A Step Toward Improving Healthcare Information Integration & Decision Support: Ontology, Sustainability and Resilience

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ABSTRACT

The healthcare industry is a complex system with numerous stakeholders, including patients, providers, insurers, and government agencies. To improve healthcare quality and population well-being, there is a growing need to leverage data and IT (Information Technology) to support better decision-making. Healthcare information systems (HIS) are developed to store, process, and disseminate healthcare data. One of the main challenges with HIS is effectively managing the large amounts of data to support decision-making. This requires integrating data from disparate sources, such as electronic health records, clinical trials, and research databases. Ontology is one approach to address this challenge. However, understanding ontology in the healthcare domain is complex and difficult. Another challenge is to use HIS on scheduling and resource allocation in a sustainable and resilient way that meets multiple conflicting objectives. This is especially important in times of crisis when demand for resources may be high, and supply may be limited.

This research thesis aims to explore ontology theory and develop a methodology for constructing HIS that can effectively support better decision-making in terms of scheduling and resource allocation while considering system resiliency and social sustainability. The objectives of the thesis are: (1) studying the theory of ontology in healthcare data and developing a deep model for constructing HIS; (2) advancing our understanding of healthcare system resiliency and social sustainability; (3) developing a methodology for scheduling with multi-objectives; and (4) developing a methodology for resource allocation with multi-objectives.

The following conclusions can be drawn from the research results: (1) A data model for rich semantics and easy data integration can be created with a clearer definition of the scope and applicability of ontology; (2) A healthcare system's resilience and sustainability can be

significantly increased by the suggested design principles; (3) Through careful consideration of both efficiency and patients' experiences and a novel optimization algorithm, a scheduling problem can be made more patient-accessible; (4) A systematic approach to evaluating efficiency, sustainability, and resilience enables the simultaneous optimization of all three criteria at the system design stage, leading to more efficient distributions of resources and locations for healthcare facilities.

The contributions of the thesis can be summarized as follows. Scientifically, this thesis work has expanded our knowledge of ontology and data modelling, as well as our comprehension of the healthcare system's resilience and sustainability. Technologically or methodologically, the work has advanced the state of knowledge for system modelling and decision-making. Overall, this thesis examines the characteristics of healthcare systems from a system viewpoint. Three ideas in this thesis—the ontology-based data modelling approach, multi-objective optimization models, and the algorithms for solving the models—can be adapted and used to affect different aspects of disparate systems.

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DEDICATED TO

My Wife Yan Yan

My Daughters Terra and Laura

My Parents and Parents-in-Law

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LIST OF ABBREVIATIONS

2G Second Generation mobile phone system
4G Fourth Generation mobile phone system
API Application Programming Interface
AtI Atkinson Index
BRKGA Biased Random-Key Genetic Algorithm
CCI Corrected Concentration Index
CDA Clinical Document Architecture
CI Concentration Index
COVID-19 Coronavirus disease 2019
DEE Discrete Event Encoding
DEE-NSGA-II Discrete Event Encoding Non-dominated Sorting Genetic Algorithm II
DL Description Logic
EC Evolutionary Computation
EDI Equity, Diversity, and Inclusion
EHR Electronic Health Record
EP Evolution Programming
E-R Entity-Relationship
FCBPSS Function-Context-Behavior-Principle-State-Structure
FHIR Fast Healthcare Interoperability Resources
GA Genetic Algorithm
GACE Genetic Algorithm using a Conventional Encoding method
GE Generalized Entropy
GINI Gini index
GOL General Ontological Language
GP Genetic Programming
HCP Healthcare Professional
HGL hospital geographical location
HIS Healthcare Information Systems
HL7 Health Level Seven International

