indicating the presence of bacteria or fungi in the bloodstream, and a negative outcome, indicating the absence of significant microbial growth. Consequently, this task falls within the purview of a classification model. To be more precise, since there are only two possible outcomes (negative or positive), the problem can be effectively addressed using a binary classification model.

In the case of tests producing a numeric result, physicians are concerned with whether the value falls within the reference range. For example, a Creatinine test yields results in the range of 0.3–0.9 mg/dL, with values within this range considered normal. Values that deviate either below or above the reference range may potentially indicate underlying medical conditions that warrant attention. Consequently, it becomes imperative to identify values that surpass the upper threshold or descend below the lower threshold. For instance, when confronted with a reference range of 0.3 to 0.9 and a patient's report indicating a value of 1.0, which exceeds the normal range, a regression model may deem predictions of 0.9 or 1.0 equally plausible, as it fails to acknowledge the numerical significance.

Consequently, a regression model, which predicts a numeric value, is not suitable for such tasks. To overcome this challenge, the test results can be classified as either positive or negative based on the numeric value obtained. This approach allows for the use of binary classification models, wherein selected patient data serves as input features, and positive or negative serves as the output, enabling the resolution of most clinical decision problems.

5.5.2.2 ML models

This section expounds upon the development and training of ANN models that employ the EHR dataset obtained from the ED of NCKUH. The objective is to substantiate the viability of utilising ANN models for CDS.

A ML model represents an algorithm or framework that is specifically designed to assimilate patterns from data and generate predictions or make decisions without relying on explicit programming (Bell, 2022). In the context of CDSS, the adoption of supervised learning models is substantiated due to their efficacy in leveraging labelled datasets to train predictive models (Jordan & Mitchell, 2015). Supervised learning algorithms acquire knowledge from instances wherein input features are conjoined with corresponding target labels, with the objective of generalising patterns to engender precise predictions concerning novel, unseen data. When constructing a CDSS, the selection of an appropriate supervised learning model assumes paramount significance, as it facilitates the system's acquisition of knowledge from historical patient data and associated outcomes, thereby furnishing valuable insights and support for medical decision-making. Amongst the assortment of supervised learning models, ANN's an influential preference for CDSS under their capacity to capture intricate, non-linear relationships amidst input variables and outcomes (Spooner, 2016). ANNs exhibit exceptional proficiency in tasks such as extracting salient features from raw data, scalability in handling extensive datasets with numerous variables, and adaptability to learn and update models as new data becomes available. These characteristics render ANNs an enticing option over other ML models, enabling them to deliver accurate predictions and invaluable insights in clinical decision-making scenarios.

To build and train the ANN models, this study employed the open-source version of TensorFlow. TensorFlow offers a comprehensive framework that enables the training of neural networks, catering to both experimental and production tasks across diverse computing environments (Abadi et al., 2015).

In conjunction with TensorFlow, this study leveraged the Keras framework as a standard high-level application programming interface for constructing and training the ANN models. Keras serves as a Python-based deep learning application programming interface, providing intuitive abstractions for resolving ML problems through the utilisation of TensorFlow (Chollet & Others, 2015).

By utilising Keras, the ML building and training process can be directed towards defining and configuring the layers, models, optimisers, loss functions, and metrics associated with the ANN models. This abstraction allows for a streamlined and focused approach to developing and refining the ML models.

5.5.2.2.1 Deep Neural Network

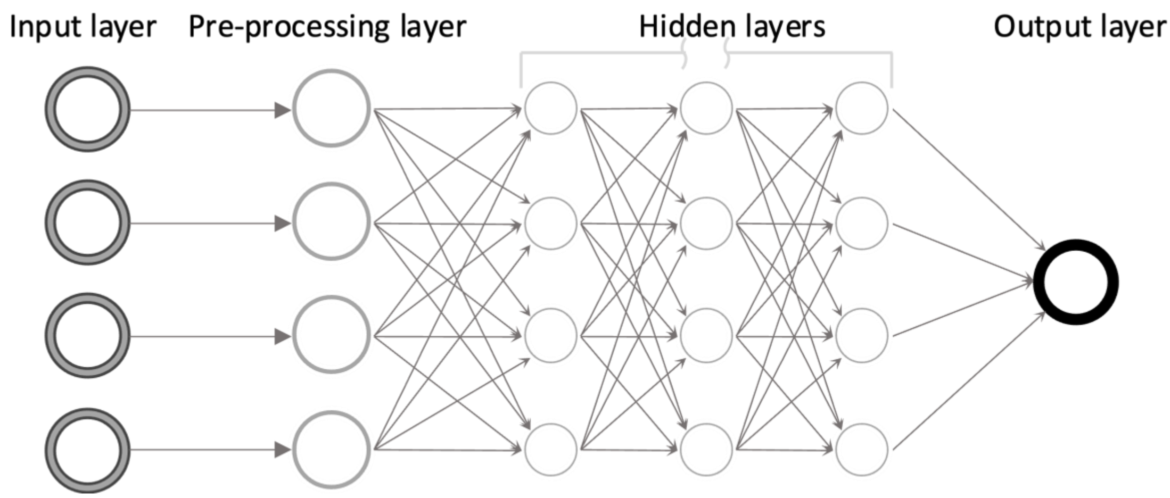
An ANN model is usually a directed acyclic graph of layers. A layer is a high-level component which receives input, applies computations and passes the output to the next layer. The first and last layers in the directed acyclic graph are the input and output layers. Any layers between the input and output layers are hidden layers.

A deep neural network (DNN) takes the concept of ANNs further by incorporating multiple hidden layers. While traditional ANNs typically have one or two hidden layers, DNNs can have a much deeper architecture with several hidden layers, hence the term "deep" in their name. This depth allows DNNs to capture and represent increasingly complex and abstract features in the data.

The structure of the DNN model is illustrated in Figure 5-10. The pre-processing layer serves the purpose of constructing process pipelines that normalise and encode the raw data intended for the DNN model. Given that each feature within the dataset necessitates distinct treatment, it becomes imperative to apply multiple pre-processing layers.

The hidden layers encompass densely-connected layers, which collectively constitute a neural network. Each layer comprises individual units functioning as neural components.

Figure 5-10: DNN model layers



5.5.2.2.2 Data Processing

The dataset utilised in this study comprises demographic information, vital signal recordings, underlying diseases, and records of tests conducted on patients who visited the ED at NCKUH from January 2015 to December 2019.

The raw data comprises 471,182 records encompassing 118 attributes that were obtained by the technical department from various HISs within the hospital. To ensure clinical relevance, the researcher collaborated with physicians at the ED of NCKUH to determine the significance of these attributes. As a result, a total of 38 attributes with 29 features were selected for further analysis, which is accessible upon the patient's arrival. Additionally, nine test results were chosen as labels to facilitate the model training process. Furthermore, nine supplementary attributes were retained to indicate whether a patient underwent the aforementioned tests. Any remaining attributes, which were deemed irrelevant to the problem defined in the preceding section, were excluded from the analysis. The justification for selecting these attributes as features and labels will be discussed in Chapter 6, providing a rationale for their inclusion.

Among the 471,182 records, certain instances exist of duplicated records which exhibit discrepancies in a single column. This occurrence arises due to the dataset's construction through the amalgamation of data from multiple tables sourced from diverse locations, achieved by matching chart numbers. Given the possibility of a patient undergoing the same test on multiple occasions, the query operation during the data-joining process could generate distinct rows for each test entry. Upon conducting a comprehensive examination of the entire dataset, this anomaly was detected specifically within the blood culture report feature. In consultation with the medical practitioners and technical staff at NCKUH, it was ascertained that such duplication may arise when a patient provides multiple blood samples for a culture test simultaneously. To identify and address these instances, the researcher employed a Python program, which successfully identified 6,608 duplicated records. Subsequent to seeking expert opinion, duplicated records indicating negative test results were subsequently eliminated from the dataset.

To prepare the raw data for model training, the subsequent step involves the classification of data into various data types. The selected features encompass numeric data, text data, and categorical data. In this study, the Python library pandas is employed to process the raw data (The pandas development team, 2020). Pandas is a potent data manipulation library in Python that offers efficient and adaptable tools for managing structured data. Furthermore, the pandas library encompasses an extensive array of functions designed for data cleansing and preprocessing. Moreover, the pandas library seamlessly integrates with other commonly used libraries within the ML ecosystem. This interoperability facilitates the smooth integration of the pandas data structures with other ML algorithms and tools, enhancing overall efficacy and flexibility.

Figure 5-11: Features of the sample data

```
1   Age
2   Gender
3   Presenting complaint
4   Body Temperature
5   Pulse
6   Respiratory rate
7   Systolic blood pressure
8   Diastolic blood pressure
9   Mean arterial pressure
10  SpO2
11  GCS(Glasgow Coma Scale)
12  Blood Sugar
13  Myocardial infarction
14  Congestive heart failure
15  Peripheral vascular disease
16  CVA/TIA
17  Dementia
18  COPD
19  Connective tissue disease
20  Peptic ulcer disease
21  Mild liver disease
22  Uncomplicate diabetes
23  Hemiplegia
24  Moderate to severe CKD
25  Diabetes with end organ damage
26  Any Tumour
27  Moderate to severe liver disease
28  Metastatic solid tumour
29  AIDS
30  CrShortName
31  CrTestValue
32  BILTShortName
33  BILTTestValue
34  BILDShortName
35  BILDTestValue
36  PlateletShortName
37  PlateletTestValue
38  WBCShortName
39  WBCTestValue
40  BandShortName
41  BandTestValue
42  SegShortName
43  SegTestValue
44  LactateShortName
45  LactateTestValue
46  BloodCultureShortName
47  BloodCultureReport
```

Although the pandas library automatically recognises the data type of each column when reading data from a file, in the case of columns containing non-numeric values, they are loaded as object types by default. In pandas, the object type is assigned to textual data or any other type of data that cannot be accurately detected. For instance, attributes 0, 10, 11, 30, 32, 34, 36, 38, 40, 42, and 44 represent numeric data that has been erroneously recognised as non-numeric due to a few existing errors in the dataset.

To address this issue, these columns are explicitly converted to numeric data types using pandas. The few incorrect data entries, such as "error", which cannot be converted to numeric values, are replaced with “NaN”, representing a NULL or empty value in pandas.

Within the selected attributes, specifically attribute 12 to attribute 28 and attribute 34, values of "Y", "N", or " NaN" are present. In the original dataset, "Y" denotes "yes", and "N" represents "no". To comply with the requirements of the ML algorithm, the values "Y" and "N" are converted to binary data, specifically 1 or 0. After consulting with physicians at the ED of NCKUH, it has been determined that for these attributes, "NaN", can be considered equivalent to "N".

Additionally, it is observed that numerous values were missing from the numeric attributes in the original dataset. However, ML cannot handle empty values within a structured dataset. Common approaches for dealing with missing values in structured datasets for ML include filling them with average values, median values, and predicted values, or deleting rows with missing values (Saar-Tsechansky & Provost, 2007). Filling missing data on such a scale is considered to render the dataset unreliable. After excluding records with empty values, the researcher still had a dataset with a sufficient amount of data, and the data distribution did not change significantly. Consequently, the records with empty numeric data were removed from the dataset.

Another issue with the raw dataset is that the range of values in some of the numeric attributes is too diverse to be directly used for model training (Singh & Singh, 2020). For instance, among the vital signal features shown in Table 5-1, the body temperature ranges from 25.7 to 43, while systolic blood pressure ranges from 1 to 298. In such cases, the researcher needed to apply feature scaling to standardise the attributes to the same scale, as most ML algorithms do not perform well with numerical features at varying scales (Géron, 2019).

Table 5-1: Vital Signal Features

Features	**std**	**min**	**mean**	**max**
body temperature	1.000224	25.7	37.02062	43
pulse	24.31627	11	96.16546	281
breathing rate	3.844427	1	20.12408	85
systolic blood pressure	26.46091	1	134.7493	298
diastolic blood pressure	16.86626	1	82.27792	293

To address this issue, a data pre-processing layer is incorporated into the ANN to normalise the numeric attributes, ensuring their values are scaled within a range of 0 to 1. This step is crucial in minimising the influence of variations in the scales and distributions of different features, which can potentially impede the efficacy and convergence of ML algorithms. This procedure is executed to guarantee equitable contributions from all features during the learning process, thereby averting the dominance of any specific feature solely due to its magnified magnitude.

5.5.2.2.3 Hyperparameters and Model Training

Hyperparameters are the parameters of a ML algorithm that govern the model structure, amount of regularisation, and learning rate (Probst et al., 2019). The configuration of hyperparameters can significantly impact the performance of a DNN model. However, due to the inherent flexibility of neural networks and the uniqueness of each problem, determining the optimal hyperparameter settings is not straightforward. It requires training the model with multiple combinations of hyperparameters to identify the configuration that yields the best results on the validation dataset.

To expeditiously construct a rudimentary model for concept validation, the focus of hyperparameter tuning centred on the most crucial parameters, including the number of hidden layers, the number of units per layer, and learning rates.

In DNN ML, an optimiser algorithm is employed to update the attributes of units within the neural network, thereby reducing loss and improving accuracy throughout the training process. The learning rate, as a hyperparameter, plays a vital role in controlling the extent of modifications made by the optimiser at each iteration. When the learning rate is too low, the training process may be prolonged. Conversely, if the learning rate is too high, the optimiser may fail to converge to the point of minimum loss.

To efficiently explore hyperparameter settings, the study employed the KerasTuner library to manage the process of hyperparameter optimisation (O'Malley et al., 2019). A search space is defined, encompassing the number of hidden layers, the number of units per layer, and learning rates. The KerasTuner is responsible for evaluating various combinations of hyperparameter settings using a subset of the dataset.

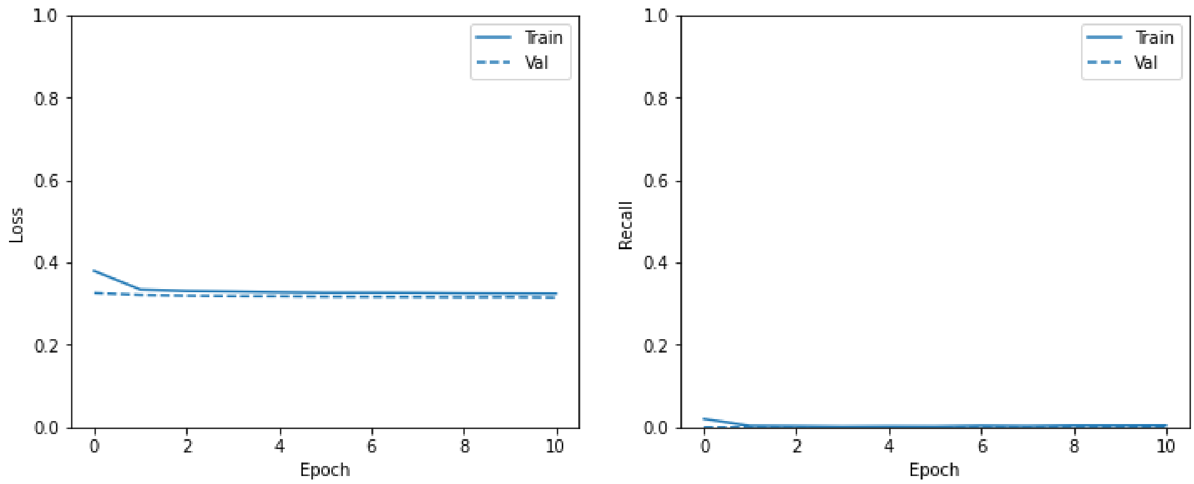
Upon discovering the optimal combination within the predefined search space, a DNN model has been trained using the entire dataset with the identified hyperparameters.

Figure 5-12 presents the training history of a model employed to predict the outcome of a blood culture test. The loss metric signifies the degree of discrepancy between the model's predicted labels and the true labels within the sample data. Since the model in question is a binary classifier, the BinaryCrossentropy function is employed to compute the loss.

The computation of BinaryCrossentropy entails the utilisation of both the true label and the predicted value. Within the dataset, the true label assumes values of either 0 or 1, while the model produces predicted values within the probability range of 0 to 1. The loss is derived by calculating the cross-entropy between the true label and the predicted label.

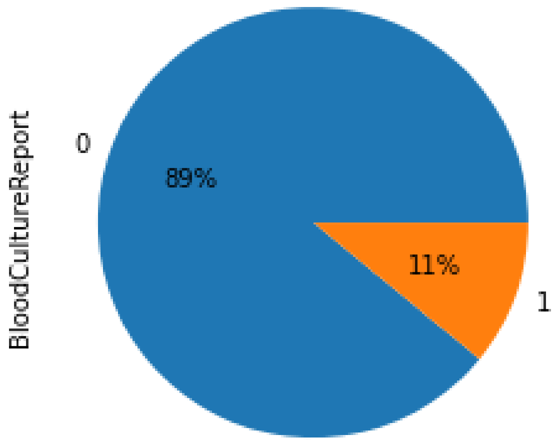
The metric of recall measures the percentage of actual positive instances that have been correctly classified. It is calculated by dividing the number of correctly predicted positive results by the total number of positive results within the dataset. The recall line in the graph indicates that the model exhibits a limited ability to correctly identify positive results. This deficiency can be attributed to the presence of imbalanced data.

Figure 5-12: Training history for the baseline model



Imbalanced data is a prevalent issue present in the NCKUH dataset as well. For instance, as depicted in Figure 5-13, a significant imbalance is observed between patients with a negative test result, constituting 89% of the dataset, and those with a positive result, accounting for only 11%. If an ML model is trained and tested using this imbalanced dataset, it would exhibit a bias towards the negative results, primarily due to their majority representation, while potentially neglecting the crucial minority of positive results. This imbalanced distribution poses challenges to achieving accurate predictions and necessitates specific considerations for addressing the inherent biases.

Figure 5-13: Distribution of blood culture test results for the whole NCKUH dataset from 2015 to 2019



The TensorFlow document proposes two approaches to tackle this issue: data resampling and class weighting. These approaches were implemented and compared within the study. The identical hyperparameter settings utilised in the baseline model were employed for both the resampling and class weighting techniques.

In the data resampling approach, the original dataset was partitioned into separate positive and negative datasets. Subsequently, a resampled dataset was created by randomly selecting an equivalent number of positive and negative samples from their respective datasets. This resampled dataset was then employed to train a model constructed with the same hyperparameters as the baseline model.

Alternatively, in the class weighting method, a model was trained using the original dataset while maintaining the same hyperparameter configuration. The only modification made was assigning a higher weight to the negative class during the training process. By assigning a higher weight to the minority class, the model assigned greater importance to samples with higher weights compared to those with lower weights.

Figure 5-14: Training history for mode trained with resampled data

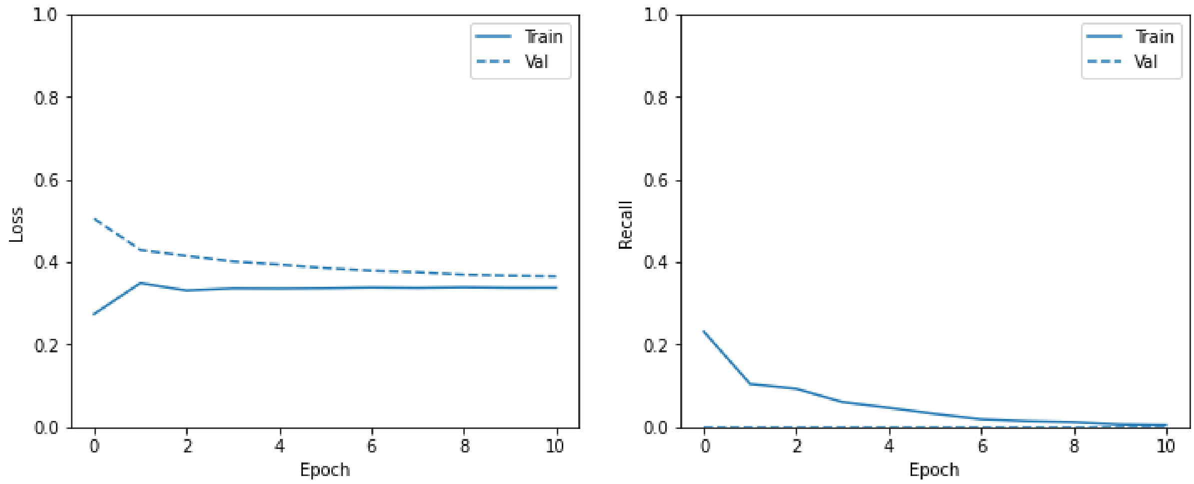
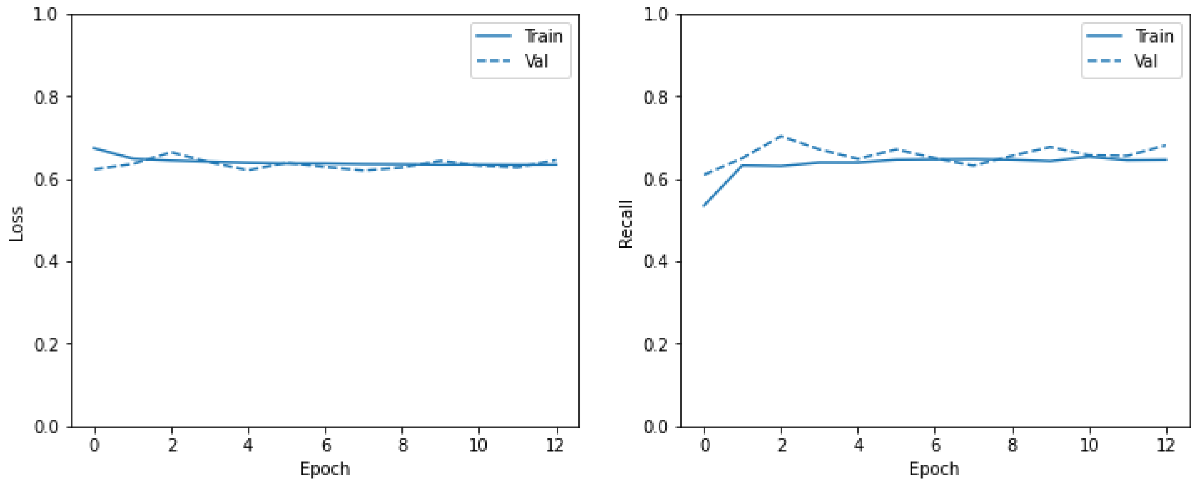
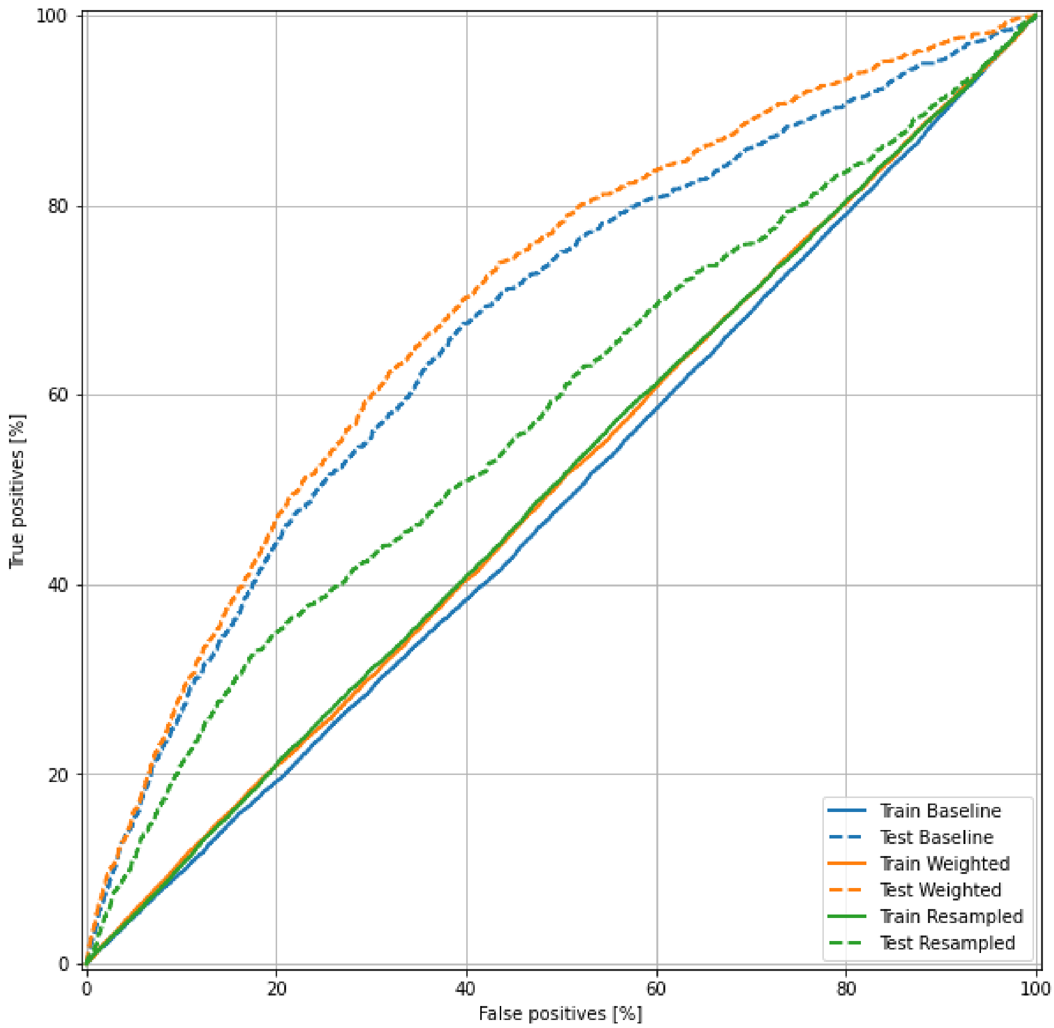


Figure 5-15: Training history for mode trained with class weight



The training history for data resampling and class weighting is depicted in Figure 5-14 and Figure 5-15, respectively. The model trained using resampled data exhibits a diminished recall rate after several iterations. Conversely, the class-weighted model maintains a higher recall, thereby enabling it to identify a greater number of positive results with the available data. The graphical representation unequivocally illustrates that the class weighting approach outperforms both the baseline model and the model trained with resampled data. Moreover, the receiver operating characteristic curve displayed in Figure 5-16 substantiates the enhancement in model performance achieved through the implementation of the class weighting approach.

Figure 5-16: Receiver operating characteristic curve



5.6 Summary

In accordance with the design science research method, this chapter elucidates the design and development activities undertaken to address the issues identified in Chapter 4. A designed artefact, encompassing a system integration architecture for HIS incorporating CDS based on ML, has been devised to augment CDS within the ED context. The system integration architecture has been meticulously planned and delineated within a three-layer architectural framework, encompassing the business layer, application layer, and technology layer. Additionally, a DNN model has been built and trained to employ authentic EHR data sourced from NCKUH to affirm the practicability of the ML-based CDSS.

By implementing the proposed system integration architecture, the aim is to overcome the existing challenges and integrate the various components of the HIS, thereby enabling the effective utilisation of ML-based CDSS in the ED. This integration will allow the seamless flow of information and facilitate the deployment of ML techniques to improve clinical decision-making processes. Furthermore, the outcomes of the ML experiment also substantiate the feasibility of employing ML in prognosticating laboratory test results, which has the potential to significantly augment CDS within the ED setting.