HPV .... Human Papillomavirus
ICU .... Intensive Care Unit
IEEE .... Institute of Electrical and Electronics Engineers
I-S .... infrastructure-substance framework
IT .... Information Technology
JDK .... Java Development Kit
JSON .... JavaScript Object Notation
MAE .... Maximal Accessibility Equity
MNS .... Mobile Network System
MOEA/D .... Multi-Objective Evolutionary Algorithm based on Decomposition
MOO .... Multi-objective Optimization
NDK .... Native Development Kit
NP-hard .... Non-deterministic Polynomial-time hard
NSGA .... Non-dominated Sorting Genetic Algorithm
NSGA-II .... Non-dominated Sorting Genetic Algorithm II
NSGA-III .... Non-dominated Sorting Genetic Algorithm III
NTD .... Number of Testing Days
NTS .... Number of Test Sites
OS .... Operating System
OWL .... Web Ontology Language
PGL .... personal geographical location
PS .... Patient Scheduling
PSO .... Particle Swarm Optimization
PSR .... Privacy, Security, and Resilience
RA .... Resource Allocation
RCA .... Regression and Correlation Analysis
RDF .... Resource Description Framework
RDFS .... Resource Description Framework Schema
REST .... Representational State Transfer
RGL .... registration geographical location
RH .... Robin Hood Index

RI..Resilience Index
R-NSGA-III .... Reference-Point based NSGA-III
ROT...Ratio Over a Threshold
SA ....Simulated Annealing
SpA .... Spatial Autocorrelation
SD ....Standard Deviation
SDK.. Software Development Kit
SHA...Saskatchewan Health Authority
SMS-EMOA ....Hypervolume Metric Selection-
Evolutionary Multi-Objective Optimization Algorithms
SOP ....Soft Open Point
SUO.. Standard Upper Ontology
SWRL .... Semantic Web Rule Language
TCD.. Test Capacity Distribution
TS ....Tabu Search
WiFi .... Wireless Fidelity
XML..eXtensible Markup Language

Chapter 1
Introduction

1.1 Background and motivation

The healthcare industry is viewed as a complex system that involves various stakeholders, such as patients, healthcare providers, insurance companies, and government agencies. The effective management of this system is crucial for the delivery of quality healthcare services and the overall well-being of the population. In recent years, there has been a growing recognition of the importance of leveraging information technology (IT) to support better decision-making in healthcare management. This includes the further development of healthcare information systems (HIS) that can facilitate the storage, processing, and dissemination of healthcare data (Wager et al., 2021; Davenport & Kalakota, 2019; Sun & Medaglia, 2019).

One of the main challenges with HIS is the need to manage large amounts of data, including so-called big data in a way that supports decision-making on improving the quality of healthcare services. One key challenge is the integration of data from a variety of sources, including electronic health records, clinical trials, and research databases. It is widely agreed in academia that the approach to tackling this challenge is to use ontology, which can be defined as a formal representation of fundamental[1] knowledge about a specific domain. By structuring and classifying

[1] The fundamental here follows the so-called information relativity principle (Zhang, 1994).

medical concepts, diseases, treatments, and other relevant information, ontology is expected to facilitate the integration and interoperability of data from different sources, enabling the development of more accurate and reliable information systems (Kiourtis et al., 2019; Subramaniyaswamy et al., 2019; García-Díaz et al., 2020). However, contemporary, understanding of ontology remain diverse with multiple perspectives, which has further contributed to the difficulty of understanding ontology in the healthcare domain and the complexity of developing an ontology model for the HIS and its applications.

Another challenge with HIS is complexity in decision-making especially for scheduling and resource allocation in a way that meets multiple conflicting objectives, which reflect common real-life situations, in a sustainable and resilient manner (Ordu et al., 2021; Halawa et al., 2020). The scheduling problem, focused on in this thesis, refers to better allocating resources (e.g., time, personnel, equipment) to reduce patient waiting time, to minimize travel distances, and to maximize resource utilization. The resource allocation problem, focused on in this thesis, is to allocate medical resources, such as COVID test kits, in a way that is effective as well as efficient. While efficiency may be more apparent, effectiveness refers to social sustainability, resilience, and so forth. Decisions on such a resource allocation can be particularly important in times of crisis when the demand for certain resources may be very high and the supply may be constrained.

On a general note, this thesis puts much emphasis on the resilience and social sustainability of healthcare systems, as these two properties are less discussed in the literature. In brief, system resiliency refers to a system's ability to maintain or recover its primary function following partial damage subject to external and/or internal disturbances or attacks, such as soaring demand or power blackouts (Zhang & Lin, 2010). Improving the resilience of a healthcare system will help to maintain the continuity and quality of healthcare services (Haldane et al., 2021). Social sustainability refers to the ethical and social acceptability of a system, which includes factors such as patient privacy, equity, and accessibility (Robards et al., 2019; Abimbola et al., 2019). It may be clear that these two properties of healthcare systems, namely resilience and sustainability, have become more important than ever before to our society today amid the COVID-19 pandemic.

1.2 Objectives and scopes

To tackle these challenges, researchers have proposed various ideas along with approaches, such as the use of big data, the development of ontologies and semantic models, and the adoption of multi-objective optimization methods (Aceto et al., 2020; Schwalbe & Wahl, 2020; Qadri et al., 2020). However, there is a need for more research to identify practical and theoretically grounded approaches that can effectively support better decision-making in HIS. This thesis aims to investigate ontology theory and to develop a methodology for building HISs that support decision-making on scheduling and resource allocation while taking system resiliency and social sustainability into account. This research can help to improve the efficiency, effectiveness, and sustainability of healthcare services, ultimately leading to better outcomes for patients.

The specific objectives of this thesis are:

- **Objective 1**: To advance our understanding of ontology in data, and to develop a methodology for building a data model for constructing healthcare management systems to support decision-making.
- **Objective 2**: To advance our understanding of the resiliency and social sustainability of a healthcare system, resulting in a comprehensive definition of these in the context of healthcare

systems and suitable to decision making for scheduling and resource allocation.

- **Objective 3**: To develop a methodology for scheduling with multiple conflicting goals, such as reduction of both patient's waiting time and reduction of patient's travel time.
- **Objective 4**: To develop a methodology for resource allocation, such as COVID-19 test kits distribution with multiple conflicting goals, which particularly addresses resiliency and the sustainability along with performances.

1.3 Thesis organization

This thesis is organized in a semi-manuscript-based style. Chapters 2, 3, 5, and 6 are presented in the form of published or submitted manuscripts, while Chapter 4 runs in a different way. In Chapter 4, first the concept of resilience and sustainability in the context of healthcare service is clarified, and after that, how the resilience is applied to privacy protection is discussed, which is in the format of a published manuscript. At the beginning of each of the manuscript-based chapters, a brief introduction is included to describe the relationship between the manuscript and the objectives of this thesis. The status of each submitted manuscript is also provided. To give the thesis a coherent form, all the manuscripts are reformatted.

The remainder of the thesis is organized as follows: Chapter 2 presents a comprehensive review pertinent to the four objectives proposed in Chapter 1: ontology-based system modelling, implementation of equity and system resiliency in healthcare, scheduling problems, and resource allocation problems. Chapter 3 proposes a unified definition of ontology in information systems and presents a methodology for building a deep model for constructing HIS. Chapter 4 discusses the concepts of healthcare system sustainability and resilience through a case study on the implementation of privacy design principles. Chapters 5 and 6 examine two typical problems in which a HIS is utilized for decision-making: scheduling and resource allocation. In these two problems, new problem models are developed, and multi-objective optimization methods are applied to enhance the efficiency, effectiveness, and sustainability of healthcare systems. Conclusions and several proposed future studies in the context of this thesis are discussed in Chapter 7. To further support our definition of ontology, an introduction of ontology-related concepts are given in Appendix A. A list of published and prepared manuscripts is given in Appendix B, and the copyright permissions of all published manuscripts used in this thesis are in Appendix C.

1.4 Contributions of the primary investigator

It is observed that all published or prepared manuscripts are co-authored. Nonetheless, all authors agree that Wenjun Lin, as the first author, is the principal investigator. The contributions of the other authors are restricted to an advisory and editorial role.