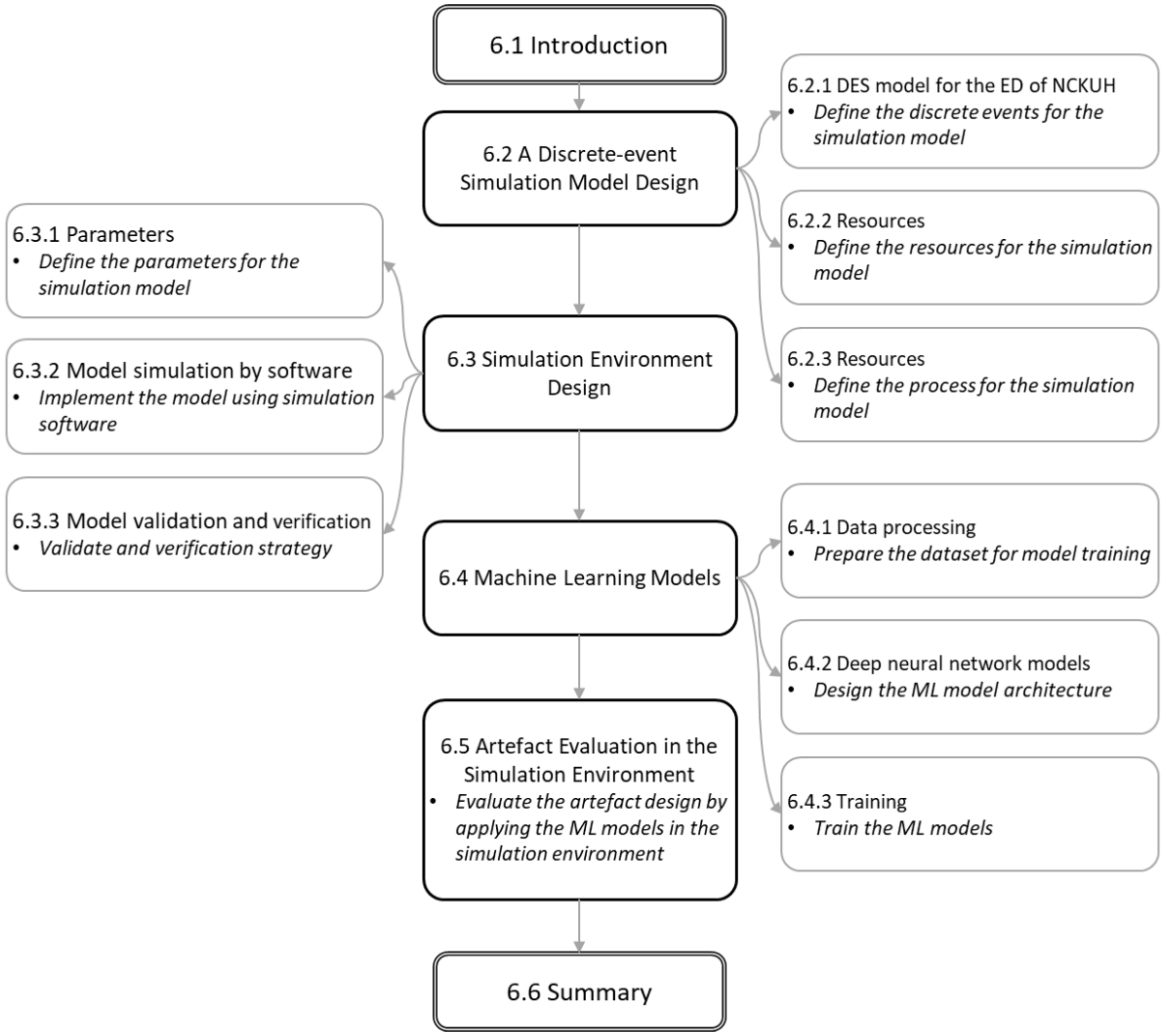
The system integration architecture and the ML model developed in this chapter have been subjected to evaluation within a simulation experiment which is reported in Chapter 6.

Chapter 6 System Simulation

6.1 Introduction

This chapter details developing and implementing a discrete-event simulation (DES) model, specifically designed to assess the system integration architecture discussed in Chapter 5. Emergency departments (EDs) operate in high-pressure environments, where prompt and efficient decision-making plays a pivotal role in patient outcomes. Clinical decision support systems (CDSSs) have been proposed to augment decision support in the ED. However, the implementation of a CDSS in this context poses challenges due to the dynamic and intricate nature of ED operations. To overcome this challenge, a machine learning (ML)-based CDSS can be developed to assist clinicians in making informed decisions. Adhering to the design science research method, the validation of an ML-based CDSS in the ED is accomplished through DES, a highly effective tool for demonstrating and evaluating the extent to which the design artefact can effectively address the identified issues (Peffers et al., 2007). The DES model is developed employing AnyLogic simulation software (The AnyLogic Company, 2023) to replicate the flow of patients within the ED at National Cheng Kung University Hospital (NCKUH). The findings of this study are to be discussed in Chapter 7.

Figure 6-1: Chapter structure



As shown in Figure 6-1, this chapter is organised as follows: In section 6.2, the DES model for the ED of a hospital is designed. The specific components of the model, including the resources and the process flow, are identified and defined. This section lays the foundation for simulating the patient flow processes in the ED. Section 6.3 focuses on designing the simulation environment. Firstly, data analytics techniques are employed to analyse and prepare the Electronic Health Records (EHR) dataset for simulation. Subsequently, the simulation model is implemented using the AnyLogic simulation software, providing a platform to simulate the behaviour of the ED. Validation of the simulation model is addressed in Section 6.3.3. Historical data is utilised to validate the model and establish a baseline performance. By simulating the ED using the historical data within the developed simulation model, a comparison between the model-generated data and actual data enables the validation of the model's accuracy. In Section 6.4, the design of the ML models is described. This includes data processing, where the dataset for ML model training is prepared, and the design of the ML model architecture, specifically deep neural network (DNN) models (Montavon et al., 2018). The ML models are then trained using the prepared dataset. The evaluation of the artefact CDSS framework in the simulation environment is covered in Section 6.5. By integrating the ML models into the simulation, the performance of the system design is evaluated. The CDSS framework acts as a decision support tool, providing suggestions for patient care based on the ML models' predictions.

6.2 A Discrete-event Simulation Model Design

Simulation is the process of using a mathematical model to mimic the behaviour of a real-world system (Maria, 1997). Simulation is a powerful tool for understanding complex systems and can be used to study a wide range of phenomena, including system performance, reliability, safety, and efficiency. It is widely used in a variety of fields, including engineering, computer science, economics, and management. Simulation models are typically implemented using specialised software tools, which allow users to specify the parameters and behaviour of the system, and to analyse the results of the simulation. The goal of the simulation is to understand and predict the behaviour of a system under various conditions, and to identify opportunities for improvement or optimisation.

Continuous simulation and discrete event simulation (DES) are two major approaches to modelling the behaviour of systems over time (Özgün & Barlas, 2009). The main difference between the two is the way in which they represent the passage of time and the processing of events.

In a continuous simulation, the system is represented as a set of continuously changing variables that are updated over a continuous range of time. This type of simulation is typically used to model systems that involve the flow of materials, energy, or information, such as chemical processes, fluid dynamics, and electrical circuits. Continuous simulation models are usually implemented using differential equations, which describe how the variables in the system change over time.

In contrast, discrete event simulation models the behaviour of a system as a series of discrete events that occur at specific points in time. Each event represents a change in the system's state, and the simulation is designed to mimic the system's behaviour over time by processing these events in the order in which they occur. Discrete event simulation is often used to model complex systems that involve the interaction of many different components or entities, such as transportation networks, manufacturing systems, and supply chains.

An ED setting is typically complex, with many different components and processes that interact in intricate ways. Discrete event simulation is well-suited to modelling such systems because it can represent the behaviour of the system as a series of discrete events, allowing users to track the flow of patients, staff, and resources through the system. Discrete event simulation can be used to model the flow of patients through the ED of a hospital, from admission to discharge. This can help to identify bottlenecks and inefficiencies in the system and to develop strategies for improving patient flow. Healthcare systems often have limited resources, such as beds, staff, and equipment, which need to be carefully managed. Discrete event simulation can help to optimise the allocation of these resources by modelling the impact of different scenarios on resource utilisation.

To design a DES model for the ED setting, the following steps are followed (Banks et al., 2010; Law, 2007):

1. Identify the system boundaries and processes to be included in the model. In this case, the processes are arrival, initial diagnosis, intervention, observation, and disposition.
2. Define the input data and parameters required for the model. This research includes the arrival time, test results, and total length of stay from the historical EHR data.
3. Identify and classify the resources required for the model.
4. Define the rules and logic for the model, including how patients and resources are allocated and released, and how patient flow is controlled.
5. Implement the model using the simulation software AnyLogic.
6. Test and validate the model using historical data. This may involve comparing the output of the model to actual ED data to ensure that the model is accurately representing the system.

6.2.1 DES Model for the ED of NCKUH

As presented in Chapter 5, the patient flow in the ED setting includes the following process:

Arrival: When a patient arrives at the ED, they are typically greeted by a triage nurse who assesses their condition and determines the severity of their symptoms. The triage nurse may also ask the patient about their medical history and any medications they are currently taking. Based on the triage assessment, the patient is given a priority level, which determines how quickly they will be seen by a physician.

Initial diagnosis: Once seen by a physician, the patient would undergo a consultation and observation. This step helps the physician understand the patient's situation and determine what examination and test might be needed.

Intervention: Depending on the patient's initial diagnosis, the physician might order more thorough diagnostic tests. These tests may include blood tests, X-rays, or other examinations. The physician will use the results of the examination and tests to make a diagnosis and provide treatments.

Observation: While the patient is receiving treatment, they will be monitored for any changes in their condition and the effectiveness of the treatment.

Disposition: Once the patient's condition has stabilised and they are no longer in need of emergency care, they will be discharged from the ED. If the patient's condition is more serious and requires ongoing treatment, they may be admitted to the hospital.

Thus, the DES model of the patient flow in the ED can be designed with the following discrete events:

Arrival: This process would be represented by the arrival of patients at the ED. The arrival time of a patient can refer to the historical EHR dataset, which can be input into the model.

Initial diagnosis: This process would involve the allocation of a physician to the patient.

Intervention: This process would involve the allocation of resources, such as nurses, laboratory capacity, or equipment, to the patient. The resource requirement for this process would be defined by the diagnostic tests taken by each patient, which can be input into the model.

Observation: This process would involve the allocation of a bed or other observation area to the patient.

Disposition: This process would involve the release of the patient from the ED or the admission of the patient to the hospital.

6.2.2 Resources

The success of a DES model depends on the accuracy and completeness of the data used to build and validate the model. In the simulation for this research, there are several types of resources that are crucial for the patient flow process. The availability and utilisation of these resources are the keys to the efficient functioning of the ED of NCKUH. The staff availability, such as nurses and physicians, is changed based on the schedule, which reflects the real-world scenario. Other resources, such as the capacity of the lab and beds, are limited by the number, which means that the simulation will reflect the real-world constraint of limited resources. The identified resources include:

Triage nurses: The nurses at triage are responsible for the initial assessment upon patient arrival, determining their level of severity, and routing them to the next appropriate process for initial diagnosis or intervention. There are two nurses available for triaging patients between 8 am and 12 am, and one nurse from 12 am to 8 am.

Physicians: There are two physicians in the general clinic room from 8 am to 12 am, and one from 12 am to 8 am. Additionally, there is one physician in the emergency room available for 24 hours.

Physicians are responsible for the diagnosis and treatment of patients, and they work closely with nurses to ensure that patients receive the appropriate care.

Intervention resources: There are several resources available for interventions, including blood tests, X-ray machines, and CT machines. These resources are used to diagnose and treat patients, and they play a critical role in the patient flow process. The blood tests involve resources including nurses who take blood samples from patients and the lab resources to proceed with. Similar to triage, there are two nurses taking blood samples from patients between 8 am and 12 am, and one nurse between 12 am and 8 am. In the lab, the blood tests are carried out in four groups and there are four machines for each group of tests. Each machine can process samples from one patient and generates a test report in around two minutes. There is one X-ray machine and one CT machine in the ED of NCKUH.

Observation beds: There are 40 beds available for observation. These beds are used to monitor the condition of patients who have completed their interventions. Patients are routed to the appropriate bed based on their condition and treatment, ensuring that they receive the appropriate level of care.

The resources in the ED simulation play a crucial role in the patient flow process. The availability and utilisation of these resources are key to the efficient functioning of the ED. It's important to monitor the performance of these resources in the simulation to identify bottlenecks or areas for improvement, which will help understand how patients are affected by the availability of resources and make informed decisions about how to improve the patient flow process.

6.2.3 Process Design

The simulation model presented in this study aims to simulate the patient flow process in an ED. This process includes various key stages such as triage, diagnosis and intervention, lab testing, and observation.

During the triage process, nurses assess the severity level of patients and assign them to the appropriate location for diagnosis or intervention.

The diagnosis and intervention process involves treating patients in accordance with their severity levels, where those with higher severity levels are sent to the emergency room for immediate intervention, while those with lower severity levels are routed to the general clinic room. This process involves the use of different resources such as blood test machines, X-ray machines, and CT machines.

Furthermore, the lab testing process involves testing blood samples taken from patients, where the lab is equipped with four types of blood test machines, with each machine processing samples from one patient and generating a test report within two minutes. Lab staff are responsible for running the test and processing the report.

Additionally, the observation process involves monitoring patients' conditions after the interventions are complete, and patients are sent to the appropriate bed based on their condition and treatment, ensuring that they receive the appropriate level of care before they can be discharged from the ED.

The simulation model also includes a scheduling function that controls the availability of human resources and logistics. The number of staff available changes based on a pre-set schedule, and blood samples are sent to the lab every 30 minutes, reflecting the real-world scenario.

The simulation process begins with the arrival of patients at the ED, where they are triaged by nurses based on their severity levels. Patients are then directed to the appropriate sector in the ED for diagnosis or intervention. During the intervention process, patients may require different resources such as blood tests, X-ray machines, and CT machines. After the interventions are complete, patients are directed to the observation process for monitoring their condition. Finally, the physician decides whether the patient can be discharged, transferred, or admitted to the inpatient department.

In conclusion, the simulation model presented in this study has been designed to model the patient flow process in an ED comprehensively. The model includes key components such as the triage process, diagnosis and intervention process, lab testing process, and observation process, as well as a scheduling function that allows the user to set the schedule for staff availability and lab testing.

6.3 Simulation Environment Design

6.3.1 Parameters

The EHR data, utilised as input for the simulation, was sourced from the ED of a partnering hospital. The data preparation procedure involved several steps to ensure the precision and comprehensiveness of the input data. Primarily, the data was scrutinised for any missing values and errors were rectified. Moreover, potential outliers or extreme values were identified and eliminated from the dataset, as they could conceivably influence the simulation outcomes. These steps were taken to ensure the reliability and validity of the simulation model and to minimise any possible sources of bias in the evaluation.

The simulation was developed under the constraint of the dataset obtained from the partner hospital. Thus, the initial step in the data preparation process involved extracting the requisite information from the Excel file provided by the hospital. The information consisted of patient identification, arrival time, triage category, diagnosis, treatment, and test results.

The objective of this patient flow simulation was to assess and enhance the efficacy of clinical decisions. In the EHR data, clinical decisions comprise diagnosis, treatment, and laboratory tests. As the EHR does not provide any information concerning the outcomes of diagnosis and treatment that can be utilised to evaluate these clinical decisions, this study focused on laboratory tests, which have quantifiable outcomes.

The EHR data contains test results for nine blood tests, some in numerical format and others in binary format. After consulting with ED physicians, the nine tests were packed into four discrete events in the simulation since some of the tests are performed together as part of a single laboratory task.

Table 6-1: Laboratory Tasks

	Discrete Events			
Blood Test	Lab Test 1	Lab Test 2	Lab Test 3	Lab Test 4
Creatinine	Y			
Total bilirubin	Y			
Bilirubin in direct form	Y			
Platelet count		Y		
White blood cell count		Y		
Neutrophil band count		Y		
Neutrophil segmented		Y		
Lactate			Y	
Blood Culture				Y

The aforementioned blood tests require the collection of blood samples, which is a task assigned to the nurses in the ED. Following collection, the blood samples are then dispatched to the laboratory for further testing. The collection of blood samples is performed on a per-patient basis. Blood samples are collected for each patient requiring blood tests and are sent to the laboratory in batches at 30-minute intervals. The laboratory houses four machines, allowing for simultaneous testing. The number of machines is based on the hospital laboratory's actual capacity.

In this simulation, the arrival rate of the patient was regulated by the authentic arrival time documented in the EHR record. To match the simulation's time units, the arrival times were extracted and transformed.

Further parameters for the simulation were identified, including the number of physicians, nurses, and laboratory capacity. These parameters were established based on the actual data from the hospital and were utilised to configure the simulation model to closely replicate the real-world conditions in the ED.

The ED's doctor and nurse schedules are categorised into morning, evening, and night shifts, which are predicated on the actual shift schedules adopted by the hospital. The staffing levels of doctors and nurses on each shift were also based on actual staffing levels.

Table 6-2: Resources, Capacity, and Time Shift

Resource Name	**Schedule Time**	**Capacity**	**Unit**
Nurse (Triage)	8 am to 12 am	2	Each
Nurse (Triage)	12 am to 8 am	1	Each
Nurse (Blood Test)	8 am to 12 am	2	Each
Nurse (Blood Test)	12 am to 8 am	1	Each
Physician	8 am to 12 am	2	Each
Physician	12 am to 8 am	1	Each
Physician (Severe)	24/7	1	Each
Physician (Observation)	24/7	1	Each
Blood Analyser	24/7	4	Each
X-ray Machine	24/7	1	Each
CT Machine	24/7	1	Each

6.3.2 Model Simulation by Software

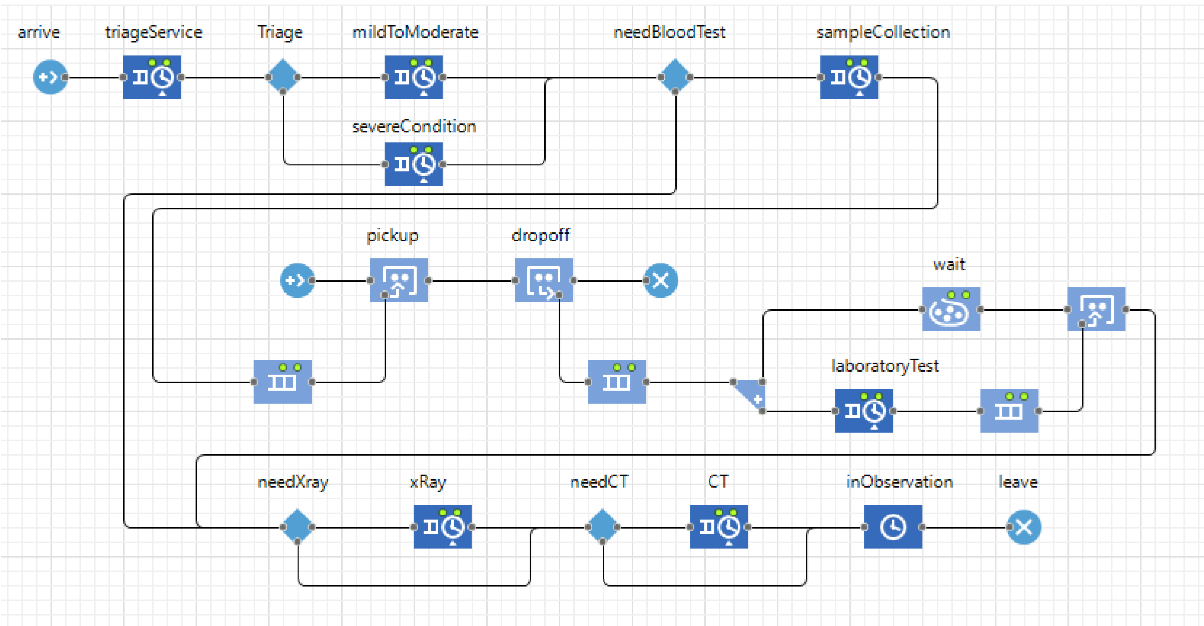
This research utilised AnyLogic software to develop a discrete event simulation model to simulate the patient flow process in an ED. AnyLogic is widely recognised in academia for its simulation and modelling capabilities and is commonly used for academic research projects, as well as for teaching simulation and modelling concepts and techniques to students. It is a powerful simulation software that can analyse and comprehend complex systems, such as transportation networks, supply chains, and manufacturing systems, making it well-suited for various academic fields, including healthcare.

The DES model was constructed based on data provided by a collaborating hospital, with the primary goal of simulating the patient flow process in the ED and improving clinical decision support (CDS) for better patient flow. The initial step in building the model was defining the entities to be used, which included patients, nurses, physicians, and laboratory equipment. The attributes and behaviour of each entity were defined based on the provided data.

To evaluate the performance of the designed DES model, EHR data and the predicted results from the ML models were utilised as input data. The evaluation process involved comparing the simulated patient flow in the ED with the actual patient flow obtained from the EHR data. The accuracy of the ML models was also evaluated by comparing their predictions with the actual outcomes.

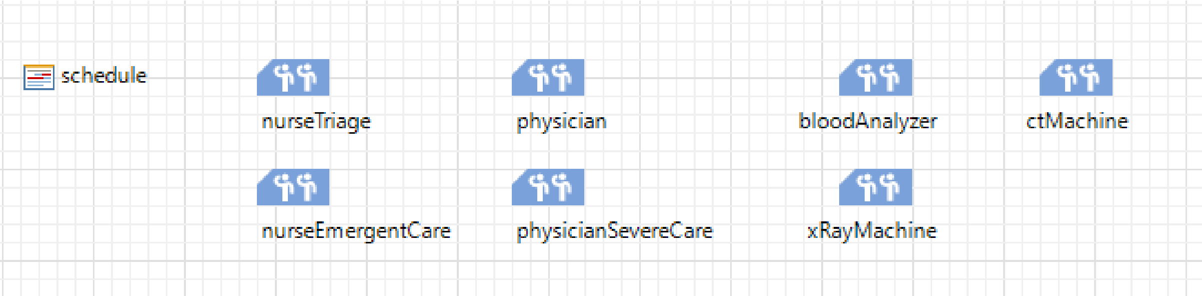
The DES model was built in the AnyLogic simulation software based on the DES model design discussed in Section 6.2.3, as shown in Figure 6-2. The simulation process commences with the arrival of a patient at the ED, followed by triage conducted by nurses based on the patients' severity level. The patients are then directed to the appropriate sector in the ED for further diagnosis and intervention. Following the initial diagnosis or treatment in the clinic room, patients may require additional procedures such as blood tests, X-rays, or CT scans. Once the interventions are complete, the patients are directed to the observation process, where their condition is closely monitored before they are discharged from the ED.

Figure 6-2:Simulation model in AnyLogic



Then the resources were defined to be allocated based on the flow of the patient's journey. Specifically, resources were assigned for each stage of the patient journey, including triage, diagnosis and intervention, and laboratory testing. These resources included the number of nurses and doctors required during each stage, as well as the number of laboratory machines needed for testing.

Figure 6-3: Resources defined in AnyLogic



These resources were categorised into resource pools in the system. The resources were dynamically assigned to the corresponding node in the simulation process based on the schedule defined in the system. The schedule included the availability of nurses and physicians during each shift, as well as the number of laboratory machines available for testing. Specifically, the schedule included two nurses during the first two shifts for triage and blood testing, one nurse during the last shift for triage and blood testing, two physicians during the first two shifts for diagnosis and intervention, one physician during the last shift for diagnosis and intervention, one physician available 24/7 for severe cases, one physician available 24/7 for observation, four blood analysers available 24/7, one X-ray machine available 24/7, and one CT machine available 24/7. These resources were dynamically assigned to their corresponding nodes in the simulation process to reflect the actual allocation of resources in the ED setting.

In the simulation environment, each incoming patient was modelled as an agent, carrying a record extracted from the EHR dataset. The order of entry for each agent into the simulation model was determined by their recorded arrival time in the EHR data. Subsequently, the route each agent traversed in the simulation model was determined by the historical EHR record that each agent carried.

6.3.3 Model Validation and Verification

The validation and verification of the DES model constitutes vital stages in ensuring its accuracy and reliability (Robert G Sargent, 2004). Model validation encompasses the assessment of the DES model's fidelity to the real system it aims to simulate. Conversely, model verification entails confirming that the implemented model functions as intended and aligns with the predetermined objectives.

To attain validation, the pursuit of face validity is undertaken. This process encompasses acquiring expert opinions and soliciting feedback from domain experts who possess extensive knowledge pertaining to the system being simulated (Banks et al., 2010). The simulation model has been formally presented to the physicians affiliated with the collaborating hospital, subsequently undergoing revisions based on the input provided by the aforementioned experts, thereby ensuring the validity of the simulation model.

In addition to validation, model verification focuses on assessing the correctness of the implemented DES model. Both static analysis and dynamic analysis are applied to ensure they evaluate the model (Whitner & Balci, 1989). Static analysis is performed by utilising the compiler integrated into the AnyLogic software, aiding in the prevention of syntax errors in the code. This guarantees the model's implementation is accurate from a syntactical perspective, thereby minimising the potential for logical errors and inconsistencies. Conversely, the dynamic analysis focuses on evaluating the behaviour of the model during runtime. It verifies the proper functioning of resource allocation and scheduling within the simulation. Moreover, dynamic analysis ensures the accurate sequencing of patients entering the simulation model and their appropriate allocation at each stage.

The simulation model underwent verification using EHR data from the collaborating hospital. This dataset comprised information such as patient arrival times, triage levels, and test orders for individuals who sought treatment in the ED. The historical data served as input for running the simulation model.

Subsequently, the simulation model was executed with the historical data, and the resultant output was compared to the actual historical data to identify any disparities. The disparities between the model-generated data and the real data were carefully analysed to enhance the accuracy of the simulation model.

Throughout the verification process, the performance of the simulation model was further assessed by comparing it against the historical data for other crucial performance indicators, including waiting times, test turnaround times, and resource utilisation. By comparing the data generated by the model to the actual historical data, any discrepancies could be detected, prompting adjustments to improve the model's accuracy.

6.4 ML Models

This section presents the process of building and training the ML models that support the CDSS within the integration architecture design discussed in Chapter 5. The CDSS framework was designed with the aim of enhancing operational efficiency in the ED with ML-based CDSS. In line with the design science methodology, the design artefact must incorporate the ML module to validate and assess the effectiveness of the design. Accordingly, a DES model was developed to simulate the patient flow process within an ED, as expounded in Section 6.3. The performance evaluation centred on the number of selected blood tests. Hence, the ML models were trained to minimise the number of blood tests administered to patients by predicting the corresponding test outcome.

6.4.1 Data Processing

The ML models were trained with historical EHR data extracted from the hospital information system (HIS) at NCKUH. The dataset contains 471,182 records of patient visits at the ED of NCKUH from 2015 to 2019. Each of the records contains 118 attributes. To identify which of the attributes from the dataset can be used as features and labels to train the model, the first task is to understand the meaning of each attribute. And because the ML models are designed to provide support to physicians in the ED, where the models take input data to predict the outcome as decision support, only data that can be collected before a patient is seen by the physicians should be used as features for the ML model. Any data generated after being seen by a physician can only be the label for the prediction of the ML models.

By consulting with the physicians at NCKUH, the 118 attributes can be categorised into 10 distinct groups based on the purpose of the data and the time of data collection.

Table 6-3: EHR Data Attribute

Group No.	Attributes
1	Visit Number, Chart Number, Age, Gender, Registration Department, Arrival Time, Registration Department, Registration Level, Condition, TTAS (Taiwan Triage and Acuity Scale) Code, Body Temperature, Pulse Rate, Respiratory Rate, Systolic Blood Pressure, Diastolic Blood Pressure, Mean Arterial Pressure (MAP), SpO2 (Oxygen saturation), Glasgow Coma Scale (GCS), Blood Glucose, Triage Level
2	Myocardial Infarction, Congestive Heart Failure, Peripheral Vascular Disease, CVA/TIA, Dementia, COPD (Chronic Obstructive Pulmonary Disease), Connective Tissue Disease, Peptic Ulcer Disease, Mild Liver Disease, Uncomplicate Diabetes, Hemiplegia, Moderate to Severe CKD, Diabetes with End Organ Damage, Any Tumour, Moderate to Severe Liver Disease, Metastatic Solid Tumour
3	Total Length of Stay, Discharge Status
4	Main Diagnosis 1, Main Diagnosis Code 1, Main Diagnosis 2, Main Diagnosis Code 2, Main Diagnosis 3, Main Diagnosis Code 3, Main Diagnosis 4, Main Diagnosis Code 4, Main Diagnosis 5, Main Diagnosis Code 5, Main Diagnosis 6, Main Diagnosis Code 6,
5	Computed Tomography (CT) Scan, Echocardiogram Scan, X-ray, Mobile X-ray, Diagnostic X-ray, Blood Test, Biochemistry Test, Urine and Stool Test, Microbiological Test, Common Pathogen Test, Endoscopy Examination, Ventilator Use, Respiratory Therapy on Ventilator, Respiratory Therapy on BiPAP (bilevel positive airway pressure), Levophed (norepinephrine), EasyDopa (levodopa), Dopamine, Epinephrine, Cardiopulmonary Resuscitation (CPCR), DC Shock
6	Medication Non-insurance Amount, Medication National Health Insurance Amount, Non-insurance Amount, National Health Insurance Amount, Total Cost
7	Admission Number, Admission Date, Discharge Date, Total Hospitalization Days, ICU Hospitalization Days, Primary Diagnosis and Codes, Discharge Outcome, Total Hospitalization Cost, Hospitalization Cost Non-insurance Amount, Hospitalisation Cost National Health Insurance Amount
8	Creatinine Test, Creatinine Value, Total bilirubin Test, Total bilirubin Value, Bilirubin in direct form Test, Bilirubin in direct form Value, Platelet count Test, Platelet count Value, White blood cell count Test, White blood cell count Value, Neutrophil band count Test, Neutrophil band count Value, Neutrophil segmented Test, Neutrophil segmented Value, Lactate Test, Lactate Value
9	Blood Culture Test, Blood Culture Report
10	Others

The first group contains demographic data, including age and gender, time of arrival, and initial assessment data. This information is collected when the patient arrives at the ED.

The second group includes attributes related to the patient's medical history, such as myocardial infarction, congestive heart failure, peripheral vascular disease, and AIDS. These attributes provide important information about the patient’s underlying diseases or pre-existing medical conditions, and these are recorded upon the patient's arrival at the ED.

The third group includes attributes related to the patient's hospital stay, such as the number of minutes spent in the ED, while “Discharge Status” records the type or status of a patient upon leaving the facility, indicating their disposition. These values are recorded when a patient is discharged from the ED.

The fourth group includes attributes related to the patient's diagnosis, including the main diagnosis and corresponding ICD (International Classification of Diseases) codes recorded for a patient. They indicate the primary medical conditions or illnesses identified for the patient's current medical episode. These diagnoses are created and recorded when a patient is discharged from the ED.

The fifth group includes different types of medical examinations, procedures, medications, and interventions performed or administered in the ED. These entries are generated and documented in accordance with the specific tests or treatments undergone by patients during their ED visits. They indicate whether specific procedures or actions were performed or administered to patients during their emergency visit. It is important to note that the dataset does not encompass the outcomes or results. Such data are generated and recorded at the time of a patient's discharge from the ED.

The sixth category encompasses factors pertaining to the patient's medical expenditures, encompassing expenses, such as medication costs and non-medication services, and the overall aggregate cost associated with their visit to the ED. The amounts paid by the patient personally, as well as those covered by the national health insurance scheme, are recorded individually. These recorded values are documented during the patient's discharge from the ED.

The seventh group includes attributes pertaining to the patient's hospitalisation within the ED, including the length of stay, ICU stay, and discharge diagnosis. This information is collected when the patient is discharged from the hospital.

The eighth group includes attributes related to the patient’s laboratory test results, including creatinine, bilirubin, platelets, white blood cells, and lactate levels. Each test is accompanied by two attributes: one indicating whether the patient underwent the test, and the other recording the resultant value of the test. These tests are performed, and the results are obtained during the patient's visit to the ED.

The ninth group includes attributes related to the patient's blood culture test. While the test is performed during the patient's visit to the ED, the report is generated within five days after the collection of blood samples, when the patient has been discharged from the ED and admitted to the admission department.

The tenth group includes the rest of the attributes which are suggested to be meaningless or irrelevant.

As part of the evaluation for the design artefact, the objective of this simulation is to evaluate how an ML-based CDSS can enhance CDS to improve the operating efficiency in the ED. The ML models should focus on decisions made by physicians in the ED with predictable and measurable outcomes. Also, the prediction outcome should help improve the efficiency of ED.

For instance, within the eighth group, documented records exist pertaining to the blood tests administered to patients, along with the corresponding values for each test. These diagnostic tests serve the purpose of analysing diverse blood components, enabling an assessment of an individual's overall well-being, aiding in the diagnosis of medical conditions, and detecting any irregularities or imbalances within the body. Typically, the outcomes of these tests are presented as numerical values accompanied by reference ranges. The dataset clearly indicates that a substantial number of test results fall within the normal range, indicating that these tests could have been potentially avoided. By leveraging predictions generated through ML-based CDSS, physicians could have judiciously ordered a reduced number of tests, thereby conserving valuable time and resources.

For diagnosis, there is no data or information in the dataset to measure how different diagnoses could affect the efficiency in the ED. In the fifth group, the dataset only indicates whether the patient underwent certain diagnostic tests, such as CT scans, X-rays, or microbiological tests, but it does not provide the corresponding results for these tests.

By reviewing the dataset, nine blood tests in the eighth group are identified as clinical tasks that are considered predictable and measurable. It is possible to train ML models to predict the outcome of these tests to provide decision support to physicians in the ED.

Since the purpose of this study is to evaluate the artefact design to validate the feasibility of enhancing CDS with ML, the ML models should be able to provide supportive information on the outcome of the clinical decision in a way that could interact with the simulation model built as described in Section 6.3.

Thus, it’s appropriate to set the scope of the ML problem to train the ML models to predict outcomes of the nine blood tests including the creatinine test, total bilirubin test, direct bilirubin test, platelet test, white blood cell test, neutrophil band test, neutrophil segmented test, lactate test, and blood culture test.

By consulting with the physicians at NCKUH, 28 attributes are selected as features for ML model training. The 28 features are from the first group and the second group, which are the patient data available when a patient is seen by a physician at the ED. The 28 features comprise a range of demographic features, including age and gender, as well as initial assessments such as blood pressure, body temperature, and pulse rate. Additionally, it includes medical history information, such as the presence of underlying conditions such as myocardial infarction, congestive heart failure, and peripheral vascular disease.

6.4.2 DNN models

DNNs are the type of ML model to be used in this study. DNNs have demonstrated remarkable efficacy across diverse tasks encompassing natural language processing, image recognition, and predictive modelling (Shickel et al., 2018). Their effectiveness stems, in part, from their relatively straightforward training process. DNNs can assimilate substantial quantities of data, including the complex and varied EHR data employed within this study. This aspect is of particular significance due to the intricate nature of EHR data, which poses challenges for conventional ML algorithms to extract meaningful insights. Moreover, DNNs exhibit excellent generalisation capabilities, enabling accurate predictions on previously unseen data. This is crucial for healthcare applications, where accurate and reliable predictions can have a significant impact on patient outcomes. Considering the overall potency and ease of training exhibited by DNNs, they emerge as a promising approach for healthcare applications, especially when confronted with intricate and heterogeneous data, such as EHR data.

There are three major types of DNNs, feedforward neural networks (FNNs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs) (Aggarwal, 2018; Schmidhuber, 2015). FNNs are a relatively simple type of neural network, which are commonly used for tasks such as classification and regression. CNNs consist of convolutional layers, pooling layers, and fully connected layers, which make these more suitable for image recognition and processing tasks. RNNs are a category of neural networks capable of handling tasks involving sequential data, such as natural language processing and speech recognition.

This study has opted for FNNs as the ML model to address the ML-based CDSS task, for several reasons. The EHR dataset employed in this study does not contain any image data or sequential data. Consequently, RNNs and CNNs, which typically require substantial computational resources, do not exhibit significant advantages in terms of performance when applied to the aforementioned dataset. Given the limited availability of computer resources in this study, FNNs emerge as a favourable alternative. They possess the advantages of being relatively easy to implement and efficient to train. Despite their simplicity, FNNs are still capable of capturing the intricate relationships present within the input data derived from the EHR dataset.

The performance of a DNN model is highly affected by the choice of its hyperparameters (Probst et al., 2019). Hyperparameters in DNNs are variables that are set before the training process begins and cannot be learned from the data. They are essential parameters that govern the behaviour of the network during training, affecting how the model learns and how well it generalises to new data.

Hyperparameters defining the model architecture include the number of layers in the network, the number of neurons in each layer, and the activation function. A DNN model architecture is composed of multiple layers of neurons arranged in a sequence. Each neuron in a layer receives input from the neurons of the previous layer and executes a specific operation, such as a weighted sum followed by an activation function. The activation function is a mathematical function that is applied to the output of each layer in a DNN model, which transforms the neuron’s input into its output and helps to determine how the model learns by introducing nonlinearity to the model. Together, the neurons in the network enable the implementation of a sophisticated nonlinear transformation from the input to the output.

Once the network architecture hyperparameters have been defined, the next step is to tune the hyperparameters that control how a model is trained, such as the learning rate, batch size, and optimiser. These hyperparameters play a crucial role in determining a model's performance, and finding the optimal values can make a significant difference in the model's accuracy and convergence speed. The learning rate determines the step size of the weight update during training, while the batch size controls the number of training examples used in each iteration. The optimiser algorithm is used to update the model weights during training.

The learning rate is an important hyperparameter to tune since it can significantly impact the training process's convergence and stability (Google, 2022b). A high learning rate can cause the model to converge quickly, but it may also overshoot the optimal solution or even diverge. In contrast, a low learning rate may result in slow convergence and getting stuck in local optima.

The batch size here plays a crucial role in the model training process, as it determines how many training examples are processed in each iteration (Masters & Luschi, 2018). A large batch size can result in more stable updates, but it may take longer to compute, while a smaller batch size can lead to more noisy updates but faster training. The optimal batch size will depend on the available computing resources and the size of the dataset.

Finally, the choice of optimiser algorithm is also an essential hyperparameter that can affect model performance. There are several optimisation algorithms, including stochastic gradient descent , Adam, and RMSProp, each with different strengths and weaknesses (Sun, 2020). The optimiser algorithm should be selected based on the specific problem and dataset being studied.

Finding the optimal hyperparameters is a crucial step to ensure that the model converges quickly and accurately to the desired solution. The hyperparameters for the DNN models built in this study were found by using the KerasTuner, an automation tool for hyperparameter tuning (O'Malley et al., 2019). The KerasTuner is built on top of the Keras API and provides a simple and efficient way to search for the best hyperparameters in the given search space for a given model architecture. To predict the outcomes of nine blood tests, nine DNN models were built with hyperparameters found by KerasTuner using Bayesian optimisation.

6.4.3 Training

Once the hyperparameters, including the number of layers, the number of neurons in each layer, the activation functions, the learning rate, and the dropout rate were selected by the KerasTuner, the models were then trained with the EHR dataset. Within the EHR dataset, there are instances where the outcomes of the blood tests are missing, as most patients only underwent a subset of the nine tests. And that was a problem because training a DNN model to predict the outcomes requires the training data to be labelled with value. In this study, the columns for the test value for the nine blood tests are the label columns. As shown in Table 6-4, the dataset contains 464,487 records after data cleaning. Data cleaning removed duplicated records and records with errors in values and missing values in feature attributes. There are nine label columns in the dataset, and some of them contain missing values, indicating that some patients did not undergo the corresponding test.

Table 6-4: Feature and Label Columns with the Count of Non-null Value

	Columns	Non-Null Count
Features	age	464,487
	gender	464,574
	body_temperature	464,419
	pulse_rate	464,574
	respiratory_rate	464,574
	systolic_blood_pressure	464,574
	diastolic_blood_pressure	464,574
	mean_arterial_pressure	464,574
	spo2	464,574
	gcs_score	464,574
	blood_glucose	464,574
	myocardial_infarction	464,574
	congestive_heart_failure	464,574
	peripheral_vascular_disease	464,574
	cva_tia	464,574
	dementia	464,574
	copd	464,574
	connective_tissue_disease	464,574
	peptic_ulcer_disease	464,574
	mild_liver_disease	464,574
	uncomplicated_diabetes	464,574
	hemiplegia	464,574
	moderate_to_severe_ckd	464,574
	diabetes_with_end_organ_damage	464,574
	any_tumour	464,574
	moderate_to_severe_liver_disease	464,574
	metastatic_solid_tumor	464,574
	AIDS	464,574
Labels	CrTestValue	235,589
	BILTTestValue	38,589
	BILDTestValue	10,583
	PlateletTestValue	245,113
	WBCTestValue	253,630
	BandTestValue	253,640
	SegTestValue	253,674
	LactateTestValue	24,310
	BloodCultureReport	106,239

One common approach to handling missing values in the label columns is to remove the rows with missing values before training the models. However, simply dropping data with missing values in any of the nine label columns would significantly reduce the data size, which might affect the performance of the models. As shown in Table 6-5, after removing data with missing values in label attributes, there were only 1705 records left.

Table 6-5: Feature and Label Columns with the Count of Non-null Value

	Columns	**Non-Null Count**
Features	age	1705
	gender	1705
	body_temperature	1705
	pulse_rate	1705
	respiratory_rate	1705
	systolic_blood_pressure	1705
	diastolic_blood_pressure	1705
	mean_arterial_pressure	1705
	spo2	1705
	gcs_score	1705
	blood_glucose	1705
	myocardial_infarction	1705
	congestive_heart_failure	1705
	peripheral_vascular_disease	1705
	cva_tia	1705
	dementia	1705
	copd	1705
	connective_tissue_disease	1705
	peptic_ulcer_disease	1705
	mild_liver_disease	1705
	uncomplicated_diabetes	1705
	hemiplegia	1705
	moderate_to_severe_ckd	1705
	diabetes_with_end_organ_damage	1705
	any_tumor	1705
	moderate_to_severe_liver_disease	1705
	metastatic_solid_tumor	1705
	AIDS	1705
Labels	CrTestValue	1705
	BILTTestValue	1705
	BILDTestValue	1705
	PlateletTestValue	1705
	WBCTestValue	1705
	BandTestValue	1705
	SegTestValue	1705
	LactateTestValue	1705
	BloodCultureReport	1705

Another way to deal with empty values is to impute them with a value, such as the mean or median of the other values in the column. However, given the large number of empty values for tests in EHR data, it is not the proper method here.

To address this issue, the method of pairwise deletion is employed to selectively incorporate the relevant attributes into the specific model training process (Gudivada et al., 2017). Within this study, a total of nine distinct datasets were derived from the original dataset, each comprising 28 feature columns and one label column. To handle missing values in the label columns, rows with missing values in each label column were removed from the corresponding dataset. For example, in the dataset used to train a model predicting creatinine outcomes, only records with missing values in the "CrTestValue" column were excluded. Consequently, this approach yielded nine datasets that encompassed an ample amount of labelled data for the purpose of model training.

Table 6-6: Size of Datasets

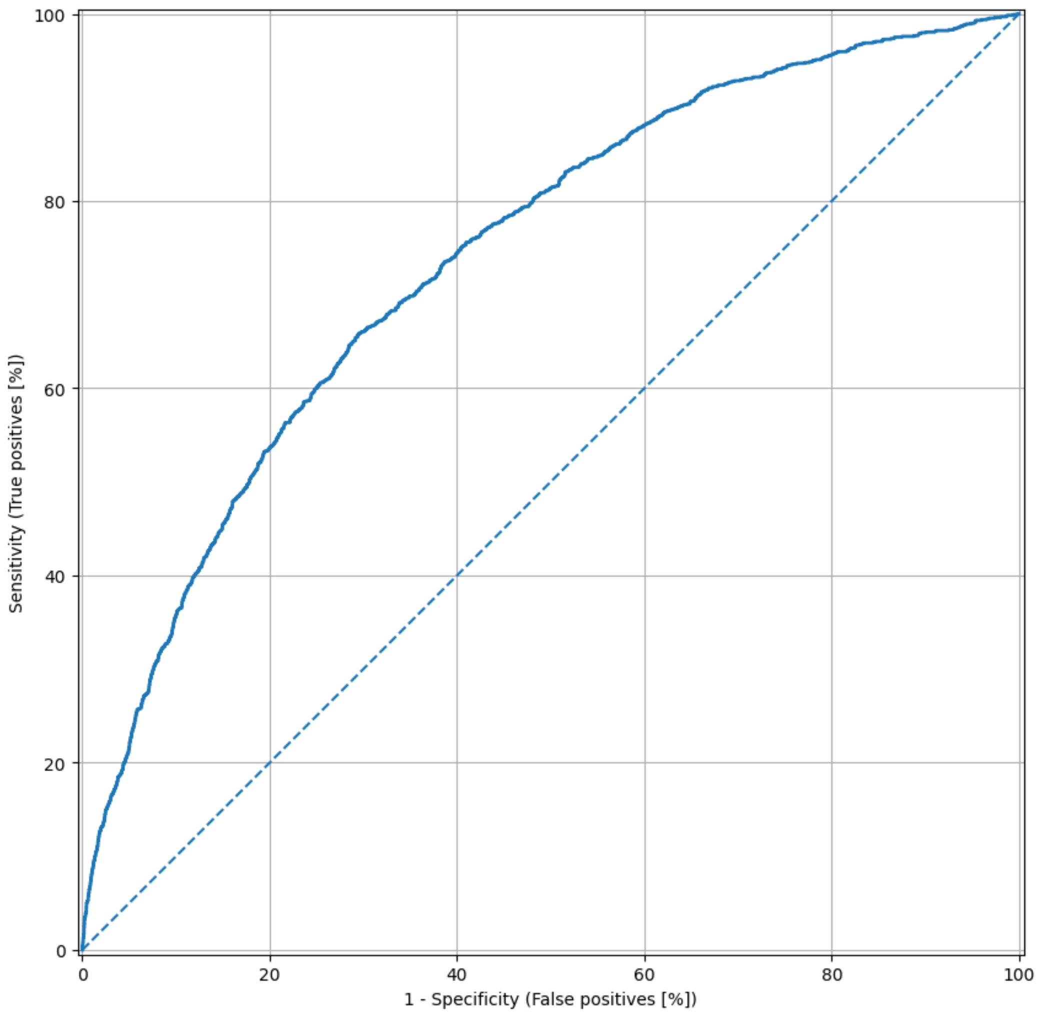
Test Name	**Column Name in Data**	**Size of Dataset**
Creatinine	CrTestValue	235,527
Total bilirubin	BILTTestValue	38,583
Bilirubin in direct form	BILDTestValue	10,581
Platelet count	PlateletTestValue	205,054
White blood cell count	WBCTestValue	253,570
Neutrophil band count	BandTestValue	55,530
Neutrophil segmented count	SegTestValue	250,741
Lactate	LactateTestValue	24,295
Blood Culture	BloodCultureReport	106,229

Table 6-6 presents the size of the dataset for each type of test after removing data errors in values and missing values for the relevant test value column. Nine DNN models were trained with the corresponding dataset to predict the outcome of the nine tests.

In the context of model training, each of the nine datasets is subdivided into three subsets, namely: training, validation, and testing sets. The training set serves the purpose of training the model, whereas the validation set is employed to monitor the model's performance during training iterations, referred to as epochs in the field of ML, to prevent overfitting. The testing set is utilised to assess the performance of the trained model on unseen data. The division ratio employed is 80:10:10, indicating that 80% of the data is allocated for training, 10% for validation, and the remaining 10% for testing. This allocation ensures that the model is exposed to a substantial amount of data for training while still retaining an adequate portion for the validation set, thus mitigating the risk of overfitting. Additionally, it provides a sufficient test set to effectively evaluate the models, considering the dataset's size.

Figure 6-4 illustrates the receiver operating characteristic (ROC) curve of the trained model for the blood culture test. The ROC curve holds significant importance in both healthcare and ML research. In the field of laboratory medicine, ROC curves find extensive application in evaluating the diagnostic precision of a test, determining the optimal threshold, and comparing the diagnostic accuracy among multiple tests(Karimollah Hajian-Tilaki, 2013). For ML model training, a ROC curve is a graphical representation of the performance of a binary classification model, by showing shows the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) of the model as the decision threshold is varied (Bradley, 1997). In this case, the model was trained to classify patients by predicting whether the outcome of the blood culture test is positive or negative. The ROC curve was generated by plotting the TPR on the y-axis against the FPR on the x-axis for different decision thresholds. The TPR is the fraction of positive instances that are correctly classified, and the FPR is the fraction of negative instances that are incorrectly classified. Each point on the ROC curve represents a specific trade-off between the TPR and FPR. The closer the curve is to the upper-left corner of the graph, the better the performance of the model. An ideal classifier will have a ROC curve that is close to the upper-left corner of the plot. This means that the classifier will correctly classify most of the positive instances and very few of the negative instances. In practice, no classifier is perfect, so the ROC curve will never be a straight line. However, a classifier with a good ROC curve will be better than random guessing. The area under the ROC curve (AUC) is a measure of the overall performance of a classifier. An AUC of 1 indicates a perfect classifier, while an AUC of 0.5 indicates a classifier that is no better than random guessing. In general, an AUC in the range of 0.7–0.8 is typically considered to be a fair to good performance, depending on the specific domain and application. In this case, the model trained for the blood culture test got an AUC of around 0.74, which indicates that the model has a moderate predictive ability.

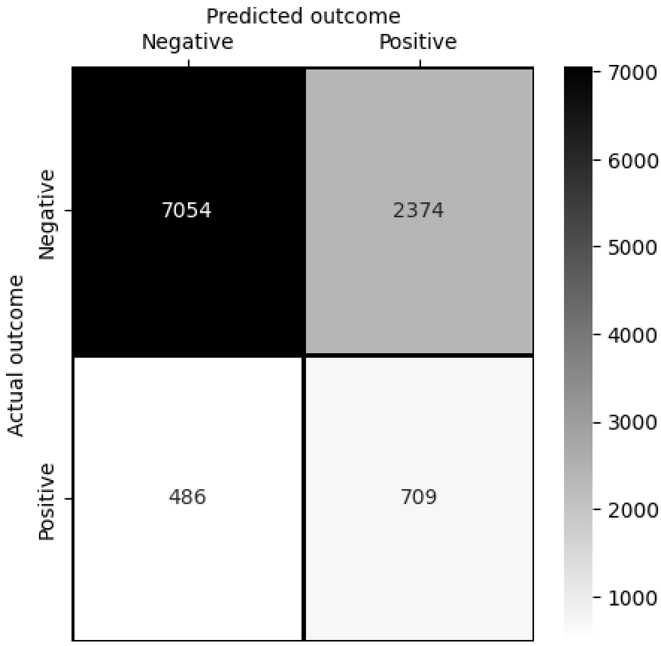
Figure 6-4: ROC curve for the DNN model



The trained ML model was then tested with the testing dataset, which had not been seen by the model during the training model. The output for the DNN model for binary classification is a probability value as a float between 0 and 1. To evaluate the performance of the DNN model for binary classification, float outputs need to be classified with predicted probabilities above a selected threshold as positive (class 1) and those below as negative (class 0).

Figure 6-5 presents the performance of the model for the blood culture test on a set of test data in the confusion matrix with a default threshold of 0.5 by TensorFlow (Abadi et al., 2015). The confusion matrix chart shows four values: true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN) (Sokolova & Lapalme, 2009). The total positives in this testing dataset are 1195, and the total negatives are 9428. With the default threshold setting, the model correctly identified 709 instances as positive (TP) and incorrectly predicted 2374 instances as positive when they were actually negative (FP). The model incorrectly predicted 486 instances as negative when they were actually positive (FN) and correctly identified 7054 instances as negative (TN). The result that incorrectly predicted 486 positive instances as negative indicates that sensitivity was relatively low, which means the default threshold of 0.5 might not be the optimal configuration.

Figure 6-5: Confusion matrix with default threshold

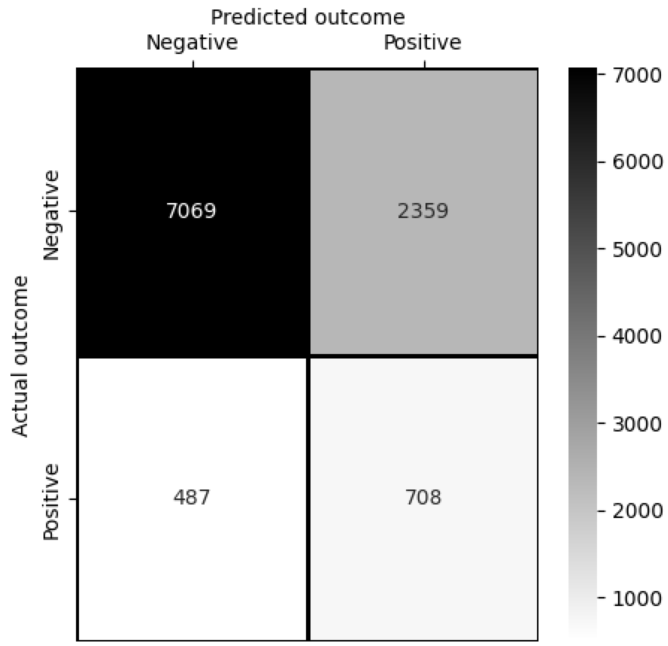


A common approach to finding the optimal threshold is to calculate Youden's J statistic, which is an index defined as the difference between the TPR and FPR for all possible thresholds. Youden's J statistic can be calculated as follows:

$$J = \frac{true\ positives}{true\ positives + false\ negatives} + \frac{true\ negatives}{true\ negatives + false\ positives} - 1$$

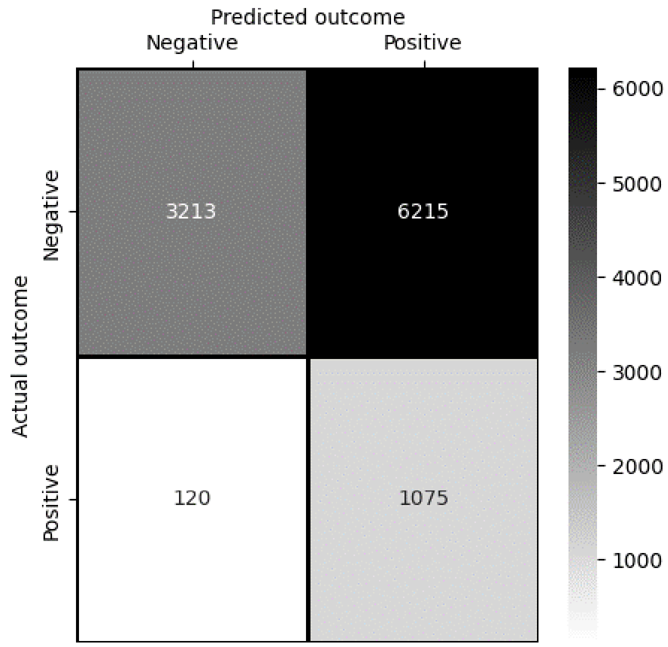
The threshold that maximises the J statistic might be considered the optimum cut-off point. However, in this case, with the threshold that maximises the J statistic, there is no improvement shown in the confusion matrix in Figure 6-6.

Figure 6-6: Confusion matrix with threshold optimised for J statistic



Because the research objective is to provide CDS to the physicians in the ED setting to improve efficiency. The purpose of these DNN models should be to help physicians to decide which patients need the tests or not. In this scenario, false negatives are more critical than false positives. Thus, it is appropriate to set a threshold where the model has a higher sensitivity. In this study, the goal was set to find a threshold where at least 90% of patients with positive outcomes could be correctly classified. As shown in Figure 6-7, with the threshold of 0.3, the model was able to correctly classify over 90% of patients with positive outcomes. With this setting, the model was able to identify around 34% of the negative outcomes in the test dataset.