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Chapter 2

Literature review

This chapter presents a review of three main topics in the field of healthcare information systems: ontology-based system modelling (Objective 1), implementation of equity and system resiliency in healthcare (Objective 2), scheduling and resource allocation problems (Objectives 3 and 4). As noted, these three topics correspond to the four objectives presented in Chapter 1. Therefore, the discussion helps to further justify the need for research related to the proposed objectives. The literature review provides a comprehensive overview, identifies knowledge gaps in these areas, and thus serves as a guide for the work in the remaining chapters. The literature review was formatted as a manuscript as "Ontology-based resilient and sustainable resource allocation and scheduling in healthcare systems: a review" to Enterprise Information Systems in 2023 (under review).

Abstract

The healthcare system in ageing societies such as Canada is currently facing a heavy burden due to the outbreak of COVID-19, leading to a shortage of labour and supplies. This calls for decision-makers to develop policies that better result in sustainable and resilient healthcare. To establish such policies, decision makers need to take a system's view of healthcare and consider the goals of social equity and resilience, along with the efficiency of a healthcare system's operations. This review covers three aspects: (1) information modelling of a healthcare system, focusing on an

ontology-based approach to information modelling, (2) concepts of system sustainability and resiliency, along with their measurements and applications in healthcare; and (3) computational approaches for resource allocation and scheduling. This review highlights the knowledge gap in each aspect and suggest future work to close the gap. At the end of this review, there is a discussion on the buzzwords of today in the field of information and knowledge systems, digital twins and big data, and their potential to add value to developing a resilient and sustainable healthcare system, which is the focus of this review.

2.1 Introduction

Healthcare burden is one of the world's major social and economic problems, particularly in an ageing society. This leads to tremendous health expenses and constrained labour resources. The COVID-19 pandemic further strained already stretched healthcare resources. Healthcare service providers are having trouble obtaining essential healthcare resources, such as testing equipment, beds, and personal protective equipment. As the additional resource is not available immediately, the solution lies in making the best use of existing resources.

It is essential to have an effective healthcare information system in order to integrate all resources and services into one decision-support system. This system should be able to: (1) capture all relevant data in the healthcare system completely, precisely, and securely; (2) evaluate the system's performance comprehensively; and (3) provide tools to support management operations, such as resource and service allocation tools and scheduling tools, with consideration of the system's sustainability and resilience.

The term “sustainability” here, in its original definition, refers to the balance between the resources available and/or their generation and the resource consumption (or demand generation). From its original definition, sustainability in this thesis refers to social sustainability (more clarification is presented in later discussions). For instance, during the COVID-19 pandemic, many hospital's resources, e.g., ICU beds, were insufficient to handle the increasing number of patients. The sustainability of a system is heavily influenced by the equitable access each individual patient has to healthcare resources. This equity ensures that sustainability is guaranteed on an individual basis. The term "resilience" here is related to a system’s ability to recover after disruptions. This ensures that the system can maintain a balance between its resources and consumption, even in unexpected circumstances.

This review investigates three topics related to the information system: 1) modelling of healthcare information systems; 2) concepts of healthcare equity and system resiliency and their measurements in healthcare resource optimization problems; 3) modelling of healthcare resource optimization problems, including allocation and scheduling, and their optimization algorithms. The primary objective of this chapter is to provide a comprehensive overview of the current state of healthcare information systems and their related operations management tools. Subsequently, a list of suggestions to advance the knowledge and methodologies in this area is presented.

This chapter is structured as follows. Section 2.2 provides an overview of data modeling[2] of information systems, focusing on the concepts, applications, and tools of ontology-based modelling. Section 2.3 explores sustainability and resilience in healthcare systems, as well as methods to measure them. Section 2.4 discusses optimization techniques for resource allocation and scheduling problems and summarizes the current state of optimization algorithms. Finally,

[2] Throughout this thesis, modeling always refers to data modeling rather than mathematical modeling.

Section 2.5 examines potential areas that need further work to improve our understanding and to develop new technologies on the three topics.

2.2 Ontology and its role and usage in information system modelling

2.2.1 Ontology of information systems

Healthcare information systems contain an extensive variety of data, including patients' medical records, treatment solutions, and test results, which are gathered from numerous medical departments and agencies over time. To ensure secure and efficient communication of such data, along with enabling higher-level decision-making among organizations, healthcare organizations must develop specific terminologies and formats within their system (Sillence, 2019). The modelling of healthcare information systems' ontology is one way to achieve this difficult task.

Ontology is the branch of philosophy that deals with the nature of existence (Merriam Webster. n.d.), or a part of philosophy that studies what it means to exist (Collins. n.d.). In the world of information technology, ontologies are used to facilitate communication between humans and between data systems. Computers can exchange semantics along with syntax via the concepts provided in the ontologies. For decades, many studies have used ontology to define their information systems.

Many studies have used ontology in information system modelling, but they often seem to have different definitions (Cai et al., 2017; Lin & Zhang, 2001, 2004). Various definitions can be categorized into two kinds. The first category of definitions believe that ontology is essentially a work domain[3] model, or a special form of it (O'Leary 2010; Sanderson et al. 2019; Singh et al. 2021; Östberg et al., 2022; Wang, Liu, and Kara, 2022). For example, O'Leary (2010) described ontology as a domain that provides a basis for a common understanding of the domain. Sanderson et al. (2019) developed an ontology model for an adaptive production system. The ontology model represents in their work the system's function, structure, and behaviour, all key components of a work domain model. Wang et al. (2016) used these two terms interchangeably in their work. Singh et al.'s (2021) study also found a similar definition, where ontology was used to build a work domain model for managing databases of an information system.

The second category of definitions of ontology describes it as a conceptual model. Gruber notes (1993): “Ontology is the explicit specification of the conceptualisation.” Borst extends this definition as (1997): “Ontology is the formal explicit specification of shared conceptualization.” This definition has been adapted in some other studies (West, 2006; Galton & Worboys 2011; Henderson-Sellers, 2011; Wong et al., 2012; Guan et al., 2013; Ismail, 2017; Tiwari, 2020; Fernández-Cejas et al., 2022). Henderson-Sellers (2011) suggested that ontology in computer systems is a conceptual structure of a domain, while Guan et al. (2013) used ontology to capture and model conceptual knowledge of a domain. Fernández-Cejas et al. (2022) saw ontology as a conceptual model providing a unifying framework, aiding in knowledge sharing and communication among computer systems within a domain.

The definitions in the above two categories either take ontology as a form of domain model or a conceptual model in a domain. Both definitions associate ontology with a given domain. However, some other studies claim that ontology can be completely independent of a domain, referred to as

[3] In this thesis, domain always refers to the domain of a work, or work domain.

top-level ontology. Examples of such ontologies include Bunge's ontology (Bunge, 1977), Sowa's upper-level ontology (Sowa, 1999), General Ontological Language (GOL) (Degen et al., 2001), and IEEE Standard Upper Ontology (SUO) (IEEE, 2003). Popular top-level ontologies that have been implemented include CYC (Lenat & Guha, 1990), WordNet (Miller, 1990), and Generalized Upper Model (Bateman et al., 1994). It is believed that the purpose of top-level ontology is to act as a framework that describes general, domain-independent categories of reality, which can then be used to create domain-specific ontology (Degen et al., 2001).

Ontology definitions can also vary in terms of their generality or formality. Nguyen summarized a multi-level ontology definition (2011) that includes a top-level ontology and a domain level ontology. The domain ontology was specific to a domain of interest and specified its concepts and their relationships. Sometimes, a mid-level ontology was used to serve as a bridge between conceptual level and domain level ontologies (Wong et al., 2012). However, such a multi-level ontology definition might harm the implementation of ontology. Different interpretations of each level of ontology can result in different ontology models, leading to incompatibilities. This can lead to obstacles when merging ontology models built on different levels of ontologies.