Figure 6-7: Confusion matrix with a threshold with 90% sensitivity



Nine DNN models were trained and evaluated with the same procedure. The performance of the nine models with different threshold settings is presented in Table 6-7.

Table 6-7: Metrics for the DNN Models

			Predicted outcome					
			Threshold = 0.5 (default)		Threshold with maximised J statistic		Threshold with 90% sensitivity	
			Negative	Positive	Negative	Positive	Negative	Positive
Actual outcome	Creatinine	Negative	11624	2776	10153	4247	7573	6827
		Positive	3389	5764	2238	6915	916	8237
	Total bilirubin	Negative	1993	679	1826	846	851	1821
		Positive	530	657	431	756	119	1068
	Bilirubin in direct form	Negative	95	107	116	86	75	127
		Positive	148	709	205	652	82	775
	Platelet count	Negative	12803	5720	11717	6806	4993	13530
		Positive	2577	3406	2154	3829	599	5384
	White blood cell count	Negative	8563	5187	8006	5744	3199	10551
		Positive	4768	6839	4287	7320	1161	10446
	Neutrophil band count	Negative	1638	1149	1845	942	787	2000
		Positive	832	1934	1012	1754	277	2489
	Neutrophil segmented	Negative	11337	3012	9958	4391	3170	11179
		Positive	5862	4864	4699	6027	1073	9653
	Lactate	Negative	1166	242	1050	358	514	894
		Positive	455	567	333	689	101	921
	Blood Culture	Negative	7054	2374	7069	2359	3213	6215
		Positive	486	709	487	708	120	1075

6.5 Artefact Evaluation in the Simulation Environment

This study was conducted utilising the design science research methodology, which aims to address real-world problems and research inquiries through the design and assessment of design artefacts. In accordance with the guidelines of the design science research methodology, the next phase of this study is to assess the efficacy of the ML-based CDSS framework design artefact by combining the DES model, as detailed in Section 6.3, with the trained ML models.

The present study has designed and implemented a DES model to evaluate the performance of the system design by simulating the patient flow within the ED. To achieve the objective of simulating patient flow and evaluating the performance of the system design, the DES model has been designed to capture the patient flow through the ED with the use of various configuration parameters, such as resource availability, schedules of physicians, nurses, and equipment, resource consumption, and time requirements for each step.

Validation of the DES model has been carried out using historical EHR data, as elaborated in Section 6.3. Each arriving patient has been modelled as an agent in the simulation environment, with each agent carrying a record from the EHR dataset. The order of the agents' entry into the simulation model depends on the recorded arrival time in the EHR data. The route each agent went through the simulation model is based on the historical EHR record carried by the agent.

The simulation experiment employs the entirety of the NCKUH EHR data spanning from 2015 to 2019. In view of constraints pertaining to computer performance and the provision of the dataset as individual spreadsheets for each year, the simulation experiment has been carried out annually. This involved simulating system operations for one year at a time within the software. The simulation has been performed both with and without the incorporation of ML models. The simulation software has been configured to collect and record process data on a daily basis within the simulation environment. Since no significant variations have been identified across different years, this section presents the findings specifically for the year 2019, serving as a demonstrative example.

To assess the effectiveness of the proposed system design, the recorded data obtained from the simulation experiment was subjected to detailed analysis. The performance of the system design was evaluated based on two key parameters, namely the number of patients who underwent blood tests and the overall number of blood tests that were conducted during the process. Furthermore, a comparative analysis was performed to evaluate the performance of the system design with and without the incorporation of the ML models, which was aimed at assessing the efficacy of the CDSS framework.

To simulate the patient flow in conjunction with the ML-based CDSS, the predicted results of each blood test from the trained ML models were incorporated as additional input data alongside the EHR data. In the simulation of the patient flow with the integration of ML models, the decision to conduct a blood test was contingent upon the predicted result for each specific test.

Figure 6-8: Blood test process in AnyLogic

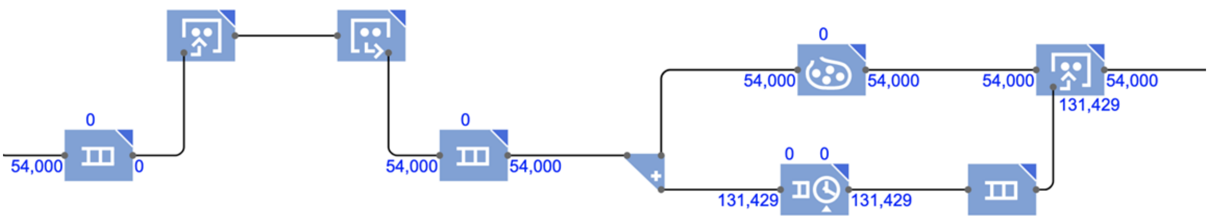
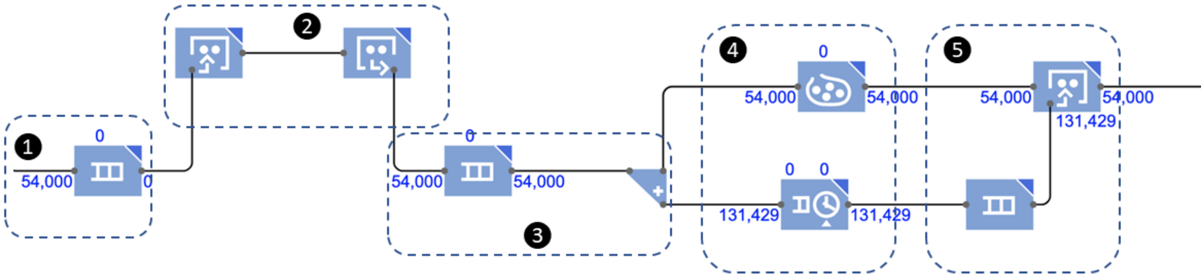


Figure 6-8 depicts the status of the nodes concerning blood tests at the end of 2019 within the simulation, without utilising the ML-based CDSS. As shown in Figure 6-9, the process of the blood test is simulated with the process modelling library blocks which can be classified into five stages.

Figure 6-9: Blood test process in AnyLogic



Stage 1 involves the collection of blood samples by nurses, which are subsequently held in anticipation of being dispatched to the laboratory. The data reveals that a total of 54,000 patients have undergone blood sample collection.

Stage 2 represents the periodic transportation of blood samples to the laboratory in batches, with a frequency of every half-hour.

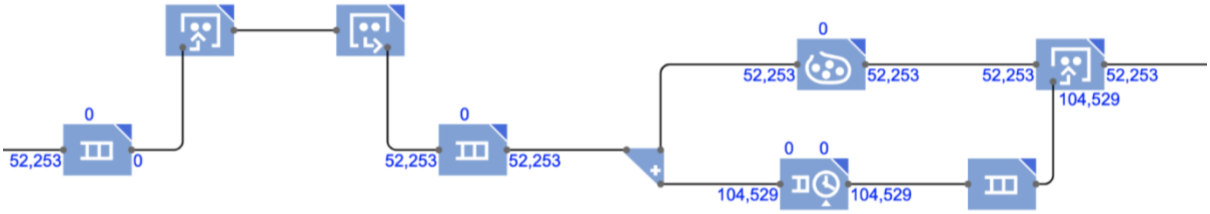
In stage 3, the system manages multiple blood tests conducted on a single patient as distinct tasks. Each laboratory test is treated as an independent task, and the allocation of resources is calculated in the subsequent stage.

Stage 4 portrays the duration patients have to wait to receive their laboratory test results while the blood tests are being conducted in the laboratory. The records indicate that the aforementioned 54,000 patients have undergone a total of 131,429 diagnostic tests.

Finally, in stage 5, patients are discharged to the subsequent process once all laboratory tests pertaining to a particular patient have been completed.

At the conclusion of the simulation, encompassing data for the entire year of 2019, a total of 16,362 patients had visited the ED. Of this cohort, 54,000 patients underwent blood tests, resulting in 131,429 laboratory tests being conducted. By incorporating the predicted outcomes from the trained ML models, the number of patients undergoing blood tests decreased to 52,253, with the total number of laboratory tests reducing to 104,529, using the same historical EHR data as input.

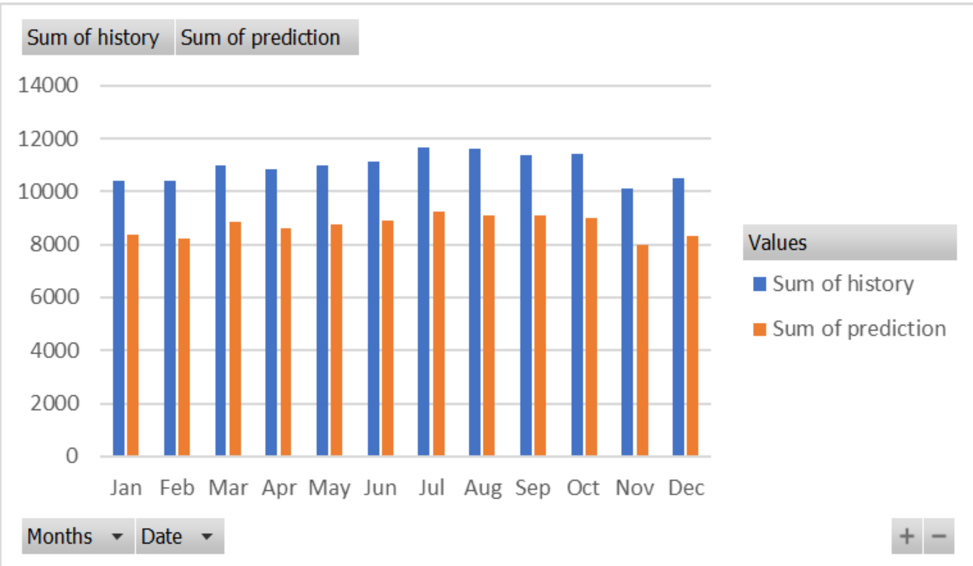
Figure 6-10 Blood test process in AnyLogic (With ML-based CDSS)



To comprehend the effectiveness of the ML-based CDSS in enhancing the operational efficiency of the process, the data for each day in the simulation environment was meticulously documented and compared. This comparison involved contrasting the historical data with the data generated by the simulation that was integrated with the ML models.

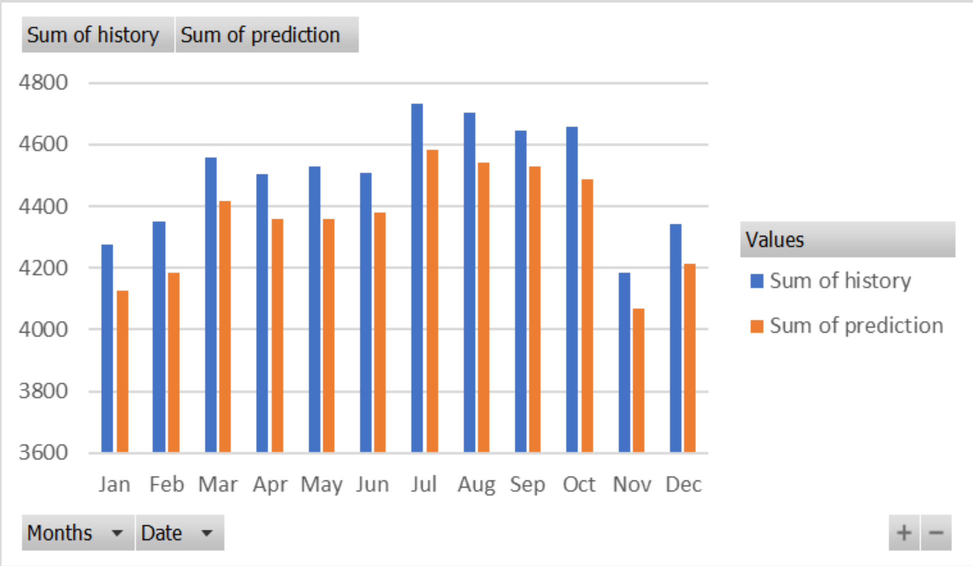
The data are grouped on a monthly basis and presented in the chart in Figure 6-11. It was observed that the utilisation of ML has enabled a reduction in the number of laboratory tests conducted. The findings also indicate a consistent level of effectiveness over time, highlighting the potential of ML models to manage new data effectively.

Figure 6-11: Total number of laboratory tests each month



The following chart in Figure 6-12 provides a comparison between the monthly number of patients who underwent blood tests in the simulation run utilising historical data and the simulation run utilising data predicted by ML models. It is notable that the decrease in the number of patients who underwent blood tests is comparatively less significant than the decrease observed in the total laboratory tests. This can be attributed to the fact that several patients may have undergone multiple laboratory tests, thereby inflating the count of patients receiving tests. Consequently, patients who have undergone fewer laboratory tests could also be included in the count of patients receiving tests, thus leading to an overestimation of the count.

Figure 6-12: Total number of patients who have blood tests each month



6.6 Summary

This chapter focuses on the development and evaluation activities of design science research. To answer the research question of how to enhance decision support in the ED setting with ML-based CDSS, ML models were trained with historical EHR data and evaluated with a DES model which implements the system design of an integrated architect for HIS incorporating ML to enhance CDS in an ED setting as described in Chapter 5.

The chapter begins by detailing the design of the DES model for the ED, including the identification of key resources and the definition of the simulation process. This sets the foundation for accurately modelling and simulating the patient flow processes in the ED.

Next, the simulation environment is developed, utilising data analytics techniques to analyse and prepare the EHR dataset. The simulation model is implemented using the AnyLogic simulation software, allowing for the representation of the ED's behaviour and dynamics.

The validation of the simulation model is performed by comparing the model-generated data with actual historical data. This process establishes a baseline performance and ensures the accuracy and reliability of the simulation model in capturing real-world ED operations.

In parallel, ML models are designed to enhance the decision-making process within the simulation environment. Data processing techniques are applied to prepare the dataset for ML model training.

DNN models are then designed and trained using the prepared dataset, enabling the ML models to provide valuable insights and suggestions for patient care.

The chapter concludes with the evaluation of the artefact CDSS framework within the simulation environment. The integration of ML models into the simulation allows for the assessment of the system design's performance, considering factors such as patient flow, waiting times, and resource utilisation. The CDSS framework acts as a valuable tool, leveraging the ML models' predictions to guide decision-making and optimise patient outcomes.

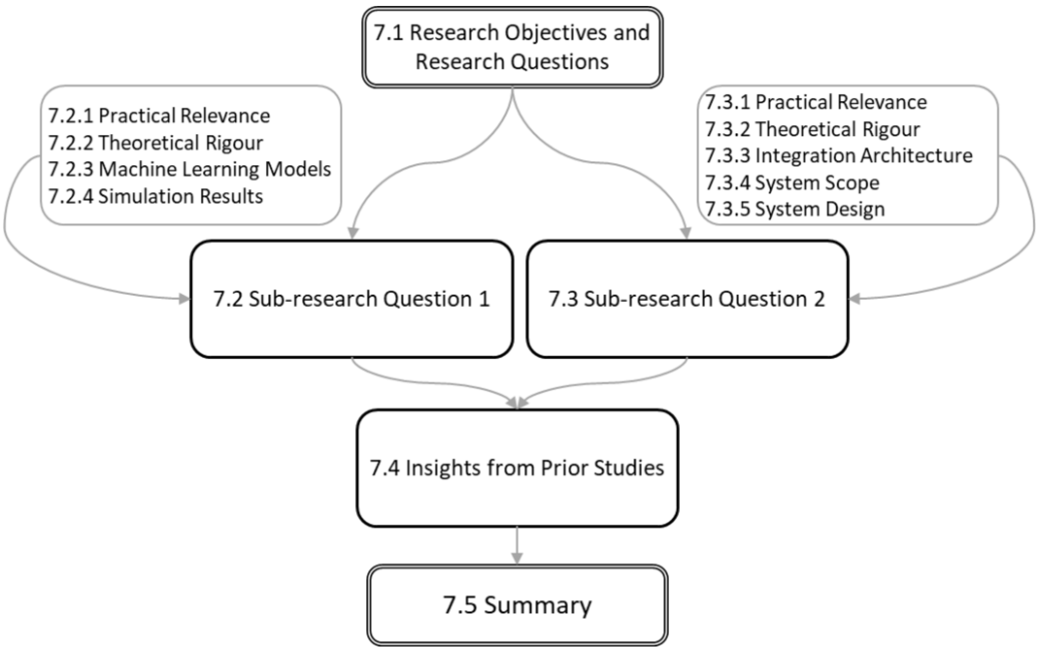
Overall, Chapter 6 presents a comprehensive approach to improving the performance of an ED through the combined use of DES modelling and ML techniques. The integration of these methodologies provides a powerful framework for understanding and optimising the complex dynamics of an ED, ultimately leading to improved patient care and operational efficiency.

Chapter 7 Discussion

This chapter provides an in-depth and comprehensive discussion of the results and insights derived from the system development and simulation activities detailed in previous chapters. These findings are intricately intertwined with the development of artefacts designed to address research questions and tackle challenges within the emergency department (ED) context. Moreover, this chapter elucidates the alignment of these findings with the theoretical foundations and addresses the identified knowledge gaps as discussed in the extensive literature review presented in Chapter 2.

Throughout the expanse of this chapter, a plethora of discoveries emerge from the research activities aimed at addressing the research questions. Each of these discoveries holds profound significance and offers prospective implications within the domains of healthcare and information systems. The research objectives have acted as a guiding compass for this study, enabling an in-depth exploration of how the integration of machine learning-based clinical decision support systems (ML-based CDSSs) can enhance decision support at the point of care within EDs. The practical relevance of this study, particularly in addressing the complexities and uncertainties inherent in clinical decision-making within EDs, becomes palpable as the subsequent findings unfold.

Figure 7-1: Results and findings



The core components of this chapter encompass the design of the system integration architecture, the implementation of ML-based CDSSs, the design science activities related to the research topic through a comparative analysis with prior studies, and the rigour applied by the theoretical framework.

To address the research questions, this chapter delves deeply into the design artefacts presented in two sub-designs, an ML-based CDSS and a system integration architecture. It meticulously scrutinises the scope, design, theoretical rigour, and practical significance of the system integration architecture. The findings reveal the potential for seamless integration of ML-based CDSSs into existing hospital information systems (HISs), thereby presenting a promising avenue for resource optimisation and enhanced patient care.

At the heart of the study, the ML-based CDSS unfolds a landscape where ML has the potential to revolutionise clinical decision-making within EDs. The findings emphasise a notable reduction in unnecessary diagnostic tests, coupled with a high degree of diagnostic accuracy. The outcomes of simulation experiments substantiate the potential for improved patient flow and operational efficiency, thereby validating the practical and theoretical implications of this work.

Subsequently, the discussion shifts to the insights drawn from both the design science research activities and a rigorous comparative analysis with existing studies. This includes findings related to the application of general systems theory and enterprise architecture in the context of the ED. Additionally, the knowledge of information system integration is discussed, considering the existing practices in HIS settings studied by this research for situational awareness. Concerning the ML-based CDSS, a comparison is made with prior works in ML and CDSSs, evaluating how they align with the findings and artefacts designed in this study.

7.1 Research Objectives and Research Questions

In the context of ED settings, the fusion of technology and data-driven decision support systems are assuming an increasingly pivotal role in elevating the quality of patient care and operational efficiency. Nevertheless, a notable knowledge gap persists, specifically concerning the effective integration of HISs to supply the requisite data for ML algorithms, thereby advancing clinical decision support (CDS). This section encapsulates the research objectives and inquiries underpinning this study, which endeavours to bridge this knowledge gap of utmost importance and pioneer advancements within the HIS domain.

The principal objective of this research is the conceptualisation of a system integration architecture aimed at amplifying CDS within a HIS, harnessed through the prism of ML, within the dynamic realm of an ED setting. The foundational premise of this research objective hinges on the acknowledgement that efficacious data-driven CDS possesses the potential to augment patient care, optimise the operations of the ED, and fine-tune resource allocation.

To effectively navigate this research objective, the study poses the following research questions:

Overarching Research Question:

"How to design an integrated architectural framework for hospital information systems to provide machine learning-based clinical decision support capabilities tailored to the exigencies of an emergency department setting?"

This core research query serves as the focal point, charting the course of the research endeavour towards the blueprint of an integrated architectural framework that squarely confronts the distinctive requisites and complexities inherent in a hospital ED.

Sub-research question 1:

"How to design a clinical decision support system imbued with machine learning capabilities?"

This auxiliary research query delves deep into the intricacies of devising a CDSS that capitalises on the potential of ML technology. It encompasses the development of ML-infused algorithms and decision-support functionalities intended to assist healthcare professionals operating within the ED.

Sub-research question 2:

“How can an integration architecture for hospital information systems be designed to accommodate the incorporation of machine learning-driven clinical decision support functionality?”

This subsidiary research question centres on the technical facets of system integration, probing the art of design and implementation of an integration architecture with the prowess to seamlessly incorporate ML-driven CDS capabilities within the broader HIS framework.

These research questions bear profound significance within the sphere of healthcare informatics. Effectively addressing them will not only contribute to the creation of an integrated architectural framework finely tuned to the distinct demands of an ED but will also offer insights into the broader challenges associated with integrating ML-based CDS within HISs. The outcomes of this research stand poised to empower healthcare establishments with innovative solutions aimed at elevating patient care and streamlining clinical decision-making processes within emergency care, with the potential for broader applications across diverse healthcare settings.

7.2 Sub-research Question 1

This section discusses the research activities and findings pertaining to sub-research question 1:

"How to design a clinical decision support system imbued with machine learning capabilities?"

Adhering to the principles outlined in design science research, this study has designed and developed an ML-based CDSS artefact, with the purpose of offering suggestions on designated clinical tasks to ED physicians at the point of care.

As elucidated by previous studies expounded in the literature review in Chapter 2 and substantiated through consultations with healthcare practitioners, as detailed in Chapter 4, the ML-driven CDSS artefact aspires to deliver actionable decision support within the ED environment.

The study into how an ML-based CDSS can effectively leverage electronic health record (EHR) data forms the foundation of the design artefact. The EHR dataset utilised is sourced from the HIS at an ED of a collaborating hospital. Although the ML models are constructed and trained using this specific dataset, the design principles and methodologies are designed to be adaptable to a wider ED context.

Collaboration with ED professionals who have provided the EHR data has delineated the scope of clinical tasks encompassed in this study. This delineation serves the purpose of assessing the effectiveness of the ML-based CDSS artefact in augmenting operational efficiency.

7.2.1 Practical Relevance

The design and implementation of ML models, along with simulation experiments, play a central role as the primary design and development activities in this study within the domain of design science research. The iterative and problem-centric nature of design science research is prominently applied throughout the process of artefact design.

The adoption of design science research methodology in this research ensures that the design of the ML model and the subsequent simulation experiment remain in harmony with practical problem-solving and innovation. Design science research underscores the creation of information technology artefacts to address real-world challenges (A. Hevner & S. Chatterjee, 2010b). In this context, the ML model serves as the information technology artefact, while the simulation experiment acts as the proving ground for its practical application. This approach aligns the research with the broader objective of enhancing healthcare operations and helps answer the research questions through innovative information technology solutions.

The utilisation of authentic data, including the ED environment setting and EHR data, plays a crucial role in ensuring the relevance of the design artefact to the intricate and multifaceted challenges encountered. The training of ML models and subsequent simulation experiments conducted as part of this research hold profound practical significance within the context of an ED. These endeavours harness ML techniques to enhance clinical decision-making and streamline resource utilisation within a hospital ED. This pragmatic application effectively addresses the pressing challenges confronted by ED physicians worldwide, by providing actionable decision support in the highly diverse and dynamic ED environment.

By developing an ML model tailored to the specific requirements of the ED, this study proposes and designs a CDSS. Furthermore, the simulation experiment yields actionable insights into the integration of ML models into ED settings, thereby extending the practical utility of the model. The simulation approach also emphasises the practical relevance of the DSR by providing an environment to evaluate the design artefact in a case where the problems and the motivation of this study lie.

7.2.2 Theoretical Rigour

This research integrates theoretical rigour by anchoring the study in General Systems Theory (GST) and enterprise architecture as the kernel theories. GST offers a comprehensive framework for comprehending complex systems, such as EDs, as interconnected entities (Bertalanffy, 1968). The application of GST to this research facilitates a holistic examination of the ED, considering not only its individual components but also the intricate interdependencies therein. This theoretical foundation substantially enhances the precision of the discrete event simulation (DES) model in capturing the intricate dynamics of patient flow, resource allocation, and system behaviour.

EA principles contribute further to the theoretical rigour by accentuating the alignment of organisational structures, processes, and technologies with strategic objectives (Gellweiler, 2022). The simulation experiment, guided by enterprise architecture principles, aids in evaluating the ED's alignment with overarching healthcare objectives. It enables the identification of the ML-based CDSS's potential to enhance operational efficiency within the ED setting.

The combination of theoretical rigour provided by GST and enterprise architecture, coupled with the practical orientation of design science research, establishes a well-balanced framework for addressing complex issues and enhancing decision support in the ED. It facilitates the development of not only technically robust ML models but also their effective implementation within the real-world context of the hospital's ED.

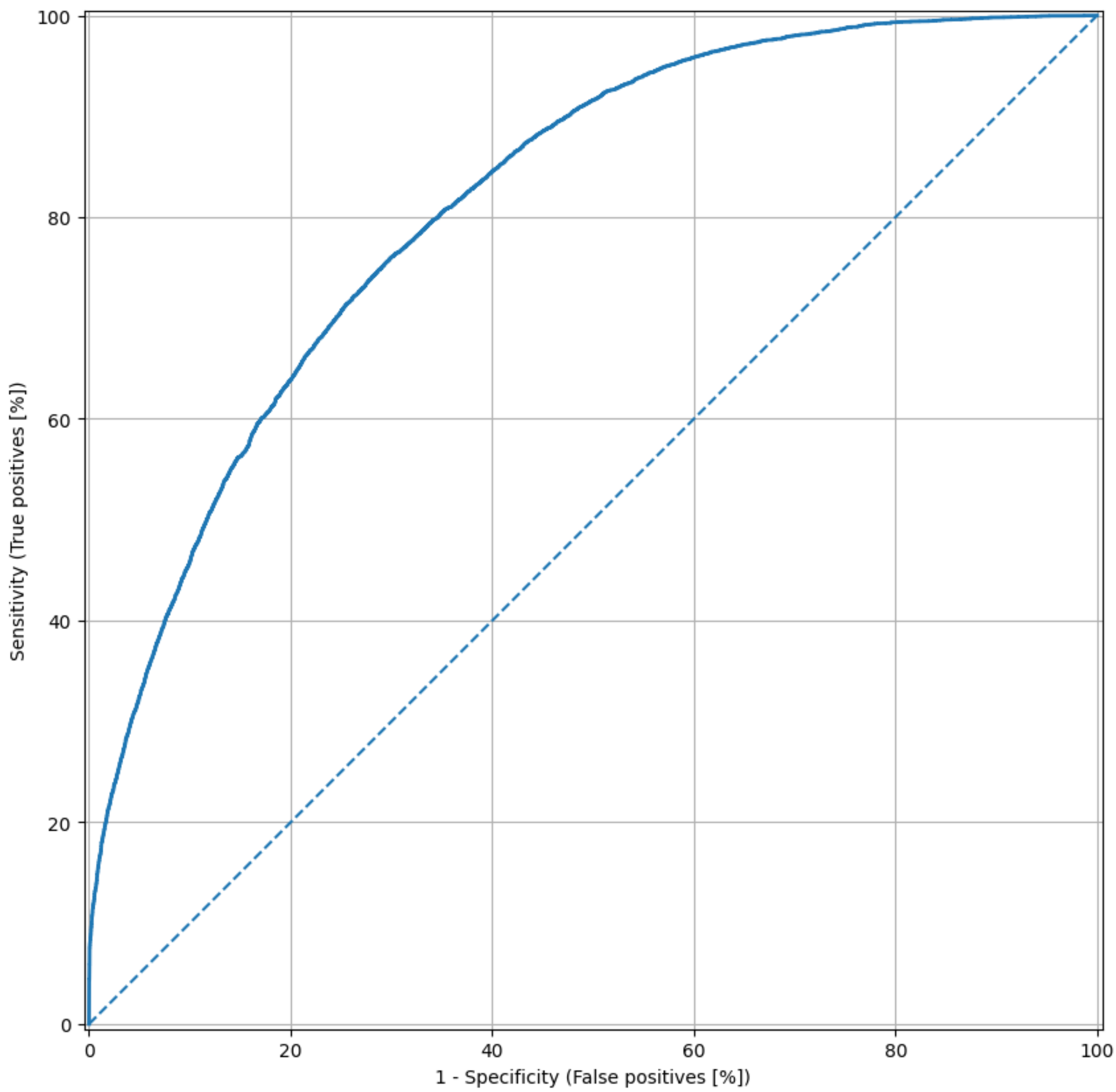
7.2.3 Machine Learning Models

ML models have been meticulously designed and developed to offer recommendations on whether specific diagnostic tests should be ordered by predicting their outcomes. This clinical suggestion approach has been influenced by feedback from ED professionals who expressed a need to assess the likelihood of, for example, a test yielding a positive result.

Consequently, the raw dataset has been segmented into sub-datasets, each containing a label column and selected feature columns relevant to specific clinical tasks associated with diagnostic tests. Early in the data preparation stage, it became apparent that certain data cleaning procedures were imperative for data preprocessing (Kamiri & Mariga, 2021). Anomalies such as outliers and non-numeric values in numeric fields, along with a substantial number of missing values attributed to patients who did not undergo tests during their visit, were addressed. Furthermore, data preprocessing techniques, as discussed in Chapter 5, were implemented to mitigate data distribution imbalances.

For the development, training, and testing of ML models, Google's TensorFlow, a well-established framework offering a high-level ML Application Programming Interface (API) widely embraced by both industry and research communities, is adopted in this study.

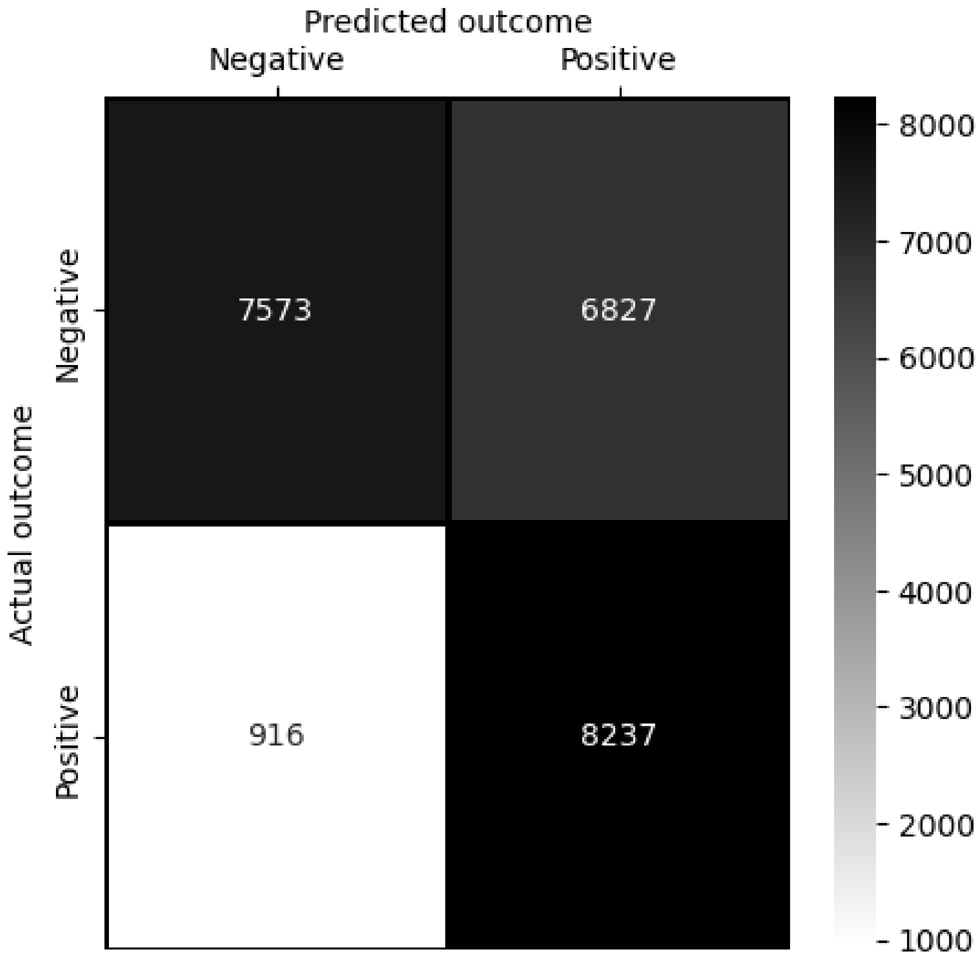
Figure 7-2: ROC curve for the DNN model for CR test



The performance of the trained Artificial Neural Network (ANN) model underwent rigorous evaluation, with ROC curve analysis employed to gauge its ability to discriminate between classes (K. Hajian-Tilaki, 2013). As illustrated by the ROC curve in Figure 7-2, the ML model has exhibited its potential to discern patterns within the dataset, classifying entities with positive results from those with negative results.

To provide further clarity, predictions of true positives, true negatives, false positives, and false negatives can be visualised through a confusion matrix, as depicted in Figure 7-3. Setting a threshold to maintain a true positive rate above 90% may potentially result in a substantial 52.6% reduction in unnecessary CR tests.

Figure 7-3: Confusion matrix with a selected threshold



To further assess the performance of ANN models for each specific test, results are presented in Table 7-1. As shown in the table, all ANN models are compared against a positive recall threshold of approximately 90%, signifying that around 90% of positive results can be accurately predicted. Model performance is additionally assessed through negative recall, indicating the percentage of negative results correctly predicted under the specified conditions. This holds the potential for a reduction in unnecessary ED tests. Remarkably, these models exhibit the ability to accurately predict approximately 90% of positive results while significantly reducing the number of unnecessary tests.

Table 7-1: Test Result for ANN Models

	Total records	Negative to Positive Ratio	Recall (Positive)	Recall (Negative)
Creatinine	23553	1600:1017	89.99%	52.59%
Total bilirubin	3859	2672:1187	89.97%	31.85%
Bilirubin in direct form	1059	202:857	90.43%	37.13%
Platelet count	24506	18523:5983	89.99%	26.96%
White blood cell count	25357	13750:11607	90.00%	23.27%
Neutrophil band count	5553	929:922	89.99%	28.24%
Neutrophil segmented	25075	14349:10726	90.00%	22.09%
Lactate	2430	704:511	90.12%	36.51%
Blood Culture	10623	9428:1195	89.96%	34.08%

7.2.4 Simulation Results

Simulation experiments were conducted to assess the efficacy of the ML-based CDSS in enhancing operational efficiency within the ED, as detailed in Chapter 6. A DES model was developed, drawing upon a generalised patient flow model synthesised from previous research and informed by consultations with professionals from two distinct hospital EDs. The DES model was thoughtfully adapted to mirror the nuanced workflows observed in the hospital ED that provides the EHR data. Iterations of this model were refined through feedback from the healthcare professionals within the hospital EDs. Furthermore, critical configuration parameters, including shift schedules and resource allocation, were judiciously sourced from the collaborating healthcare institution.

To implement the DES model and glean insights into the dynamics of patient flow within the hospital ED, the computational power has been harnessed with the simulation software, AnyLogic. To ensure fidelity to real-world scenarios, the DES model underwent rigorous validation against the aforementioned configuration parameters and patient visit data extracted from the EHR system. Notably, the simulation experiment commenced by running the DES model independently, thus establishing a baseline performance metric for the ED system devoid of ML-based CDSS intervention. This step served a dual purpose: it validated the correctness of the model and verified its accuracy.

Table 7-2 Total Count for Diagnostic Tests in 2019

	History	Suggested by CDSS
Creatinine	48896	31077
Total bilirubin	8425	6284
Bilirubin in direct form	2499	2020
Platelet count	50455	38911
White blood cell count	51706	43358

	History	Suggested by CDSS
Neutrophil band count	9084	7047
Neutrophil segmented	51291	42633
Lactate	6186	4482
Blood Culture	23988	16581
Grand Total	**252530**	**192393**

The ML models have been subsequently deployed on historical data to generate recommendations for diagnostic tests based on EHR information. As illustrated in Table 7-2, the ML models suggested a significantly reduced number of diagnostic tests compared to those traditionally administered. Consequently, the predictions produced by these ML models for individual patients are seamlessly integrated into the simulation environment, thereby replicating decision-making processes guided by the CDSS.

Table 7-3 Count of Blood Tests Conducted in 2019

	History	Suggested by CDSS
Jan	10412	8366
Feb	10404	8242
Mar	10989	8832
Apr	10831	8623
May	10974	8774
Jun	11135	8925
Jul	11649	9259
Aug	11605	9117
Sep	11385	9087
Oct	11423	9009
Nov	10120	7978
Dec	10502	8317
Grand Total	**131429**	**104529**

A comprehensive analysis of the simulation data demonstrated that CDSS recommendations effectively led to a reduction in the number of diagnostic tests required, along with a decrease in the necessity for blood tests, as summarised in Table 7-3 and Table 7-4. As previously reported in Chapter 6, it is noteworthy that some diagnostic tests coincided with the same blood tests, resulting in a lower count for blood tests compared to diagnostic tests. However, this reduction in both categories holds substantial significance, as diagnostic tests represent fee-charge items on medical bills, and blood tests are resource-intensive tasks, consuming human and facility resources. Notably, the number of patients queued for blood tests directly mirrors the throughput of patients within the ED.

Table 7-4: Count of Patients Undergoing Blood Tests in 2019

	History	Suggested by CDSS
Jan	4276	4127
Feb	4352	4185
Mar	4559	4417
Apr	4505	4359
May	4531	4360
Jun	4510	4381
Jul	4731	4583
Aug	4703	4541
Sep	4647	4529
Oct	4658	4488
Nov	4184	4069
Dec	4344	4214
Grand Total	**54000**	**52253**

7.3 Sub-research Question 2

This section discusses the research activities and findings to sub-research question 2:
"How can an integration architecture for hospital information systems be designed to accommodate the incorporation of machine learning-driven clinical decision support functionality?"

According to prior studies detailed in Chapter 2 and substantiated by consultations with healthcare professionals, as part of the situation awareness activities reported in Chapter 4, the issue of system integration is the major obstacle to building an ML-based CDSS. As discussed in the system development and simulation activities, the ML-based CDSS replies on local EHR data from the on-premises HISs to provide the recommendations. It won't work without access to essential EHR data.

This sub-research question endeavours to bridge the knowledge gap concerning the integration of HISs to facilitate the implementation of ML-based CDSS within the clinical environment, offering real-time, actionable clinical decision support to enhance efficiency within the ED.

7.3.1 Practical Relevance

The study underscores the intricate challenges involved in the integration of HISs to incorporate the ML-driven CDS functionality. This underscores the pragmatic hurdles faced by healthcare institutions when endeavouring to implement advanced technologies within their pre-existing systems.

Furthermore, the research underscores the paramount importance of enhancing clinical workflow efficiency, particularly within the ED. The proposed architecture aims to rationalise data accessibility, thereby diminishing the necessity for healthcare practitioners to navigate through multiple systems during the process of patient care. This bears profound implications for augmenting both the overall efficiency and quality of patient care.

Additionally, the study introduces the concept of Lambda architecture (Marz, 2011), originally derived from big data applications, as a viable solution for the effective management of EHR data. This concept offers pragmatic advantages for healthcare organisations seeking to proficiently manage both historical data for the training of ML models and real-time data for immediate patient support.

Considering these findings, the research suggests that healthcare institutions can capitalise on their pre-existing technological infrastructure. For instance, repurposing data warehouses for the storage of historical EHR data or implementing communication servers for real-time data exchange can significantly streamline integration endeavours while simultaneously building upon prior investments.

7.3.2 Theoretical Rigour

GST, functioning as a comprehensive framework, offers a holistic perspective through which the integration architecture is conceptualised and structured. It underscores the interconnectedness and interdependence of various components within a system. In the context of the HIS integration architecture, GST fosters a profound understanding of the hospital ecosystem. It acknowledges the intricate links between individual HISs, departments, and processes. This systemic outlook is reflected in the design artefact.

The artefact, influenced by GST, portrays the HIS as a unified entity rather than an assortment of disconnected subsystems. It highlights the imperative need for seamless communication and data exchange across diverse domains within the healthcare environment. By perceiving the HIS as a holistic entity, the design artefact underscores the significance of integration in attaining system-wide objectives, such as enhancing real-time CDS. GST's emphasis on feedback loops and dynamic interactions further guides the design process by facilitating continuous refinement and adaptation of the CDSS component in response to the evolving clinical landscape.

On the other hand, enterprise architecture introduces a structured methodology into the design process, aligning the integration architecture with the overarching goals and strategies of the ED. Enterprise architecture brings a systematic approach to designing, documenting, and managing the integration solution, which is distinctly evident in several aspects of the artefact.

Firstly, enterprise architecture’s focus on alignment with business objectives is clearly apparent, as the design artefact emphasises how the integration of CDSS supports the efficiency of patient care within the ED. The design is not perceived solely as a technical solution but as a strategic enabler of enhanced healthcare delivery.

Secondly, the layered approach advocated by enterprise architecture is mirrored in the artefact's categorisation into layers—process, application, and technology. This alignment with enterprise architecture’s emphasis on distinct architectural domains ensures that each facet of the system is meticulously designed with a well-defined purpose and functionality.

Lastly, enterprise architecture’s consideration of technology choices and their alignment with organisational objectives is evident in the artefact's exploration of Lambda architecture as a fitting solution. Enterprise architecture principles guide the selection of technology not only based on immediate needs but also with a view towards long-term scalability and adaptability.

7.3.3 Integration Architecture

The findings underscore the adoption of a systematic approach in developing an integration architecture for HISs. This approach incorporates fundamental principles from GST, enterprise architecture, and Lambda architecture.

GST played a pivotal role throughout the design process by aiding in the conceptualisation of the integration architecture as a holistic HIS. This comprehensive view addressed various facets, spanning from user experience and application functionality to data management. This broad perspective was instrumental in achieving a profound understanding of how the diverse components and subsystems within HISs should intricately interact to improve integration.

Enterprise architecture served as another critical component in the design approach. Through the application of enterprise architecture principles, the architecture was meticulously structured, not only with a focus on technical aspects but also with a keen eye on aligning HISs operating efficiency with clinical workflows. This alignment fostered a deeper comprehension of how CDSS could be integrated into the clinical processes within the ED, consequently streamlining patient care and enhancing decision-making processes.

Lambda architecture, originally designed to address the intricacies of big data, was skilfully adapted to tackle the data integration challenges inherent in HISs. It emerged as a proficient solution to reconcile the oftentimes conflicting demands of data availability and consistency. Lambda architecture allowed for the simultaneous processing of EHR data for the purpose of training ML models, while also accommodating real-time data processing to furnish current, patient-specific recommendations. This novel approach ensured that the ML-based CDSS had access to a rich repository of historical knowledge, complemented by real-time patient data, thereby fortifying its capabilities.

Overall, within the framework of design science research, the integration architecture was meticulously developed, harmonising principles from GST to perceive HISs as an integrated, cohesive system; enterprise architecture to align it with the intricate workflows of clinical environments; and Lambda architecture to effectively surmount data integration challenges. This multifaceted approach not only ensured the technical robustness of the design but also established functional synergy with the exigencies of the healthcare domain. Ultimately, this endeavour led to a marked enhancement in CDS and patient care delivery within the ED.

7.3.4 System Scope

The scope of this system is defined through an extensive literature review of the existing HIS landscape within hospital EDs, coupled with consultations involving physicians from a specific hospital ED and information technology professionals overseeing HISs in a district health board. It's noteworthy that these entities are situated in different, relatively well-developed regions within the Asia-Pacific area, each serving substantial patient populations. The HIS attributes, technologies, and challenges frequently documented in the literature are found to be consistent in both environments. For instance, the high degree of autonomy observed among sub-HISs, as illustrated in figures 4-3 and 4-7, is a commonality. Furthermore, both settings feature HISs provided by various vendors and owned by distinct entities. While most HISs are departmentally owned within the same hospital, such as clinical systems, pharmacy systems, and LIS, some are under government ownership, as exemplified by the RIS/PACS system in the case of Sun Yat-Sen Memorial Hospital (SYSH) and the NHI (National Health Identifier) system in the case of Health New Zealand Waikato (HNZW).

Upon scrutinising the system structure at HNZW, as depicted in Figure 4-7, it becomes apparent that major HIS integration approaches, including message-oriented integration, application-oriented integration, coordinated-oriented integration, and middleware-oriented integration, are all in use to a certain extent. However, these diverse integration methods often serve specific applications without comprehensively integrating the entire HIS ecosystem. Consequently, each existing integration implementation facilitates data exchange within isolated clusters, leading to persistent integration gaps among these clusters. Consequently, issues such as data duplication and data integrity persist at the data level.

7.3.5 System Design

The proposed system integration architecture design effectively addresses the sub-research question by employing the concepts of GST and enterprise architecture. It conceives the architecture as an all-encompassing HIS, detailing its various layers from the user, application, and data perspectives.

At the business process level, the primary concern revolves around how CDSS can be seamlessly integrated into the clinical workflow within the ED to enhance patient flow efficiency. As demonstrated in Figure 5-5, the proposed architecture enables CDSS to collect real-time data generated in stages preceding the intervention phase, where critical clinical decisions are made. Data generated during patient arrival, triage, and initial diagnosis may be recorded by different healthcare practitioners and entered into distinct systems with separate databases. This data, pertaining to the same patient, should be consolidated and readily available at the intervention phase, serving as input for decision support, thereby empowering ED physicians with informed decision-making support.

On the application front, the primary concern is defining how users interact with CDSS. This entails designing the two CDSS components: input and output. Given the highly dynamic nature of the ED environment, the major obstacle for users, as corroborated by literature and professional consultations, lies in the need to log in and navigate through various HISs during point-of-care interactions. Consequently, the design artefact should minimise the need for information retrieval from disparate interfaces. It should enable CDSS to automatically gather patient data, eliminating the manual search across various systems and data entry for CDSS input. Furthermore, in terms of output, CDSS should identify the current patient, triggering the inference engine to generate tailored suggestions based on the patient's data, all presented within the same interface where physicians enter clinical orders for tests or prescriptions.

At the technological layer, the foremost concern is how CDSS can access data generated within heterogeneous systems at different stages of patient flow. CDSS requires access to EHR data in two forms: historical EHR data in batches for training ML models and up-to-date data for real-time patient-specific suggestions. A solution known as Lambda architecture from the realm of big data applications is identified as a viable approach. Lambda architecture addresses the trade-off between data availability and consistency within databases, proposing the concurrent operation of two data-processing mechanisms: one handling large volumes of historical data and another processing real-time data in smaller batches, achieving synchronisation at a faster pace.

This approach can be effectively adapted to HIS integration, leveraging existing technologies within current HIS integration approaches. For instance, at HNZW, a data warehouse has already been established to integrate data from select systems for data analysis and reporting. This technology can be expanded to serve as a unified data repository for all historical EHR data originally dispersed across various systems, facilitating model training. For real-time data, an application-oriented integration approach, involving a communication server facilitating data exchange across HISs via message protocols such as HL7, is a viable option.

7.4 Insights from Prior Studies

This section discusses the findings from the design science research activities and comparison with prior studies.

7.4.1 Emergency Department

A System of Systems

The situation awareness activity detailed in Chapter 4 reveals that an ED constitutes a complex healthcare system amenable to effective analysis through the prism of GST. This theoretical framework perceives systems as intricate assemblies of interconnected and interdependent components collaboratively striving to achieve specific objectives (Bertalanffy, 1968; Katrakazas et al., 2020). Within the context of this study, which is centred on the integration of HISs and clinical processes in the ED, it becomes evident that the design of the current HISs and their functionality are influenced by the human factors associated with clinical processes (Garrity, 2001). This serves as a clear illustration of the premise of GST that elements within a system exert influence on each other through their interactions (Baskerville et al., 2014). Within the ED environment, these interactions between human users and HISs can even be likened to loosely coupled sub-systems.

Consider, for example, the triage system, which serves as the initial point of entry into the ED. It encompasses various components, such as healthcare practitioners responsible for assessing the arrival condition of patients, information systems for recording patient data, and the dynamic milieu of a fast-paced ED. Triage plays a pivotal role in establishing the framework for prioritising care based on the severity of patients' conditions. The pharmacy and lab systems assume a critical role in diagnostics and medication management, involving healthcare professionals like pharmacists and lab technicians, as well as information systems for tracking prescriptions and lab results. Meanwhile, the inpatient system is tasked with overseeing the care of patients necessitating hospitalisation. It relies on the interaction between healthcare practitioners, EHRs, and the dynamic ED environment to ensure seamless patient transitions and the continuity of care.

In a broader context, all these sub-systems within the ED are interconnected, functioning as integral components of a larger system (Lee, 2010). Consequently, when developing the information system artefact for the ED, it is imperative to take into account how users interact with the HIS at each node of the patient flow process and how data traverses the entire clinical workflow.

Ultimately, the activities associated with situation awareness underscore the applicability of the GST in information systems research within the healthcare domain, specifically in the setting of a hospital ED. This study effectively demonstrates how the end users, HISs, and the intricate relationships among these diverse elements within an ED setting can be comprehensively expounded upon through the lens of GST.

Enterprise Architecture of the ED

The system design and development activities detailed in Chapter 5 exemplify the integration of enterprise architecture within the domain of information system design research, particularly within the context of a hospital ED. Grounded in GST, which provides a holistic perspective on systems, encompassing entities and their interrelationships, enterprise architecture offers a strategic methodology for comprehending and managing the intricacies of an organisation (Henderson & Venkatraman, 1999). It facilitates alignment between business processes, information technology, and broader organisational objectives. Within the ED context, enterprise architecture plays a pivotal role in designing a system integration architecture conducive to the deployment of ML-based CDSS. This alignment is purposefully directed towards enhancing operational efficiency within the ED.

An essential facet of enterprise architecture in the ED is the seamless integration of existing HISs. In this study, the preliminary step is to gain a comprehensive understanding of the current HIS landscape. This encompasses the identification of existing HISs, the nature of data generated and stored within each system, the prevailing patterns of user interaction with clinical systems, and the methodologies employed for querying patient data across various systems. To acquire this in-depth knowledge, the researcher undertook field visits to hospitals, directly observing the HISs deployed within the ED.

The development of a data-driven, ML-based CDSS integrated into the clinical workflow necessitates a profound understanding of the prevailing workflow and clinical processes. This understanding is mandated by enterprise architecture's fundamental requirement to harmonise technology with the core business objectives. Within the context of this study, an intimate grasp of the clinical processes is of paramount significance. It dictates the specific points in the workflow where pertinent patient data is generated and becomes available as input for the CDSS. Furthermore, it delineates the stages at which the CDSS should be activated to generate recommendations.

This study leverages enterprise architecture as a guiding framework to scrutinise the current situation and formulate a blueprint for future system design within the context of enhancing the functionality of HISs in a hospital ED. This strategic approach aligns technology, operational processes, and resource allocation with the overarching mission of optimising operational efficiency and enhancing CDS. The result is a comprehensive framework for system design, encompassing modifications to processes, applications, and technology infrastructure.

7.4.2 HIS integration

When it comes to system integration, the examination of the present system landscape reveals that some integration approaches outlined in prior studies have been incorporated, such as peer-to-peer message exchange and data warehousing.

Messaging Exchange: Peer-to-Peer and Via a Mediator

A cornerstone of system integration within an EHR context is the utilisation of messaging exchange (Kuhn & Giuse, 2001). This method facilitates the fundamental sharing of data across various systems (Gulledge, 2006). Messaging exchange transpires through either peer-to-peer connections or mediation.

Peer-to-peer messaging exchange entails direct communication between systems, enabling the sharing of essential EHR data across HISs. For instance, within the scenario of HNZW, the NHI and associated demographic data, encompassing name, gender, and age, can traverse different systems. This method primarily finds utility in external inter-organisational integration, such as when patient data from the NHI system interconnects with the local patient management system.

Conversely, employing a mediator serves as a conduit for data exchange among systems that may not inherently harmonise. Acting as a bridge, it translates and relays information between disparate systems. This approach also features prominently within the HNZW system architecture for facilitating communication among specific systems owned by the same organisation.

Data Warehousing

An alternative approach to system integration within the EHR domain revolves around the deployment of a data warehouse (Gulledge, 2006; Kuhn & Giuse, 2001). This strategy involves the replication of data from various systems into a centralised repository. By consolidating data in this manner, it becomes more readily accessible and can be leveraged for a multitude of purposes, including analytical endeavours, reporting, and decision support.

In the context of HNZW, this technology is also operational, as the database contents of the clinical system and patient management systems have been duplicated to construct a data warehouse. This data repository serves the critical purpose of enabling data analysis and reporting functions within HNZW, thereby facilitating data analysis tasks within a dedicated database, without impacting the operational systems in the clinical environment.

Achieving Comprehensive Clinical Process Integration

While messaging exchange and data warehousing constitute valuable integration methods, realising full integration of clinical processes within the EHR environment remains an intricate challenge. Several factors are found to contribute to the complexity of this endeavour:

Heterogeneity of Systems: EDs often encompass a plethora of legacy systems, each characterised by its unique architecture and data formats. The comprehensive integration of these systems presents a formidable task.

Vendor-Specific Solutions: Numerous healthcare information technology vendors offer proprietary solutions that may not readily interoperate with solutions from other providers. This proprietary vendor lock-in can impede interoperability initiatives.

Limited Standardisation: Despite the existence of industry standards like HL7 and FHIR (Fast Healthcare Interoperability Resources) for healthcare data exchange, universal adoption remains elusive, leading to complications in data consistency and formatting.

Previous studies in the domain of information system integration underscore the significance of this practice and provide comparative analyses of major system integration approaches. These studies posit that, owing to the merits and demerits of various approaches, it is commonplace to employ multiple system integration approaches for diverse purposes within the same organisation (Lynne Markus, 2001). This is indeed the approach observed within the HIS of situational awareness in this study.

In addition to the two approaches identified in the healthcare cases analysed in this study, other integration approaches not present in the system scope of these cases, such as application-oriented, coordinated-oriented, and middleware-oriented integration approaches, have their limitations and challenges in addressing the aforementioned complexity factors (Gulledge, 2006; Kuhn & Giuse, 2001; Sabooniha et al., 2012).

In response to the limitations of traditional HIS integration approaches, this study has designed a novel system integration architecture. This design draws inspiration from the dual data processing mechanism inherent in the Lambda architecture, a data processing paradigm tailored for big data applications and distributed databases.

This novel architecture advocates a hybrid integration approach that amalgamates two well-established integration methods to surmount the respective shortcomings of each. It aims to support an ML-based CDSS. Specifically, the proposed architecture advocates the expansion of the existing mediator-based message-oriented integration and data warehousing approach to enable the comprehensive integration of EHR data in real-time and batch processing modes.

7.4.3 Machine Learning with EHR Data

EHR data have emerged as an extensive repository of patient information, with ML technology leading the effort to extract insightful recommendations from this wealth of data (Qiao et al., 2018; Rajkomar et al., 2018; Shickel et al., 2018; Wu et al., 2010). This research endeavour presents a design artefact that scrutinises the viability of ML technology's integration within CDSS, specifically focusing on delivering actionable recommendations, notably concerning the prescription of essential medical tests. The paramount importance of this study arises from its deviation from conventional CDSS models, as it seamlessly incorporates ML technology to pioneer a data-driven approach aimed at providing adaptable and informative decision support within the dynamic and multifaceted environment of an ED.

The incorporation of ML technology within CDSS to generate actionable recommendations represents a novel and promising paradigm. Although CDSS has been under development along with the HISs for some time, prior iterations predominantly relied on rule-based algorithms (Greenes, 2011; Moore & Loper, 2011). These systems excelled in providing guidance grounded in pre-defined rules but faltered in their ability to adapt and evolve alongside the ever-expanding intricacies of medical data. This is where ML technology shines. ML algorithms possess the capacity to scrutinise vast datasets, derive insights, and evolve over time. This transformative capability empowers ML-driven CDSS to personalise recommendations based on evolving patient data—a feature conspicuously absent in rule-based systems (Sutton et al., 2020).

A salient aspect of this study is the application of ML technology in crafting recommendations for medical tests. Prior research has explored CDSS in diverse capacities, offering decision support for clinicians in domains such as medication prescription, disease diagnosis, and treatment planning (Bright et al., 2012; Fernandes et al., 2020; Horng et al., 2017). Nevertheless, the focused approach on recommending medical tests stands as a pioneering endeavour. This departure from conventional CDSS domains ushers in new prospects for refining the diagnostic process and optimising resource allocation within healthcare facilities.

Traditionally, the majority of ML technologies within the healthcare sector have concentrated on diagnostic applications (Graber & VanScoy, 2003; Kawamoto et al., 2005). Algorithms have been devised to assist in interpreting medical images, early disease detection, and prognostic assessments. While these applications undeniably hold substantial value, the potential of ML in the ED remains underutilised in the context of CDSSs for generating actionable recommendations. This study lays the foundation for extending the scope of ML-based CDSSs to proffer practical and evidence-based suggestions regarding the necessity of medical tests.

The study employs ML algorithms to meticulously scrutinise EHR data, uncovering intricate patterns and trends that might elude human observation. By analysing extensive datasets, the system can comprehensively evaluate patient histories, symptoms, and other pertinent data points, enabling it to provide well-informed recommendations concerning the requirement for specific medical tests. In doing so, physicians in the ED receive invaluable support when making crucial clinical decisions at the point of care.

Within this study, a design artefact has been meticulously crafted to facilitate the integration of ML technology into CDSSs, specifically aimed at generating actionable recommendations, with a particular focus on medical test recommendations. This signifies a notable enhancement in operational and cost efficiency by curtailing unnecessary tests.

7.5 Summary

In this chapter, a thorough examination of the research findings is presented. The research has been purposefully aligned with well-defined objectives, with a central focus on augmenting decision support within hospital EDs. It takes into account the intricacies and uncertainties routinely faced by healthcare practitioners in this demanding clinical setting. The practical implications of this research are substantial, ranging from the reduction of unnecessary diagnostic tests to the optimisation of operational efficiencies.

An ML-based CDSS has been designed and developed to provide recommendations for clinical tasks to ED physicians at the point of care. The initial test results underscore the potential of ML models in enhancing operational and cost efficiency within the ED, primarily through the reduction of superfluous diagnostic tests. A simulation model has been built to demostrate how the ML-based CDSS can be integrated into the clinical workflow within the ED. The validity of this simulation model has been established and confirmed through implementation with specialised simulation software. The effectiveness of this design artefact, the ML-based CDSS, is further assessed through simulation experiments employing actual ED data. The results unequivocally indicate the positive impact of the design artefact, the ML-based CDSS, on patient flow within the ED, manifesting in reduced resource consumption and improved patient throughput.

To address the existing challenge of HIS integration hindering the implementation of the ML-based CDSS within the ED, a novel system integration architecture has been designed. This integration architecture introduces a hybrid approach, combining both batch data processing and real-time data processing technologies to facilitate the integration of HISs, thus meeting the requisites for incorporating ML technology within the HIS landscape.

The research outcomes herald a transformative shift towards data-driven decision support, underscoring the potential of ML technology within the context of EDs. The application of the ML-based CDSS has yielded remarkable reductions in unnecessary diagnostic tests while maintaining diagnostic accuracy at a consistently high standard. Furthermore, through meticulously executed simulation experiments, the discernible improvements in patient flow and heightened operational efficiency attributable to the CDSS are evident, promising an elevated standard of patient care.

Chapter 8 Conclusion

In the pursuit of enhancing clinical decision-making through the application of machine learning (ML) within the emergency department (ED) setting, this thesis embarked on a comprehensive journey that spanned across the domains of literature review, research methodology, system development, and system simulation. The overarching objective of this research was to address a critical challenge in the healthcare sector—the deficiency of system integration within hospital information systems (HISs) and the pressing need for ML-based clinical decision support systems (CDSS) in the ED.

The journey commenced in Chapter 2, where an extensive review of existing knowledge was conducted, meticulously crafting a theoretical framework while identifying a notable knowledge gap. This phase laid the groundwork for the subsequent chapters, setting the stage for an insightful investigation.

Chapter 3 introduced the research methodology, embracing the principles of design science research to construct a solution to the identified problem. As the journey progressed, the focus shifted to the core of the issue, as elucidated in Chapter 4, revealing the stark reality of insufficient system integration within HISs and the urgent need for ML-based CDSSs in the high-pressure environment of the ED. This chapter shed light on the crucial role of actionable decision support for physicians, an integral aspect of modern healthcare.

Chapter 5 marked a pivotal juncture, where a strategic framework for system integration architecture was proposed, and the development of ML models commenced. These models were trained with electronic health record (EHR) data to explore the feasibility of ML-based CDSSs. The foray into system development laid the foundation for innovation, a cornerstone of healthcare evolution.

In Chapter 6, the focus shifted to the evaluation of the ML-based CDSS in a simulated ED environment, allowing for the assessment of its performance in real-world scenarios. Patient flow and clinical processes were scrutinised, and the results were instrumental in understanding the efficacy of the solution.

Chapter 7 presented the crucial discussion and validation of the key findings of the journey. The results obtained from the simulation provided robust support for the design artefact, addressing fundamental research questions, and reinforcing the importance of the work. This chapter also offered reflections on the literature.

In this final chapter, Chapter 8, the journey draws to a close as the contributions of this study are summarised. The broader implications for both research and practical application are explored, while acknowledging the limitations encountered during this research endeavour. This chapter also lays the groundwork for future researchers in this continuously evolving field.

8.1 Research Implications

8.1.1 Solving the Business Issues with Design Artefacts

This study addresses the knowledge gap concerning the design of a system integration architecture that collaboratively employs ML-based CDSSs to enhance decision support at the point of care for physicians, ultimately aiming to improve operating efficiency in the ED setting.

Clinical Decision Support in the Emergency Department

Extensive research and consultations with healthcare practitioners in the ED have highlighted the substantial challenges faced by physicians when making clinical decisions in an environment marked by uncertainty and diversity. These dedicated healthcare professionals must prudently allocate available resources, including diagnostic tests, to ensure accurate diagnoses and the stability of patients in the ED. They are also tasked with adhering to the requirements of public funding agencies, often entailing the reduction of unnecessary tests and admissions to enhance cost efficiency. Consequently, ED physicians grapple with pivotal clinical decisions, including the necessity of specific diagnostic tests and the appropriate duration of patient observation before discharge.

This study illustrates how these multifaceted challenges can be effectively mitigated through data-driven decision-making employing ML technology. By harnessing the potential of ML and leveraging existing EHR data, a non-knowledge-based CDSS has been conceived to offer decision support within the ED. Throughout this research endeavour, ML models were rigorously trained and applied to historical data, shedding light on the significant enhancements in both operational efficiency and cost-effectiveness achievable with an ML-based CDSS. Notably, the CDSS recommends a notable reduction in diagnostic tests while maintaining a commendable level of accuracy in identifying patients who genuinely require such assessments.

Moreover, the incorporation of the ML model, combined with a simulation experiment, has profound implications for enhancing patient flow within the ED through a data-driven approach. The simulation experiment results validate the decrease in resource consumption following the integration of the ML-based CDSS into the clinical workflow. In practical terms, this improvement can translate into improved patient throughput within the existing resource and capacity confines of the ED setting.

System Integration Architecture for Hospital Information Systems

Another pressing practical challenge is the issue of system integration, leading to fragmented data. This fragmentation results in EHR data being dispersed across various independent sub-systems within the HIS, which poses a significant technical obstacle to the implementation of ML-based CDSS.

The issue of system integration generates data silos, rendering it difficult to access and harness the full potential of the accumulated patient information. The integration of diverse data sources within the HIS can create a holistic perspective of medical data for a patient, enabling the CDSS to provide more precise and comprehensive clinical decision recommendations. System integration effectively transforms disparate data into a coherent, centralised repository, enabling accurate data-driven decision support for ED physicians.

To address this challenge, this study proposes a system integration architecture, adapted from the Lambda architecture, designed to bolster the ML-based CDSS by offering data processing capabilities for both historical dataset and real-time data queries. This architecture serves as a repository for historical EHR data, utilised for training ML models, while simultaneously delivering real-time data streams to collect medical information for individual patients, thus serving as input for the CDSS at the point of care.

The integration of this architecture not only resolves data fragmentation but also guarantees a continuous and comprehensive data flow. This integrated system promotes a seamless exchange of data between various healthcare processes, enabling healthcare professionals to access vital patient data rapidly and efficiently. This is particularly invaluable for ML-based CDSS, as it empowers the system to access up-to-the-minute patient information, enabling recommendations based on the most current data available. Improved data integration enhances system agility and responsiveness, enabling physicians to make well-informed decisions promptly at the point of care.

In summary, this study holds numerous practical implications. These implications encompass the advancement of operational efficiency within the ED by implementing ML-based CDSS, with a potential for improvements in patient flow. By addressing the complex issues associated with system integration challenges within HISs, this research not only contributes to the promotion of data-driven decision-making in healthcare but also underscores the critical role of information system integration within healthcare settings.

8.1.2 Information System Design Theory in the Context of Healthcare

Design science research in information systems operates at the dynamic crossroads of theory and practical application, with the primary objective of conceiving, executing, and assessing innovative information technology solutions aimed at resolving real-world issues. This comprehensive research, which orchestrates ML-based CDSS within the ED environment, introduces substantial theoretical implications, particularly in its advocacy for the assimilation of Information System Design Theory (ISDT) in the realm of healthcare.

The theoretical implications within the realm of design science research are rooted in the scholarly exploration of ISDT and its pragmatic utilisation in healthcare. The design of healthcare information systems has habitually relied on conventional information system design theories and methodologies, which do not inherently cater to the distinctive demands of healthcare settings and the singular attributes of HIS. The embracement of ISDT as a foundational principle constitutes a pivotal theoretical development, ushering in a systematic and theory-driven approach to the design of information systems.

By firmly grounding this study in ISDT, the research underscores the imperative of structuring HIS predicated on a holistic view of General Systems Theory (GST). This theoretical foundation highlights that healthcare information technology constructs should not be conceived in isolation but should instead be integral to a broader design philosophy that prioritises elements such as usability, efficacy, and efficiency. This paradigm shift lays the theoretical groundwork necessary for achieving the practical objectives of this research.

GST, in particular, introduces an all-encompassing framework for comprehending the intricate healthcare context of the ED as interconnected systems. It accentuates the intrinsic interdependencies between various components within the healthcare ecosystem, spanning from patient care procedures to the integration of HISs. The associated theoretical implication suggests that the architectural design of HIS integration should harmonise with these systemic principles, factoring in not only individual components but also their holistic interplay.

Enterprise architecture, an integral component of the overarching theoretical framework, underscores the significance of aligning processes and technologies within hospital EDs with their overarching strategic objectives. This theoretical underpinning is indispensable in assuring that the integration of ML-based CDSSs augments, rather than disrupts, the strategic aims of a hospital ED. It accentuates the necessity of integrating technological solutions that concretely contribute to the broader mission of enhancing patient care and operational efficiency.

8.2 Limitations

8.2.1 Data Limitations

The dataset employed in this study, while a valuable resource for research, is not without its inherent limitations. It is imperative to acknowledge that the dataset comprises EHR data shared by the collaborating hospital, collected from selected components of their HIS. However, it is important to note that this data represents only a subset of the HISs utilised within the hospital. This limited scope may not encompass the entirety of clinical processes, leading to inevitable data gaps. Consequently, the study's findings are constrained by these data limitations, potentially impacting the comprehensiveness of the design artefacts.

Furthermore, the absence of certain data elements, such as diagnostic images, specific interventions, and admissions, presents challenges. Some clinical decisions were excluded from the dataset due to the unavailability of relevant data or the absence of outcomes associated with particular medical activities. For example, while records indicate that physicians conducted procedures such as X-rays, CT scans, or ECGs, the results of these tests were often absent. This incomplete data limits the breadth and depth of the ML-based CDSS, affecting its capacity to offer comprehensive decision support.

8.2.2 Machine Learning Model

The ML models employed in this study, though effective in their application, do possess certain limitations. It is essential to underscore that these ML models were constructed using standard algorithms provided by the ML frameworks and libraries employed in this research. The choice of relatively standard algorithms was influenced, in part, by the computational resources available, which constrained the complexity of the ML models.

While the primary objective of this study was not to advance ML algorithms for CDSS applications, it is crucial to note that the performance of the ML models and the ML-based CDSS developed in this research may not be fully optimised. The limitations resulting from the simplicity of the neural network architectures used in the study can impact the ability of the design artefact to harness the full potential of ML for CDS.

8.2.3 Scope of Clinical Decisions

The scope of clinical decisions addressed by the ML-based CDSS in this study is another substantial limitation. Notably, certain critical clinical decisions, including those related to diagnostic images, interventions, and admissions, were not incorporated into the decision support system. This limitation primarily stems from the data constraints in the dataset and the absence of comprehensive records.

The lack of detailed data, such as diagnostic test outcomes or admission criteria, restricted the ability of ML models to provide decision support for these specific aspects of patient care. While the system could recommend tests based on existing data, it lacked the capacity to make informed decisions about the necessity of diagnostic images or specific interventions, which are integral elements of clinical practice. This limitation underscores the need for more comprehensive data collection and the development of algorithms capable of addressing a broader spectrum of clinical decisions.

8.2.4 Simulation Limitations

The simulation conducted in this study, while valuable for assessing the impact of the CDSS, has certain limitations that warrant acknowledgement. Notably, the simulation does not encompass an evaluation of how the artefact affects the length of patient stays in the ED. This omission is significant, as patient length of stay is a crucial performance indicator for ED efficiency and patient outcomes.

The limitation in assessing length of stay arises from data constraints within the dataset. The dataset lacks sufficient information to determine the time taken by each clinical event or the timestamps associated with each activity. Consequently, the time intervals applied to event nodes within the simulation may not wholly mirror the realities of the collaborating ED. As a result, the simulation experiments may not fully capture the potential impact of the design artefact on patient flow and ED efficiency.

8.2.5 Evaluation Limitations

The evaluation of the CDSS design artefact is a pivotal aspect of this study. However, it is essential to acknowledge that the evaluation has certain limitations. While the design artefact underwent iterative development and received feedback from professionals within the ED and information technology teams, the evaluation primarily transpired within a simulated environment.

While simulation is an acceptable evaluation method for design science research, the primary limitation of this evaluation approach is that it may not wholly reflect the performance of the design artefact in a real-world clinical setting. Simulations provide controlled environments, but real-world healthcare systems are intricate and subject to a multitude of dynamic factors. The outcomes may differ when implemented in actual clinical practice, influenced by variables that were challenging to replicate in the simulation. Consequently, the impact on patient care and ED operations may only be fully realised once it is deployed and operational in the clinical environment.

8.3 Future Work

8.3.1 Data Expansion

EHR data from more HISs

To enhance the breadth and depth of available medical data, forthcoming research endeavours should prioritise the inclusion of EHR data from a wider array of HISs. Expanding the dataset to encompass data from a myriad of HISs will provide an enriched source of information for ML-based CDSS. This could involve collaborative efforts with multiple healthcare facilities to acquire a diverse dataset, thereby establishing a more comprehensive repository for training ML models.

Result data for clinical tasks

The incorporation of clinical task outcomes into the dataset can profoundly enrich the capabilities of the CDSS. Future work should aim to compile comprehensive data, including the results of clinical procedures, diagnostic imagery, and medical interventions. The integration of such data would enable the training of ML models to support a broader spectrum of clinical decision-making. This expansion has the potential to transform the CDSS into a tool that offers guidance on diagnostic processes, medical interventions, and patient admissions, thus enhancing its value for healthcare practitioners.

Time data for accurate simulation

The gathering of time-related data linked to clinical activities is of paramount importance for accurately simulating the Length of Stay (LoS) within the experimental environment. Future research can concentrate on accumulating time-related information, such as timestamps for patient care events. This additional data will enable simulations to more faithfully replicate real-world clinical scenarios, leading to more precise assessments of the CDSS's impact on ED operations and patient flow.

8.3.2 Machine Learning Technologies

Exploration of diverse ML technologies

Subsequent research should involve the exploration of a broader spectrum of ML technologies and algorithms, with a focus on evaluating their comparative performance. This approach will offer insights into the effectiveness of different ML techniques for specific clinical tasks. Through comparative studies, researchers can ascertain the optimal ML algorithms for a variety of decision-support applications, thereby refining the CDSS.

Clinical task-specific ML algorithms

Tailoring ML models to suit specific clinical tasks represents an exciting avenue for research. Future studies can centre on the development of task-specific ML models that excel in providing decision support for particular medical procedures or diagnoses. Customised ML algorithms designed to assist with diagnostic imaging or medical interventions should be explored, maximising the CDSS's potential to enhance clinical decision-making.

8.3.3 Technical Validation

Integration with HISs

A pivotal step in future research lies in the practical validation of the system integration architecture with HIS components. This process ensures the viability of the design artefact within real clinical settings. Collaboration with healthcare facilities to implement the system integration architecture within a technology environment which duplicates a HIS setting is essential to assess its functionality, compatibility, and impact on HIS design.

Involvement of healthcare practitioners

Rigorous testing user interface of the CDSS and usability by healthcare practitioners is imperative. Engaging physicians, nurses, and other medical professionals in the validation process can yield invaluable insights into the alignment of the system with their clinical needs and workflow. Their feedback can lead to refinements that enhance the user-friendliness and effectiveness factors of the system design.

8.3.4 Integration Testing

Real-world testing with new patient visits

The next phase of research should encompass extensive integration testing by deploying the ML-based CDSS within the ED setting during new patient visits. This testing should evaluate the performance of the system in real clinical scenarios, including the decision-making processes of individual physicians, those utilising the CDSS, and combinations thereof. The evaluation should assess the impact of the CDSS on clinical outcomes, resource utilisation, and patient throughput. This real-world testing allows for a comprehensive analysis of the efficiency of the CDSS and its potential to optimise patient care in various clinical settings.

Performance comparison

Future research can delve into a thorough performance comparison to measure the efficiency of the CDSS and the quality of care it provides. Researchers should assess how the system influences clinical decision-making, patient outcomes, and ED workflow. By comparing the performance of various decision-making approaches, such as a physician working independently, the CDSS operating autonomously, and a combination of both, a comprehensive evaluation can be conducted to determine the effectiveness of the CDSS and its role within the ED. This approach elucidates the benefits of integrating ML-based decision support into healthcare practices.

8.4 Overall Conclusion

This study underscores the imperative for augmenting clinical decision support (CDS) within the context of an ED. It has been revealed that the proliferation of HISs and the vast reservoir of EHR data maintained by hospitals necessitate a dedicated exploration of ML technology as a potential remedy for addressing the specific needs of ED environments.

An investigation has revealed that the primary hurdles hampering the implementation of ML-based CDSSs with EHR data primarily revolve around integration issues among various HISs. This study is centred on the enhancement of operational efficiency within a hospital's ED through the empowerment of CDS for ED physicians.

From the perspective of information systems, with a distinct focus on the utilisation of artefacts within human-machine systems and the emergence of unique phenomena resulting from the interaction between technological and social systems, this investigation comprehensively addresses both the technical challenges inherent in the deployment of ML-based CDSS in an ED and the potential enhancements in the existing clinical workflows facilitated by the adoption of novel technology.

Following the design science research methodology, multiple design artefacts have been crafted, constructed, and subsequently evaluated, as detailed in this thesis. These ML-based CDSS artefacts serve as compelling demonstrations of how ML technology can provide actionable CDS by harnessing the rich data contained within EHRs.

The outcomes of simulation experiments presented in this study illustrate how ML-based CDSS can significantly enhance the efficiency of clinical processes and subsequently optimise patient flow within the ED. To facilitate the practical implementation of this solution, a comprehensive system integration architecture design has been proposed. This design offers a strategic framework for effecting changes at multiple levels, encompassing processes, applications, and technological infrastructure, outlining a clear path towards achieving the outlined objectives.

References

Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G. S., Davis, A., Dean, J., Devin, M., Ghemawat, S., Goodfellow, I., Harp, A., Irving, G., Isard, M., Jia, Y., Jozefowicz, R., Kaiser, L., Kudlur, M., . . . Zheng, X. (2015). *Tensorflow: Large-scale machine learning on heterogeneous systems*. https://www.tensorflow.org/

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon*, *4*(11).

Aggarwal, C. C. (2018). *Neural networks and deep learning*. Springer Cham. https://doi.org/10.1007/978-3-319-94463-0

Alanazi, A., Al Rabiah, F., Gadi, H., Househ, M., & Al Dosari, B. (2018). Factors influencing pharmacists' intentions to use pharmacy information systems. *Informatics in Medicine Unlocked*, *11*, 1-8.

Alghamdi, M., Al-Mallah, M., Keteyian, S., Brawner, C., Ehrman, J., & Sakr, S. (2017). Predicting diabetes mellitus using smote and ensemble machine learning approach: The henry ford exercise testing (fit) project. *PLoS One*, *12*(7), e0179805.

Alvarez, C., Rojas, E., Arias, M., Munoz-Gama, J., Sepulveda, M., Herskovic, V., & Capurro, D. (2018). Discovering role interaction models in the emergency room using process mining. *J Biomed Inform*, *78*, 60-77. https://doi.org/10.1016/j.jbi.2017.12.015

Alwosheel, A., van Cranenburgh, S., & Chorus, C. G. (2018). Is your dataset big enough? Sample size requirements when using artificial neural networks for discrete choice analysis. *Journal of choice modelling*, *28*, 167–182.

Anderson, B. R. (2016). Improving health care by embracing systems theory. *J Thorac Cardiovasc Surg*, *152*(2), 593-594. https://doi.org/10.1016/j.jtcvs.2016.03.029

Anessi-Pessina, E., Nieddu, L., & Rizzo, M. G. (2019). Does drg funding encourage hospital specialization? Evidence from the italian national health service. *The International Journal of Health Planning and Management*, *34*(2), 534-552. https://doi.org/10.1002/hpm.2715

Anowar, F., Sadaoui, S., & Selim, B. (2021). Conceptual and empirical comparison of dimensionality reduction algorithms (pca, kpca, lda, mds, svd, lle, isomap, le, ica, t-sne). *Computer Science Review*, *40*, 100378.

Aronsky, D., Jones, I., Raines, B., Hemphill, R., Mayberry, S. R., Luther, M. A., & Slusser, T. (2008). An integrated computerized triage system in the emergency department. *AMIA ... Annual Symposium proceedings. AMIA Symposium*, *2008*, 16-20.

Ash, J. S., Sittig, D. F., Campbell, E. M., Guappone, K. P., & Dykstra, R. H. (2007). Some unintended consequences of clinical decision support systems. *AMIA ... Annual Symposium proceedings. AMIA Symposium*, *2007*, 26-30. https://www.ncbi.nlm.nih.gov/pubmed/18693791

Avgerou, C. (2000). Information systems: What sort of science is it? *Omega*, *28*(5), 567-579.

Avison, D., & Fitzgerald, G. (2003). *Information systems development: Methodologies, techniques and tools*. McGraw-Hill.

Baker, L. (2006). Observation: A complex research method. *Library Trends*, *55*(1), 171-189. https://doi.org/10.1353/lib.2006.0045

Balki, I., Amirabadi, A., Levman, J., Martel, A. L., Emersic, Z., Meden, B., Garcia-Pedrero, A., Ramirez, S. C., Kong, D., Moody, A. R., & Tyrrell, P. N. (2019). Sample-size determination methodologies for machine learning in medical imaging research: A systematic review. *Can Assoc Radiol J*, *70*(4), 344-353. https://doi.org/10.1016/j.carj.2019.06.002

Banks, J., Carson II, J. S., Nelson, B. L., & Nicol, D. M. (2010). *Discrete event system simulation* (5th ed.). Pearson Prentice Hall.

Baskerville, R., Davison, R., Kaul, M., & Wong, L. (2014). Designing artifacts for systems of information. In B. Doolin, E. Lamprou, N. Mitev, & L. McLeod (Eds.), *Information systems and global assemblages: (re)configuring actors, artefacts, organizations* (Vol. 446, pp. 233-245). Springer. https://doi.org/10.1007/978-3-662-45708-5_15

Baskerville, R., & Pries-Heje, J. (2010). Explanatory design theory. *Business & Information Systems Engineering*, *2*(5), 271-282. https://doi.org/10.1007/s12599-010-0118-4

Bates, D. W., Teich, J. M., Lee, J., Seger, D., Kuperman, G. J., Ma'Luf, N., Boyle, D., & Leape, L. (1999). The impact of computerized physician order entry on medication error prevention. *Journal of the American Medical Informatics Association*, *6*(4), 313-321.

Bell, J. (2022). What is machine learning? In S. Carta (Ed.), *Machine learning and the city* (pp. 207-216). https://doi.org/10.1002/9781119815075.ch18

Ben-Assuli, O., Sagi, D., Leshno, M., Ironi, A., & Ziv, A. (2015). Improving diagnostic accuracy using ehr in emergency departments: A simulation-based study. *J Biomed Inform*, *55*, 31-40. https://doi.org/10.1016/j.jbi.2015.03.004

Ben-Assuli, O., Shabtai, I., & Leshno, M. (2013). The influence of ehr components on admission decisions. *Health and Technology*, *3*(1), 29-35.

Bernard, S. A. (2012). *An introduction to enterprise architecture*. AuthorHouse.

Berner, E. S., & La Lande, T. J. (2007). Overview of clinical decision support systems. In E. S. Berner (Ed.), *Clinical decision support systems: Theory and practice* (pp. 3–22). Springer. https://doi.org/10.1007/978-0-387-38319-4_1

Berner, E. S., & Lande, T. J. L. (2007). Overview of clinical decision support systems. In *Clinical decision support systems* (pp. 3-22). Springer.

Bertalanffy, L. v. (1968). *General system theory: Foundations, development, applications*. G. Braziller.

Birkhead, G. S., Klompas, M., & Shah, N. R. (2015). Uses of electronic health records for public health surveillance to advance public health. *Annual review of public health*, *36*, 345-359.

Blobel, B., & Holena, M. (1997). Comparing middleware concepts for advanced healthcare system architectures. *Int J Med Inform*, *46*(2), 69-85. https://doi.org/10.1016/s1386-5056(97)00058-0

Boell, S. K., & Cecez-Kecmanovic, D. (2015, 5-8 Jan. 2015). What is an information system? 2015 48th Hawaii International Conference on System Sciences, https://doi.org/10.1109/HICSS.2015.587

Boochever, S. S. (2004). His/ris/pacs integration: Getting to the gold standard. *Radiology management*, *26*(3), 16-24; quiz 25.

Bradley, A. P. (1997). The use of the area under the roc curve in the evaluation of machine learning algorithms. *Pattern recognition*, *30*(7), 1145-1159.

Bright, T. J., Wong, A., Dhurjati, R., Bristow, E., Bastian, L., Coeytaux, R. R., Samsa, G., Hasselblad, V., Williams, J. W., Musty, M. D., Wing, L., Kendrick, A. S., Sanders, G. D., & Lobach, D. (2012). Effect of clinical decision-support systems. *Annals of Internal Medicine*, *157*(1), 29-43. https://doi.org/10.7326/0003-4819-157-1-201207030-00450

Chan, F. K., & Thong, J. Y. (2009). Acceptance of agile methodologies: A critical review and conceptual framework. *Decision support systems*, *46*(4), 803-814.

Chang, Y. T., Chen, C. C., Chang, C. Y., & Kuo, Y. C. (2004). Evaluation of unpredictable critical conditions of patients treated in the observation unit of the emergency department. *J Emerg Med*, *27*(2), 109-113. https://doi.org/10.1016/j.jemermed.2004.02.016

Chapman, C. S., & Kihn, L.-A. (2009). Information system integration, enabling control and performance. *Accounting, organizations and society*, *34*(2), 151-169.

Chatterjee, S., Sarker, S., Lee, M. J., Xiao, X., & Elbanna, A. (2020). A possible conceptualization of the information systems (is) artifact: A general systems theory perspective1. *Information Systems Journal*, *31*(4), 550-578. https://doi.org/10.1111/isj.12320

Cheerkoot-Jalim, S., Khedo, K. K., & Jodheea-Jutton, A. (2019). An exploratory study of evidence-based clinical decision support systems. Information Systems Design and Intelligent Applications: Proceedings of Fifth International Conference INDIA 2018 Volume 2,

Chief Information Officer Council. (2001). *A practical guide to federal enterprise architecture* (Chief Information Officer Council, Version, Issue.

chinabaogao.com. (2019). *In 2018, china's electronic medical record industry has strong market demand. The future will usher in a leap-forward development.* http://free.chinabaogao.com/yiyao/201901/0112392A52019.html

Choi, E., Bahadori, M. T., Searles, E., Coffey, C., Thompson, M., Bost, J., Tejedor-Sojo, J., & Sun, J. (2016, August). Multi-layer representation learning for medical concepts. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, California, USA. https://doi.org/10.1145/2939672.2939823

Chok, L., Bachli, E. B., Steiger, P., Bettex, D., Cottini, S. R., Keller, E., Maggiorini, M., & Schuepbach, R. A. (2018). Effect of diagnosis related groups implementation on the intensive care unit of a swiss tertiary hospital: A cohort study. *BMC Health Services Research*, *18*(1), 84. https://doi.org/10.1186/s12913-018-2869-4

Chollet, F., & Others. (2015). *Keras*. https://keras.io

Cortes, C., Jackel, L. D., & Chiang, W.-P. (1994). Limits on learning machine accuracy imposed by data quality. *Advances in Neural Information Processing Systems*, *7*.

Deloitte. (2015). *Independent review of new zealand's electronic health record strategy*. Retrieved from https://www.health.govt.nz/publication/independent-review-new-zealands-electronic-health-record-strategy

Derlet, R. W., & Richards, J. R. (2000). Overcrowding in the nation's emergency departments: Complex causes and disturbing effects. *Annals of emergency medicine*, *35*(1), 63-68.

Dhanda, P., & Sharma, N. (2016). Extract transform load data with etl tools. *International Journal of Advanced Research in Computer Science*, *7*(3).

Di Laura, D., D'Angiolella, L., Mantovani, L., Squassabia, G., Clemente, F., Santalucia, I., Improta, G., & Triassi, M. (2021). Efficiency measures of emergency departments: An italian systematic literature review. *BMJ Open Quality*, *10*(3), e001058. https://doi.org/10.1136/bmjoq-2020-001058

Ding, Z., Shi, H., Zhang, H., Meng, L., Fan, M., Han, C., Zhang, K., Ming, F., Xie, X., & Liu, H. (2019). Gastroenterologist-level identification of small bowel diseases and normal variants by capsule endoscopy using a deep-learning model. *Gastroenterology*, *157*(4), 1044-1054 e1045. https://doi.org/10.1053/j.gastro.2019.06.025

Dolin, R. H., Alschuler, L., Beebe, C., Biron, P. V., Boyer, S. L., Essin, D., Kimber, E., Lincoln, T., & Mattison, J. E. (2001). The hl7 clinical document architecture. *Journal of the American Medical Informatics Association*, *8*(6), 552-569. https://doi.org/10.1136/jamia.2001.0080552

Donders, A. R., van der Heijden, G. J., Stijnen, T., & Moons, K. G. (2006). Review: A gentle introduction to imputation of missing values. *J Clin Epidemiol*, *59*(10), 1087-1091. https://doi.org/10.1016/j.jclinepi.2006.01.014

Dongare, A., Kharde, R., & Kachare, A. D. (2012). Introduction to artificial neural network. *International Journal of Engineering and Innovative Technology (IJEIT)*, *2*(1), 189-194.

El Misilmani, H. M., Naous, T., & Al Khatib, S. K. (2020). A review on the design and optimization of antennas using machine learning algorithms and techniques. *International Journal of RF and Microwave Computer-Aided Engineering*, *30*(10), e22356. https://doi.org/10.1002/mmce.22356

Embi, P. J., Yackel, T. R., Logan, J. R., Bowen, J. L., Cooney, T. G., & Gorman, P. N. (2004). Impacts of computerized physician documentation in a teaching hospital: Perceptions of faculty and resident physicians. *Journal of the American Medical Informatics Association*, *11*(4), 300-309.

Evans, R. S., Pestotnik, S. L., Classen, D. C., Clemmer, T. P., Weaver, L. K., Orme Jr, J. F., Lloyd, J. F., & Burke, J. P. (1998). A computer-assisted management program for antibiotics and other antiinfective agents. *New England journal of medicine*, *338*(4), 232-238.

Everson, J., Kocher, K. E., & Adler-Milstein, J. (2017). Health information exchange associated with improved emergency department care through faster accessing of patient information from outside organizations. *Journal of the American Medical Informatics Association*, *24*(e1), e103-e110.

Fang, Y., Lim, K. H., Qian, Y., & Feng, B. (2018). System dynamics modeling for information systems research: Theory development and practical application. *MIS quarterly*, *42*(4).

Farley, H. L., Baumlin, K. M., Hamedani, A. G., Cheung, D. S., Edwards, M. R., Fuller, D. C., Genes, N., Griffey, R. T., Kelly, J. J., McClay, J. C., Nielson, J., Phelan, M. P., Shapiro, J. S., Stone-Griffith, S., & Pines, J. M. (2013). Quality and safety implications of emergency department information systems. *Ann Emerg Med*, *62*(4), 399-407. https://doi.org/10.1016/j.annemergmed.2013.05.019

Fernandes, C., Claro, N., Monteiro, S., Pires, I. M., & Gouveia, A. J. (2022). The evolution of is/it in health care in last decades. *Procedia Computer Science*, *203*, 707-713. https://doi.org/10.1016/j.procs.2022.07.105

Fernandes, M., Vieira, S. M., Leite, F., Palos, C., Finkelstein, S., & Sousa, J. M. C. (2020). Clinical decision support systems for triage in the emergency department using intelligent systems: A review. *Artif Intell Med*, *102*, 101762. https://doi.org/10.1016/j.artmed.2019.101762

Fitzmaurice, J. M., Adams, K., & Eisenberg, J. M. (2002). Three decades of research on computer applications in health care: Medical informatics support at the agency for healthcare research and quality. *Journal of the American Medical Informatics Association*, *9*(2), 144-160.

Fong, E. N., & Goldfine, A. H. (1989). *Information management directions: The integration challenge* (NIST Special publication, Issue.

Frize, M., Ennett, C. M., Stevenson, M., & Trigg, H. C. (2001). Clinical decision support systems for intensive care units: Using artificial neural networks. *Med Eng Phys*, *23*(3), 217-225. https://doi.org/10.1016/s1350-4533(01)00041-8

Garrity, E. J. (2001). Synthesizing user centered and designer centered is development approaches using general systems theory. *Information systems frontiers*, *3*(1), 107-121. https://doi.org/10.1023/A:1011457822609

Gartner, I. (n.d.). *Definition of system integration - gartner information technology glossary*. https://www.gartner.com/en/information-technology/glossary/system-integration

Gartner Inc. (2020). *His (hospital information system or healthcare information system)*. https://web.archive.org/web/20201023224851/https://www.gartner.com/en/information-technology/glossary/his-hospital-information-system-or-healthcare-information-system

Gellweiler, C. (2022). It architects and it-business alignment: A theoretical review. *Procedia Computer Science*, *196*, 13-20. https://doi.org/10.1016/j.procs.2021.11.067

Géron, A. (2019). *Hands-on machine learning with scikit-learn, keras, and tensorflow : Concepts, tools, and techniques to build intelligent systems*. O'Reilly Media, Incorporated. http://ebookcentral.proquest.com/lib/waikato/detail.action?docID=5892320

Ghahramani, Z. (2004). Unsupervised learning. In O. Bousquet, U. Luxburg, & G. Rätsch (Eds.), *Advanced lectures on machine learning* (pp. 72-112). Springer. https://doi.org/10.1007/978-3-540-28650-9_5

Google. (2020, 2020/03/17). *Validation set: Another partition | machine learning crash course*. https://developers.google.com/machine-learning/crash-course/validation/another-partition

Google. (2022a). *Decision trees*. Google. https://developers.google.com/machine-learning/decision-forests/decision-trees

Google. (2022b, July, 14). *Reducing loss: Learning rate*. https://developers.google.com/machine-learning/crash-course/reducing-loss/learning-rate

Google Developers. (2022, July 18). *The size and quality of a data set*. https://developers.google.com/machine-learning/data-prep/construct/collect/data-size-quality

Gorry, G. A. (1968). Strategies for computer-aided diagnosis. *Mathematical Biosciences*, *2*(3-4), 293-318. https://doi.org/10.1016/0025-5564(68)90022-9

Gorry, G. A., & Barnett, G. O. (1968). Experience with a model of sequential diagnosis. *Computers and Biomedical Research*, *1*(5), 490-507. https://doi.org/10.1016/0010-4809(68)90016-5

Graber, M. A., & VanScoy, D. (2003). How well does decision support software perform in the emergency department? *Emergency Medicine Journal*, *20*(5), 426-428. https://doi.org/10.1136/emj.20.5.426

Graham, B., Bond, R., Quinn, M., & Mulvenna, M. (2018). Using data mining to predict hospital admissions from the emergency department. *IEEE Access*, *6*, 10458-10469. https://doi.org/10.1109/ACCESS.2018.2808843

Grant, L., Xue, X., Vajihi, Z., Azuelos, A., Rosenthal, S., Hopkins, D., Aroutiunian, R., Unger, B., Guttman, A., & Afilalo, M. (2020). Lo32: Artificial intelligence to predict disposition to improve flow in the emergency department. *Canadian Journal of Emergency Medicine*, *22*(S1), S18-S19.

Green, S. M., Martinez-Rumayor, A., Gregory, S. A., Baggish, A. L., O'Donoghue, M. L., Green, J. A., Lewandrowski, K. B., & Januzzi, J. L., Jr. (2008). Clinical uncertainty, diagnostic accuracy, and outcomes in emergency department patients presenting with dyspnea. *Archives of internal medicine*, *168*(7), 741-748. https://doi.org/10.1001/archinte.168.7.741

Greenes, R. (2011). *Clinical decision support: The road ahead*. Elsevier.

Gregor, S. (2006). The nature of theory in information systems. *MIS quarterly*, *30*(3), 611-642. https://doi.org/10.2307/25148742

Gregor, S., Chandra Kruse, L., & Seidel, S. (2020). Research perspectives: The anatomy of a design principle. *Journal of the Association for Information Systems*, *21*(6), 2.

Gregor, S., & Jones, D. (2007). The anatomy of a design theory. *Journal of the Association for Information Systems*, *8*(5), 312-323,325-335.

Grimson, J., Grimson, W., & Hasselbring, W. (2000). The si challenge in health care. *Communications of the ACM*, *43*(6), 48–55. https://doi.org/10.1145/336460.336474

Gu, Q., Jitpaipoon, T., & Yang, J. (2017). The impact of information integration on financial performance: A knowledge-based view. *International Journal of Production Economics*, *191*, 221-232. https://doi.org/10.1016/j.ijpe.2017.06.005

Guba, E. G., & Lincoln, Y. S. (1994). Competing paradigms in qualitative research. *Handbook of qualitative research*, *2*(163-194), 105.

Gudivada, V., Apon, A., & Ding, J. (2017). Data quality considerations for big data and machine learning: Going beyond data cleaning and transformations. *International Journal on Advances in Software*, *10*(1), 1-20.

Gul, M., & Guneri, A. F. (2012). A computer simulation model to reduce patient length of stay and to improve resource utilization rate in an emergency department service system. *International Journal of Industrial Engineering*, *19*(5), 221-231.

Gulledge, T. (2006). What is integration? *Industrial Management & Data Systems*, *106*(1), 5-20. https://doi.org/10.1108/02635570610640979

Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., Venugopalan, S., Widner, K., Madams, T., Cuadros, J., Kim, R., Raman, R., Nelson, P. C., Mega, J. L., & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA*, *316*(22), 2402-2410. https://doi.org/10.1001/jama.2016.17216

Hajian-Tilaki, K. (2013). Receiver operating characteristic (roc) curve analysis for medical diagnostic test evaluation. *Caspian journal of internal medicine*, *4*(2), 627-635. https://www.ncbi.nlm.nih.gov/pubmed/24009950

Hajian-Tilaki, K. (2013). Receiver operating characteristic (roc) curve analysis for medical diagnostic test evaluation. *Caspian journal of internal medicine*, *4*(2), 627.

Handel, D. A., & Hackman, J. L. (2010). Implementing electronic health records in the emergency department. *The Journal of emergency medicine*, *38*(2), 257-263.

Hasselbring, W. (1997). Federated integration of replicated information within hospitals. *International Journal on Digital Libraries*, *1*(3), 192-208.

Hasselbring, W. (2000). Information system integration. *Communications of the ACM*, *43*(6), 32-38.

Haux, R. (2006). Health information systems - past, present, future. *Int J Med Inform*, *75*(3-4), 268-281. https://doi.org/10.1016/j.ijmedinf.2005.08.002

Healthdirect Australia. (2023). *Emergency departments*. https://www.healthdirect.gov.au/hospital-emergency-departments

Henderson, J. C., & Venkatraman, H. (1999). Strategic alignment: Leveraging information technology for transforming organizations. *IBM Systems Journal*, *38*(2/3), 472-484.

Hevner, A., & Chatterjee, S. (2010a). Design science research frameworks. In *Design research in information systems: Theory and practice* (pp. 23-31). Springer US. https://doi.org/10.1007/978-1-4419-5653-8_3

Hevner, A., & Chatterjee, S. (2010b). Design science research in information systems. In *Design research in information systems* (pp. 9-22). Springer.

Hevner, A., & Chatterjee, S. (2010c). Introduction to design science research. In *Design research in information systems: Theory and practice* (pp. 1-8). Springer US. https://doi.org/10.1007/978-1-4419-5653-8_1

Hevner, A. R. (2007). A three cycle view of design science research. *Scandinavian journal of information systems*, *19*(2), 4. https://aisel.aisnet.org/sjis/vol19/iss2/4

Hevner, A. R., & Chatterjee, S. (2010). *Design research in information systems : Theory and practice*. Springer.

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS quarterly*, *28*(1), 75-105. https://doi.org/10.2307/25148625

Hibbs, S. P., Nielsen, N. D., Brunskill, S., Doree, C., Yazer, M. H., Kaufman, R. M., & Murphy, M. F. (2015). The impact of electronic decision support on transfusion practice: A systematic review. *Transfusion Medicine Reviews*, *29*(1), 14-23.

Hinton, G., Deng, L., Yu, D., Dahl, G. E., Mohamed, A. r., Jaitly, N., Senior, A., Vanhoucke, V., Nguyen, P., Sainath, T. N., & Kingsbury, B. (2012). Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal Processing Magazine*, *29*(6), 82-97. https://doi.org/10.1109/MSP.2012.2205597

Hong, W. S., Haimovich, A. D., & Taylor, R. A. (2018). Predicting hospital admission at emergency department triage using machine learning. *PLoS One*, *13*(7), e0201016.

Horng, S., Sontag, D. A., Halpern, Y., Jernite, Y., Shapiro, N. I., & Nathanson, L. A. (2017). Creating an automated trigger for sepsis clinical decision support at emergency department triage using machine learning. *PLoS One*, *12*(4), e0174708.

Hunter-Zinck, H. S., Peck, J. S., Strout, T. D., & Gaehde, S. A. (2019). Predicting emergency department orders with multilabel machine learning techniques and simulating effects on length of stay. *J Am Med Inform Assoc*, *26*(12), 1427-1436. https://doi.org/10.1093/jamia/ocz171

Iqbal, S. M., Mahgoub, I., Du, E., Leavitt, M. A., & Asghar, W. (2021). Advances in healthcare wearable devices. *NPJ Flexible Electronics*, *5*(1), 9.

Ivosev, G., Burton, L., & Bonner, R. (2008). Dimensionality reduction and visualization in principal component analysis. *Analytical chemistry*, *80*(13), 4933-4944.

Jadhav, S. D., & Channe, H. (2016). Comparative study of k-nn, naive bayes and decision tree classification techniques. *International Journal of Science and Research (IJSR)*, *5*(1), 1842-1845.

Jain, A. K., Mao, J., & Mohiuddin, K. M. (1996). Artificial neural networks: A tutorial. *Computer*, *29*(3), 31-44.

Jakovljević, B. (2008). Health information system. In W. Kirch (Ed.), *Encyclopedia of public health* (pp. 603-607). Springer Netherlands. https://doi.org/10.1007/978-1-4020-5614-7_1425

Jee, K., & Kim, G.-H. (2013). Potentiality of big data in the medical sector: Focus on how to reshape the healthcare system. *Healthcare informatics research*, *19*(2), 79-85. https://doi.org/10.4258/hir.2013.19.2.79

Jiao, W.-P. (2018). Diagnosis-related groups' payment reform in beijing. *Chinese medical journal*, *131*(14), 1763-1764. https://doi.org/10.4103/0366-6999.235869

Johannesson, P., & Perjons, E. (2021). Introduction. In *An introduction to design science* (pp. 1-21). Springer International Publishing. https://doi.org/10.1007/978-3-030-78132-3_1

Johannink, T., Bahl, S., Nair, A., Luo, J., Kumar, A., Loskyll, M., Ojea, J. A., Solowjow, E., & Levine, S. (2019). Residual reinforcement learning for robot control. 2019 International Conference on Robotics and Automation (ICRA), Montreal, QC, Canada. https://doi.org/10.1109/ICRA.2019.8794127

Johnson, S. G., Speedie, S., Simon, G., Kumar, V., & Westra, B. L. (2015). A data quality ontology for the secondary use of ehr data. *AMIA ... Annual Symposium proceedings. AMIA Symposium*, *2015*, 1937-1946. https://www.ncbi.nlm.nih.gov/pubmed/26958293

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255-260. https://doi.org/10.1126/science.aaa8415

Josey, A. (2018). *An introduction to the togaf® standard, version 9.2* [White Paper]. The Open Group.

Josey, A., Lankhorst, M., Band, I., Jonkers, H., & Quartel, D. (2016). *An introduction to the archimate® 3.0 specification* [White Paper]. The Open Group.

Júnior, S. H. d. L., Silva, F. Í. C., Albuquerque, G. S. G., de Medeiros, F. P. A., & Lira, H. B. (2020). Enterprise architecture in healthcare systems: A systematic literature review. *arXiv preprint arXiv:2007.06767*.

Kadhim, A. I., Cheah, Y.-N., & Ahamed, N. H. (2014). Text document preprocessing and dimension reduction techniques for text document clustering. 2014 4th International Conference on Artificial Intelligence with Applications in Engineering and Technology, Kota Kinabalu, Malaysia. https://doi.org/10.1109/ICAIET.2014.21

Kadri, F., Chaabane, S., & Tahon, C. (2014). A simulation-based decision support system to prevent and predict strain situations in emergency department systems. *Simulation Modelling Practice and Theory*, *42*, 32-52. https://doi.org/10.1016/j.simpat.2013.12.004

Kaelbling, L. P., Littman, M. L., & Moore, A. W. (1996). Reinforcement learning: A survey. *Journal of artificial intelligence research*, *4*, 237-285.

Kamiri, J., & Mariga, G. W. (2021). Research methods in machine learning: A content analysis. *International Journal of Computer and Information Technology*, *10*(2), 78–91. https://doi.org/10.24203/ijcit.v10i2.79

Kannan, R., & Vasanthi, V. (2019). Machine learning algorithms with roc curve for predicting and diagnosing the heart disease. In *Soft computing and medical bioinformatics* (pp. 63-72). Springer. https://doi.org/10.1007/978-981-13-0059-2_8

Kao, H.-Y., Yu, M.-C., Masud, M., Wu, W.-H., Chen, L.-J., & 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. https://doi.org/10.1016/j.chb.2016.04.021

Kasper, G. M. (1996). A theory of decision support system design for user calibration. *Information systems research*, *7*(2), 215-232. http://www.jstor.org.ezproxy.waikato.ac.nz/stable/23010860

Katrakazas, P., Pastiadis, K., Bibas, A., & Koutsouris, D. (2020). A general systems theory approach in public hearing health: Lessons learned from a systematic review of general systems theory in healthcare. *IEEE Access*, *8*, 53018-53033. https://doi.org/10.1109/ACCESS.2020.2981160

Kawaler, E., Cobian, A., Peissig, P., Cross, D., Yale, S., & Craven, M. (2012). Learning to predict post-hospitalization vte risk from ehr data. AMIA annual symposium proceedings,

Kawamoto, K., Houlihan, C. A., Balas, E. A., & Lobach, D. F. (2005). Improving clinical practice using clinical decision support systems: A systematic review of trials to identify features critical to success. *BMJ*, *330*(7494), 765. https://doi.org/10.1136/bmj.38398.500764.8F

Ketkar, N. (2017). Stochastic gradient descent. In *Deep learning with python: A hands-on introduction* (pp. 113-132). Apress L. P. http://ebookcentral.proquest.com/lib/waikato/detail.action?docID=6363117

Kleijnen, J. P. C. (1995). Verification and validation of simulation models. *European Journal of Operational Research*, *82*(1), 145-162. https://doi.org/10.1016/0377-2217(94)00016-6

Klügl, F. (2008). A validation methodology for agent-based simulations. Proceedings of the 2008 ACM symposium on Applied computing, https://doi.org/10.1145/1363686.1363696

Knepper, M. M., Castillo, E. M., Chan, T. C., & Guss, D. A. (2018). The effect of access to electronic health records on throughput efficiency and imaging utilization in the emergency department. *Health Serv Res*, *53*(2), 787-802. https://doi.org/10.1111/1475-6773.12695

Kotsiantis, S. B. (2011). Decision trees: A recent overview. *Artificial Intelligence Review*, *39*(4), 261-283. https://doi.org/10.1007/s10462-011-9272-4

Kotsiantis, S. B., Kanellopoulos, D., & Pintelas, P. E. (2006). Data preprocessing for supervised leaning. *International journal of computer science*, *1*(2), 111-117.

Krawczyk, B. (2016). Learning from imbalanced data: Open challenges and future directions. *Progress in Artificial Intelligence*, *5*(4), 221-232. https://doi.org/10.1007/s13748-016-0094-0

Kreps, J. (2014, July 2). Questioning the lambda architecture. http://radar.oreilly.com/2014/07/questioning-the-lambda-architecture.html

Krogh, A. (2008). What are artificial neural networks? *Nature biotechnology*, *26*(2), 195-197.

Kuhn, K. A., & Giuse, D. A. (2001). From hospital information systems to health information systems - problems, challenges, perspectives. *Methods of information in medicine*, *40*(04), 275-287.

Kukreja, H., Bharath, N., Siddesh, C., & Kuldeep, S. (2016). An introduction to artificial neural network. *International Journal Of Advance Research And Innovative Ideas In Education*, *1*(5), 27-30.

Lakshminarayan, K., Harp, S. A., & Samad, T. (1999). Imputation of missing data in industrial databases. *Applied Intelligence*, *11*(3), 259-275. https://doi.org/10.1023/A:1008334909089

Landman, A. B., Bernstein, S. L., Hsiao, A. L., & Desai, R. A. (2010). Emergency department information system adoption in the united states. *Acad Emerg Med*, *17*(5), 536-544. https://doi.org/10.1111/j.1553-2712.2010.00722.x

Law, A. M. (2007). *Simulation modeling and analysis* (4th ed.). McGraw-Hill.

Lawton, R., Robinson, O., Harrison, R., Mason, S., Conner, M., & Wilson, B. (2019). Are more experienced clinicians better able to tolerate uncertainty and manage risks? A vignette study of doctors in three nhs emergency departments in england. *BMJ Qual Saf*, *28*(5), 382-388. https://doi.org/10.1136/bmjqs-2018-008390

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436-444. https://doi.org/10.1038/nature14539

Ledley, R. S., & Lusted, L. B. (1959). Reasoning foundations of medical diagnosis: Symbolic logic, probability, and value theory aid our understanding of how physicians reason. *Science*, *130*(3366), 9-21.

Lee, A. S. (2010). Retrospect and prospect: Information systems research in the last and next 25 years. *Journal of Information Technology*, *25*(4), 336-348. https://doi.org/10.1057/jit.2010.24

Lee, J. A., & Verleysen, M. (2007). High-dimensional data. In J. A. Lee & M. Verleysen (Eds.), *Nonlinear dimensionality reduction* (pp. 1-16). Springer New York. https://doi.org/10.1007/978-0-387-39351-3_1

Levy-Fix, G., Kuperman, G. J., & Elhadad, N. (2019). Machine learning and visualization in clinical decision support: Current state and future directions. *arXiv preprint arXiv:.02664*.

Lindner, G., & Woitok, B. K. (2021). Emergency department overcrowding. *Wiener klinische Wochenschrift*, *133*(5), 229-233. https://doi.org/10.1007/s00508-019-01596-7

Lindstrom, L., & Jeffries, R. (2004). Extreme programming and agile software development methodologies. *Information systems management*, *21*(3), 41-52.

Liu, Y., Liu, X., & Yang, L. (2010, April 16-18). Analysis and design of heterogeneous bioinformatics database integration system based on middleware. 2010 2nd IEEE International Conference on Information Management and Engineering, Chengdu, Sichuan, China. https://doi.org/10.1109/ICIME.2010.5477628

Lynne Markus, M. (2001). Reflections on the systems integration enterprise. *Business Process Management Journal*, *7*(3). https://doi.org/10.1108/bpmj.2001.15707caf.001

Mahesh, B. (2020). Machine learning algorithms-a review. *International Journal of Science and Research (IJSR).[Internet]*, *9*(1), 381-386.

Maiga, A. S., Nilsson, A., & Ax, C. (2015). Relationships between internal and external information systems integration, cost and quality performance, and firm profitability. *International Journal of Production Economics*, *169*, 422-434. https://doi.org/10.1016/j.ijpe.2015.08.030

Manrique-Rodríguez, S., Sánchez-Galindo, A., Fernández-Llamazares, C. M., López-Herce, J., Echarri-Martínez, L., Escudero-Vilaplana, V., Sanjuro-Sáez, M., & Carrillo-Álvarez, Á. (2012). Smart pump alerts: All that glitters is not gold. *International journal of medical informatics*, *81*(5), 344-350.

March, S. T., & Smith, G. F. (1995). Design and natural science research on information technology. *Decision support systems*, *15*(4), 251-266.

March, S. T., & Storey, V. C. J. M. q. (2008). Design science in the information systems discipline: An introduction to the special issue on design science research. *32*(4), 725-730.

Marchildon, G. (2019). The integration challenge in canadian regionalization. *Cad Saude Publica*, *35Suppl 2*(Suppl 2), e00084418. https://doi.org/10.1590/0102-311X00084418

Maria, A. (1997, December 07-10). Introduction to modeling and simulation. Proceedings of the 29th conference on Winter simulation, Atlanta, GA, USA. https://doi.org/10.1145/268437.268440

Marques, I. C., & Ferreira, J. J. (2020). Digital transformation in the area of health: Systematic review of 45 years of evolution. *Health and Technology*, *10*(3), 575-586.

Martin, N., Bergs, J., Eerdekens, D., Depaire, B., & Verelst, S. (2018). Developing an emergency department crowding dashboard: A design science approach. *Int Emerg Nurs*, *39*, 68-76. https://doi.org/10.1016/j.ienj.2017.08.001

Marz, N. (2011, Octorber 13). How to beat the cap theorem. *Thoughts from the Red Planet*. http://nathanmarz.com/blog/how-to-beat-the-cap-theorem.html

Marz, N., & Warren, J. (2015). *Big data : Principles and best practices of scalable real-time data systems*. Manning. https://www.manning.com/books/big-data

Masters, D., & Luschi, C. (2018). Revisiting small batch training for deep neural networks. *arXiv preprint arXiv:1804.07612*.

Matook, S., & Brown, S. A. (2016). Characteristics of it artifacts: A systems thinking‐based framework for delineating and theorizing it artifacts. *Information Systems Journal*, *27*(3), 309-346. https://doi.org/10.1111/isj.12108

Maulud, D., & Abdulazeez, A. M. (2020). A review on linear regression comprehensive in machine learning. *Journal of Applied Science and Technology Trends*, *1*(4), 140-147.

Mazor, I., Heart, T., & Even, A. (2016). Simulating the impact of an online digital dashboard in emergency departments on patients length of stay. *Journal of Decision Systems*, *25*(sup1), 343-353. https://doi.org/10.1080/12460125.2016.1187422

McBride, K., & Draheim, D. (2020). On complex adaptive systems and electronic government: A proposed theoretical approach for electronic government studies. *Electronic Journal of E-Government*, *18*(1), 43-53. https://doi.org/10.34190/ejeg.18.1.004

McCabe, J. B. (2001). Emergency department overcrowding: A national crisis. *Academic medicine*, *76*(7), 672-674.

Metzger, J., & MacDonald, K. (2002). *Clinical decision support for the independent physician practice*. California Healthcare Foundation.

Miah, S. J., Blake, J., & Kerr, D. (2020). Meta-design knowledge for clinical decision support systems. *Australasian Journal of Information Systems*, *24*, 1-26.

Middleton, B., Sittig, D., & Wright, A. (2016). Clinical decision support: A 25 year retrospective and a 25 year vision. *Yearbook of medical informatics*, *25*(S 01), S103-S116.

Miller, A. R., & Tucker, C. (2014). Health information exchange, system size and information silos. *J Health Econ*, *33*, 28-42. https://doi.org/10.1016/j.jhealeco.2013.10.004

Miller, R. A. (2009). Computer-assisted diagnostic decision support: History, challenges, and possible paths forward. *Advances in Health Sciences Education*, *14*(1), 89-106. https://doi.org/10.1007/s10459-009-9186-y

Miotto, R., Li, L., Kidd, B. A., & Dudley, J. T. (2016). Deep patient: An unsupervised representation to predict the future of patients from the electronic health records. *Scientific reports*, *6*(1), 1-10. https://doi.org/10.1038/srep26094

Mitchell, T. M. (1997). *Machine learning*. McGraw-Hill

Mohamed, N., Mahadi, B., Miskon, S., Haghshenas, H., & Adnan, H. M. (2013). Information system integration: A review of literature and a case analysis. *Mathematics and computers in contemporary science. Wseas LLC*, 68-77.

Mohan, S., Thirumalai, C., & Srivastava, G. (2019). Effective heart disease prediction using hybrid machine learning techniques. *IEEE Access*, *7*, 81542-81554. https://doi.org/10.1109/ACCESS.2019.2923707

Montavon, G., Samek, W., & Müller, K.-R. (2018). Methods for interpreting and understanding deep neural networks. *Digital signal processing*, *73*, 1-15.

Moore, M., & Loper, K. A. (2011). An introduction to clinical decision support systems. *Journal of Electronic Resources in Medical Libraries*, *8*(4), 348-366. https://doi.org/10.1080/15424065.2011.626345

Musen, M. A., Middleton, B., & Greenes, R. A. (2021). Clinical decision-support systems. In E. H. Shortliffe & J. J. Cimino (Eds.), *Biomedical informatics* (pp. 795-840). Springer.

Myles, A. J., Feudale, R. N., Liu, Y., Woody, N. A., & Brown, S. D. (2004). An introduction to decision tree modeling. *Journal of Chemometrics: A Journal of the Chemometrics Society*, *18*(6), 275-285.

Nance Jr, J. W., Meenan, C., & Nagy, P. G. (2013). The future of the radiology information system. *American Journal of Roentgenology*, *200*(5), 1064-1070.

Narayana, V. L., Sirisha, S., Divya, G., Pooja, N. L. S., & Nouf, S. A. (2022). Mall customer segmentation using machine learning. 2022 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India. https://doi.org/10.1109/ICEARS53579.2022.9752447

Nasteski, V. (2017). An overview of the supervised machine learning methods. *Horizons. b*, *4*, 51-62.

Navada, A., Ansari, A. N., Patil, S., & Sonkamble, B. A. (2011, June 27-28). Overview of use of decision tree algorithms in machine learning. 2011 IEEE Control and System Graduate Research Colloquium, Shah Alam, Malaysia. https://doi.org/10.1109/ICSGRC.2011.5991826

Ngai, E. W. T., Poon, J. K. L., Suk, F. F. C., & Ng, C. C. (2009). Design of an rfid-based healthcare management system using an information system design theory. *Information systems frontiers*, *11*(4), 405-417. https://doi.org/10.1007/s10796-009-9154-3

Nielsen, A. L., Henriksen, D. P., Marinakis, C., Hellebek, A., Birn, H., Nybo, M., Søndergaard, J., Nymark, A., & Pedersen, C. (2014). Drug dosing in patients with renal insufficiency in a hospital setting using electronic prescribing and automated reporting of estimated glomerular filtration rate. *Basic & clinical pharmacology & toxicology*, *114*(5), 407-413.

Nilashi, M., Ahmadi, H., Ahani, A., Ravangard, R., & Ibrahim, O. b. (2016). Determining the importance of hospital information system adoption factors using fuzzy analytic network process (anp). *technological forecasting and social change*, *111*(111), 244-264. https://doi.org/10.1016/J.TECHFORE.2016.07.008

Nunamaker Jr, J. F., Chen, M., & Purdin, T. D. (1990). Systems development in information systems research. *Journal of Management Information Systems*, *7*(3), 89-106.

O'Malley, T., Bursztein, E., Long, J., Chollet, F., Jin, H., Invernizzi, L., & Others. (2019). *Kerastuner*. https://github.com/keras-team/keras-tuner

Office of the National Coordinator for Health Information Technology. (2018). *Percent of hospitals, by type, that possess certified health it*. Office of the National Coordinator for Health Information Technology. dashboard.healthit.gov/quickstats/pages/certified-electronic-health-record-technology-in-hospitals.php

Oh, C., Novotny, A. M., Carter, P. L., Ready, R. K., Campbell, D. D., & Leckie, M. C. (2016). Use of a simulation-based decision support tool to improve emergency department throughput. *Operations Research for Health Care*, *9*, 29-39. https://doi.org/10.1016/j.orhc.2016.03.002

Orlikowski, W. J., & Baroudi, J. J. (1991). Studying information technology in organizations: Research approaches and assumptions. *Information systems research*, *2*(1), 1-28.

Özgün, O., & Barlas, Y. (2009, July, 26 – 30). Discrete vs. Continuous simulation: When does it matter. Proceedings of the 27th international conference of the system dynamics society, Albuquerque, NM, US.

Panerai, R. (2014). Health information systems. *Global perspectives in health: Health information systems. nd*, 1-6.

Papazoglou, M. P., & van den Heuvel, W.-J. (2007). Service oriented architectures: Approaches, technologies and research issues. *The VLDB Journal*, *16*(3), 389-415. https://doi.org/10.1007/s00778-007-0044-3

Parks, R., Wigand, R. T., Othmani, M. B., Serhier, Z., & Bouhaddou, O. (2019). Electronic health records implementation in morocco: Challenges of silo efforts and recommendations for improvements. *International journal of medical informatics*, *129*, 430-437. https://doi.org/10.1016/j.ijmedinf.2019.05.026

Patil, R., & Shah, K. (2022). Machine learning in healthcare: Applications, current status, and future prospects. In M. Mangla, S. K. Shinde, V. Mehta, N. Sharma, & S. N. Mohanty (Eds.), *Handbook of research on machine learning* (1st ed., pp. 163-186). Apple Academic Press.

Patterson, B. W., Pulia, M. S., Ravi, S., Hoonakker, P. L., Hundt, A. S., Wiegmann, D., Wirkus, E. J., Johnson, S., & Carayon, P. (2019). Scope and influence of electronic health record–

integrated clinical decision support in the emergency department: A systematic review. *Annals of emergency medicine*, *74*(2), 285-296. https://doi.org/10.1016/j.annemergmed.2018.10.034

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, *24*(3), 45-77. https://doi.org/10.2753/MIS0742-1222240302

Peiffer-Smadja, N., Rawson, T. M., Ahmad, R., Buchard, A., Georgiou, P., Lescure, F. X., Birgand, G., & Holmes, A. H. (2020). Machine learning for clinical decision support in infectious diseases: A narrative review of current applications. *Clin Microbiol Infect*, *26*(5), 584-595. https://doi.org/10.1016/j.cmi.2019.09.009

Peña, J. M., Lozano, J. A., & Larrañaga, P. (1999). An empirical comparison of four initialization methods for the k-means algorithm. *Pattern Recognition Letters*, *20*(10), 1027-1040. https://doi.org/10.1016/s0167-8655(99)00069-0

Poissant, L., Pereira, J., Tamblyn, R., & Kawasumi, Y. (2005). The impact of electronic health records on time efficiency of physicians and nurses: A systematic review. *Journal of the American Medical Informatics Association*, *12*(5), 505-516.

Porra, J., Hirschheim, R., & Parks, M. S. (2005). The history of texaco's corporate information technology function: A general systems theoretical interpretation1. *MIS quarterly*, *29*(4), 721-746.

Portugal, I., Alencar, P., & Cowan, D. (2018). The use of machine learning algorithms in recommender systems: A systematic review. *Expert Systems with Applications*, *97*, 205-227. https://doi.org/10.1016/j.eswa.2017.12.020

Probst, P., Boulesteix, A.-L., & Bischl, B. (2019). Tunability: Importance of hyperparameters of machine learning algorithms. *The Journal of Machine Learning Research*, *20*(1), 1934-1965.

Protti, D., & Bowden, T. (2010). *Electronic medical record adoption in new zealand primary care physician offices* (Vol. 96).

Qiao, Z., Sun, N., Li, X., Xia, E., Zhao, S., & Qin, Y. (2018). Using machine learning approaches for emergency room visit prediction based on electronic health record data. *Studies in health technology and informatics*, *247*, 111-115.

Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. *New England journal of medicine*, *380*(14), 1347-1358.

Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., Liu, P. J., Liu, X., Marcus, J., Sun, M., Sundberg, P., Yee, H., Zhang, K., Zhang, Y., Flores, G., Duggan, G. E., Irvine, J., Le, Q., Litsch, K., . . . Dean, J. (2018). Scalable and accurate deep learning with electronic health records. *npj Digital Medicine*, *1*(1), 18. https://doi.org/10.1038/s41746-018-0029-1

Rasamoelina, A. D., Adjailia, F., & Sinčák, P. (2020, January 23-25). A review of activation function for artificial neural network. 2020 IEEE 18th World Symposium on Applied Machine Intelligence and Informatics (SAMI), Herlany, Slovakia. https://doi.org/10.1109/SAMI48414.2020.9108717

Raschka, S. (2015). Giving computers the ability to learn from data. In *Python machine learning* (pp. 1-16). Packt publishing ltd.

Ravì, D., Wong, C., Deligianni, F., Berthelot, M., Andreu-Perez, J., Lo, B., Yang, G.-Z. J. I. j. o. b., & informatics, h. (2016). Deep learning for health informatics. *21*(1), 4-21.

Ray, S. (2019, 14-16 Feb. 2019). A quick review of machine learning algorithms. 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), https://doi.org/10.1109/COMITCon.2019.8862451

Reichertz, P. L. (2006). Hospital information systems—past, present, future. *International journal of medical informatics*, *75*(3), 282-299. https://doi.org/10.1016/J.IJMEDINF.2005.10.001

Roessler, M., & Zuzan, O. (2006). Ems systems in germany. *Resuscitation*, *68*(1), 45-49. https://doi.org/10.1016/j.resuscitation.2005.08.004

Ruder, S. (2016). An overview of gradient descent optimization algorithms. *arXiv preprint arXiv:1609.04747*.

Saar-Tsechansky, M., & Provost, F. (2007). Handling missing values when applying classification models. *J. Mach. Learn. Res.*, *8*, 1623–1657. https://dl.acm.org/doi/10.5555/1314498.1314553

Sabooniha, N., Toohey, D., & Lee, K. (2012, August, 3-5). An evaluation of hospital information systems integration approaches. Proceedings of the International Conference on Advances in Computing, Communications and Informatics, Chennai, India. https://doi.org/10.1145/2345396.2345479

Sailusha, R., Gnaneswar, V., Ramesh, R., & Rao, G. R. (2020, 13-15 May 2020). Credit card fraud detection using machine learning. 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), https://doi.org/10.1109/ICICCS48265.2020.9121114

Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development*, *3*(3), 210-229. https://doi.org/10.1147/rd.33.0210

Samwald, M., Fehre, K., de Bruin, J., & Adlassnig, K. P. (2012). The arden syntax standard for clinical decision support: Experiences and directions. *J Biomed Inform*, *45*(4), 711-718. https://doi.org/10.1016/j.jbi.2012.02.001

Sandiford, P., Annett, H., & Cibulskis, R. (1992). What can information systems do for primary health care? An international perspective. *Soc Sci Med*, *34*(10), 1077-1087. https://doi.org/10.1016/0277-9536(92)90281-t

Sargent, R. G. (2004, 5-8 December). Validation and verification of simulation models. Proceedings of the 2004 Winter Simulation Conference, 2004., https://doi.org/10.1109/WSC.2004.1371298

Sargent, R. G. (2004). Validation and verification of simulation models. Proceedings of the 2004 Winter Simulation Conference, 2004.,

Sartini, M., Carbone, A., Demartini, A., Giribone, L., Oliva, M., Spagnolo, A. M., Cremonesi, P., Canale, F., & Cristina, M. L. (2022). Overcrowding in emergency department: Causes, consequences, and solutions-a narrative review. *Healthcare (Basel)*, *10*(9), 1625. https://doi.org/10.3390/healthcare10091625

Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural networks*, *61*, 85-117. https://doi.org/10.1016/j.neunet.2014.09.003

Schmidt, R., Geisler, S., & Spreckelsen, C. (2013). Decision support for hospital bed management using adaptable individual length of stay estimations and shared resources. *BMC medical informatics and decision making*, *13*(1), 1-19.

Schneider, A., & Feussner, H. (2017). Health informatics/health information technology. In A. Schneider & H. Feussner (Eds.), *Biomedical engineering in gastrointestinal surgery* (pp. 473-489). Academic Press. https://doi.org/10.1016/b978-0-12-803230-5.00012-9

Selvaraj, S., & Sundaravaradhan, S. (2020). Challenges and opportunities in iot healthcare systems: A systematic review. *SN Applied Sciences*, *2*(1), 139.

Seo, H., Badiei Khuzani, M., Vasudevan, V., Huang, C., Ren, H., Xiao, R., Jia, X., & Xing, L. (2020). Machine learning techniques for biomedical image segmentation: An overview of technical aspects and introduction to state‐of‐art applications. *Medical physics*, *47*(5), e148-e167.

Sepulveda, J. L., & Young, D. S. (2013). The ideal laboratory information system. *Archives of Pathology and Laboratory Medicine*, *137*(8), 1129-1140.

Shanks, G. (2002). Guidelines for conducting positivist case study research in information systems. *Australasian Journal of Information Systems*, *10*(1).

Sharma, S., Sharma, S., & Athaiya, A. (2017). Activation functions in neural networks. *Towards Data Sci*, *6*(12), 310-316.

Shen, B., Guo, J., & Yang, Y. (2019). Medchain: Efficient healthcare data sharing via blockchain. *Applied sciences*, *9*(6), 1207.

Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2018). Deep ehr: A survey of recent advances in deep learning techniques for electronic health record (ehr) analysis. *IEEE journal of biomedical and health informatics*, *22*(5), 1589-1604. https://doi.org/10.1109/JBHI.2017.2767063

Shortliffe, E. H., Axline, S. G., Buchanan, B. G., Merigan, T. C., & Cohen, S. N. (1973). An artificial intelligence program to advise physicians regarding antimicrobial therapy. *Comput Biomed Res*, *6*(6), 544-560. https://doi.org/10.1016/0010-4809(73)90029-3

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., & Lanctot, M. (2016). Mastering the game of go with deep neural networks and tree search. *Nature*, *529*(7587), 484-489.

Simon, H. A. (1988). The science of design: Creating the artificial. *Design Issues*, *4*(1/2), 67-82. https://doi.org/10.2307/1511391

Sinaga, K. P., & Yang, M. S. (2020). Unsupervised k-means clustering algorithm. *IEEE Access*, *8*, 80716-80727. https://doi.org/10.1109/ACCESS.2020.2988796

Singh, D., & Singh, B. (2020). Investigating the impact of data normalization on classification performance. *Applied Soft Computing*, *97*, 105524. https://doi.org/10.1016/j.asoc.2019.105524

Sokolova, M., & Lapalme, G. (2009). A systematic analysis of performance measures for classification tasks. *Information processing & management*, *45*(4), 427-437.

Song, Y. Y., & Lu, Y. (2015). Decision tree methods: Applications for classification and prediction. *Shanghai Arch Psychiatry*, *27*(2), 130-135. https://doi.org/10.11919/j.issn.1002-0829.215044

Sowa, J. F., & Zachman, J. A. (1992). Extending and formalizing the framework for information systems architecture. *IBM Systems Journal*, *31*(3), 590-616.

Spewak, S. H., & Hill, S. C. (1993). *Enterprise architecture planning: Developing a blueprint for data, applications and technology*. QED Information Sciences, Inc.

Spewak, S. H., & Tiemann, M. (2006). Updating the enterprise architecture planning model. *Journal of Enterprise Architecture*, *2*(2), 11-19.

Spooner, S. A. (2016). Mathematical foundations of decision support systems. In E. S. Berner (Ed.), *Clinical decision support systems* (pp. 19-43). Springer. https://doi.org/10.1007/978-3-319-31913-1

Stout, W., & Tawney, B. (2005, April 29). An excel forecasting model to aid in decision making that affects hospital resource/bed utilization-hospital capability to admit emergency room patients. 2005 IEEE Design Symposium, Systems and Information Engineering, Charlottesville, VA, USA.

Sugrue, M., Maier, R., Moore, E. E., Boermeester, M., Catena, F., Coccolini, F., Leppaniemi, A., Peitzman, A., Velmahos, G., Ansaloni, L., Abu-Zidan, F., Balfe, P., Bendinelli, C., Biffl, W., Bowyer, M., DeMoya, M., De Waele, J., Di Saverio, S., Drake, A., . . . Woods, L. (2017). Proceedings of resources for optimal care of acute care and emergency surgery consensus summit donegal ireland. *World Journal of Emergency Surgery*, *12*(1), 47. https://doi.org/10.1186/s13017-017-0158-x

Sun, R.-Y. (2020). Optimization for deep learning: An overview. *Journal of the Operations Research Society of China*, *8*(2), 249-294.

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT press.

Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: Benefits, risks, and strategies for success. *npj Digital Medicine*, *3*(1), 17. https://doi.org/10.1038/s41746-020-0221-y

Syarif, I., Prugel-Bennett, A., & Wills, G. (2012). Unsupervised clustering approach for network anomaly detection. In R. Benlamri (Ed.), *Networked digital technologies* (pp. 135-145). Springer https://doi.org/10.1007/978-3-642-30507-8_13

Takeda, H., Veerkamp, P., & Yoshikawa, H. (1990). Modeling design process. *AI magazine*, *11*(4), 37-37.

Taylor, R. A., Pare, J. R., Venkatesh, A. K., Mowafi, H., Melnick, E. R., Fleischman, W., & Hall, M. K. (2016). Prediction of in-hospital mortality in emergency department patients with sepsis: A local big data–driven, machine learning approach. *23*(3), 269-278. https://doi.org/10.1111/acem.12876

The AnyLogic Company. (2023). *Anylogic 8*. In https://www.anylogic.com/

The Open Group. (n.d.). *Adm and the zachman framework*. Retrieved 05/10/2022 from https://pubs.opengroup.org/architecture/togaf8-doc/arch/chap39.html

The pandas development team. (2020). *Pandas-dev/pandas: Pandas* Zenodo. https://doi.org/10.5281/zenodo.3509134

Tuzii, J. (2017). Healthcare information technology in italy, critiques and suggestions for european digitalization. *Pharmaceuticals Policy and Law*, *19*(3-4), 161-176.

Vaishnavi, V. K., & Kuechler, W. (2015a). Aggregate design science research cycle as a perspective on the evolution of computing communities of interest. In *Design science research methods and patterns* (pp. 92-101). CRC Press. https://doi.org/10.1201/b18448-6

Vaishnavi, V. K., & Kuechler, W. (2015b). Introduction to design science research in information and communication technology. In *Design science research methods and patterns* (pp. 52-91). CRC Press. https://doi.org/10.1201/b18448-5

Van Wilder, P., Van Den Bulcke, J., Martins, D., Leclercq, P., & Pirson, M. (2018). Evaluation of cost and length of stay's homogeneity per apr-drg for oncological inpatient stays in 11 belgian hospitals. *Journal de gestion et d'economie medicales*, *36*(4), 217-233.

Wager, K. A. (2017). Health care information systems. In *Health care information systems : A practical approach for health care management* (4th ed., pp. 93 - 96). Jossey-Bass. http://ebookcentral.proquest.com/lib/waikato/detail.action?docID=7104515

Walls, J. G., Widmeyer, G. R., & El Sawy, O. A. (1992). Building an information system design theory for vigilant eis. *Information systems research*, *3*(1), 36-59.

Wang, Q., Ma, Y., Zhao, K., & Tian, Y. (2022). A comprehensive survey of loss functions in machine learning. *Annals of Data Science*, *9*(2), 187-212. https://doi.org/10.1007/s40745-020-00253-5

Weber, S. (2010). Design science research: Paradigm or approach? AMCIS 2010 Proceedings, https://aisel.aisnet.org/amcis2010/214

Weiskopf, N. G., Bakken, S., Hripcsak, G., & Weng, C. (2017). A data quality assessment guideline for electronic health record data reuse. *EGEMS (Washington, DC)*, *5*(1), 14-14. https://doi.org/10.5334/egems.218

Weiskopf, N. G., & Weng, C. (2013). Methods and dimensions of electronic health record data quality assessment: Enabling reuse for clinical research. *Journal of the American Medical Informatics Association*, *20*(1), 144-151. https://doi.org/10.1136/amiajnl-2011-000681

Whitner, R. B., & Balci, O. (1989, December, 4 - 6). Guidelines for selecting and using simulation model verification techniques. Proceedings of the 21st conference on Winter simulation, Washington D.C. USA.

Wiederhold, G. (1992). Mediators in the architecture of future information systems. *Computer*, *25*(3), 38-49. https://doi.org/10.1109/2.121508

Wu, J., Roy, J., & Stewart, W. F. (2010). Prediction modeling using ehr data: Challenges, strategies, and a comparison of machine learning approaches. *Med Care*, *48*(6 Suppl), S106-113. https://doi.org/10.1097/MLR.0b013e3181de9e17

Xiao, C., Choi, E., & Sun, J. (2018). Opportunities and challenges in developing deep learning models using electronic health records data: A systematic review. *Journal of the American Medical Informatics Association*, *25*(10), 1419-1428. https://doi.org/10.1093/jamia/ocy068

Xu, Y., Sauquet, D., Zapletal, E., Lemaitre, D., & Degoulet, P. (2000). Integration of medical applications: The 'mediator service' of the synex platform. *Int J Med Inform*, *58-59*, 157-166. https://doi.org/10.1016/s1386-5056(00)00084-8

Yaqoob, I., Salah, K., Jayaraman, R., & Al-Hammadi, Y. (2021). Blockchain for healthcare data management: Opportunities, challenges, and future recommendations. *Neural Computing and Applications*, 1-16.

Zachman, J. A. (1987). A framework for information systems architecture. *IBM Systems Journal*, *26*(3), 276-292.

Zavala, A. M., Day, G. E., Plummer, D., & Bamford-Wade, A. (2018). Decision-making under pressure: Medical errors in uncertain and dynamic environments. *Australian Health Review*, *42*(4), 395-402.

Zheng, T., Xie, W., Xu, L., He, X., Zhang, Y., You, M., Yang, G., & Chen, Y. (2017). A machine learning-based framework to identify type 2 diabetes through electronic health records. *International journal of medical informatics*, *97*, 120-127.

Appendix A: Research Activities and Publication

Posters and presentations:

Jiang H., Wang YC., Goh T. (2019). Enhancing decision making in a hospital emergency department with data analytics. *International Conference on Information Resources Management (Conf–IRM). Auckland, New Zealand.*

Jiang H., Wang YC., Goh T. (2019). Enhancing decision making in a hospital emergency department with data analytics. *New Zealand Information Systems Doctoral Consortium. Hamilton, Waikato, New Zealand.*

Jiang, H., Wang, W. Y. C., Goh, T. T., & Zhu, J. (2020). Digital Contact Tracing in the Covid-19 Pandemic Control. *International Conference on Digital Health and Medical Analytics. Beijing, China*

Jiang H., Wang YC., Goh T. (2023). Designing a System Integration Architecture for a Machine Learning-Based Clinical Decision Support System in the Emergency Department Setting: A Design Science Approach. *New Zealand Information Systems Doctoral Consortium. Hamilton, Waikato, New Zealand.*

Conference proceedings:

Jiang, H., Wang, W. Y. C., Goh, T. T., & Zhu, J. (2020, August). Enhancing Decision Making with Deep Reinforcement Learning in a Context of Novel Coronavirus Outbreak: an Example in Emergency Department. In *Proceedings of the 4th International Conference on Medical and Health Informatics* (pp. 113-117).

Wang, W. Y. C., Jiang, P. H. W., Tiong, T. G., & Hsieh, C. C. (2022, May). Gauging the Gaps for Decision Support-Data integration in the Hospital Information Systems with Machine Learning. In *Proceedings of the 6th International Conference on Medical and Health Informatics* (pp. 43-47).

Journal Article:

Jiang, P. H. W., & Wang, W. Y. C. (2022). Comparison of SaaS and IaaS in cloud ERP implementation: the lessons from the practitioners. *VINE Journal of Information and Knowledge Management Systems*. https://doi.org/10.1108/VJIKMS-10-2021-0238

Working Papers:

Jiang, P. H. W., Wang, W. Y. C., Tiong, T. G., & Hsieh, C. C. Designing a System Integration Architecture for a Machine Learning-Based Clinical Decision Support System in the

Emergency Department. Submitted to the 8th International Conference on Medical and Health Informatics (ICMHI 2024)

Jiang, P. H. W., Wang, W. Y. C., & Tiong, T. G. Challenges in Hospital Information Systems Integration: A Multi-Institutional Case Study.

Jiang, P. H. W., Wang, W. Y. C., & Tiong, T. G. Enhancing Clinical Decision Support in the Emergency Department: Applying Machine Learning to Electronic Health Records.