2.2.2 Applications of ontology modelling in healthcare

Despite differing definitions of ontology, researchers generally agree that its purpose is to enable machines to better comprehend concepts. This, in turn, facilitates communication and understanding between information systems. In the past decade, research on ontology-based healthcare information systems has seen exponential growth. Various ontology models have been proposed for various applications. We can divide these models into three levels: patient level, organizational level, and regional level. This chapter will review and compare each study's main research goal, modelling method, and contributions.

Research on patient-level studies mainly focuses on utilizing patients' personal data, such as Electronic Health Record (EHR), to improve service delivery, such as personalized medication and homecare. For example, Mukasine (2014), Rahimi et al. (2012), Riano et al. (2012), Ismail et al. (2017), and Tiwari & Abraham (2020) have described ontology models that integrate healthcare data related to chronic diseases. These models help patients or healthcare providers monitor health data at a higher frequency in a home setting. The other research focus is on the classification of diseases, which has been conducted by several authors, such as Bertaud-Gounot et al. (2011), Forbes et al. (2012), and Romero-Tris et al. (2009). They developed ontology models that could represent patient conditions under a specific disease class based on diagnostic criteria. Their research showed that operational definitions of diseases can be represented using ontology models and that real patient cases can be classified accordingly.

For organizational level studies, Vyas & Pal (2012), Ramadoss (2014), Lasierra et al. (2014), and Spoladore & Pessot (2021) have all used ontology models to develop data management systems. These systems provide healthcare providers with quick access to specialized healthcare services and up-to-date patient health data, thereby increasing the usability and reliability of the information. Ontologies in these studies enable high scalability in searching, extracting, maintaining, and generating information. Another type of organizational level study related to healthcare management is proposed by Dias et al. (2012). They proposed a method to study organizations and their processes to identify non-value-added transactions. These processes were modelled using an enterprise ontology model and redesigned for improving healthcare management.

Research goals at the regional level often involve the processing of large amounts of data. For instance, Sunitha & Babu (2014), Spoladore & Pessot (2021), and Cameron et al. (2015) developed healthcare knowledge base systems that contain various domain concepts such as diseases, environments, and locations. This system produces semantically integrated data, which resolves interoperability and reusability issues across different health applications. White et al. (2014) attempted to reduce the effort necessary to identify healthcare quality indicators and to ascertain areas for future computer-interpretable quality indicator development. To this end, they created an ontology model with a catalogue of quality indicators. This ontology when integrated was found to be beneficial to clinical auditing communities, quality indicator developers, and organizers of quality indicators. Moreover, it was concluded that the ontology reduces the effort required for healthcare quality monitoring.

Table 2.1 indicates that most of the ontology modelling studies have been centred around the patient level. This includes gathering patient data from a variety of sources, such as EHRs, wearable devices, and Internet of Things devices. At the organization level, there is an emphasis on integrating patient information with other hospital information systems, such as patient activity recognition, safety monitoring, and building management. Regarding the regional level, most of the work is on creating a centralized knowledge database. The challenge at the regional level is data management, such as data integrity, data extraction, transformation, and privacy protection. A common theme among all works is that many existing studies work on separate existing systems that have already been developed with their own individual ontology models. To integrate these information systems, a new ontology model must be built from scratch. This is a laborious and time-consuming process since it requires both domain experts and information technology specialists to be involved in the definition of the knowledge to be modelled.

Table 2.1 Recent publications on healthcare ontology modelling

System-level	Author	Research goal	Contribution
Patient	Mukasine (2014)	Chronic diseases remote supervision	Improved diabetic home patient self-management capability
Patient	Bertaud-Gounot et al. (2011)	Disease classification	A diagnostic classification of real patient cases
Patient	Forbes et al. (2012)	Primary care and Patient Practitioner Interview	Improved communication between the patient and healthcare provider by classifying diseases based on phenotype for Indigenous communities
Patient	Ismail et al. (2017)	Store maternal and child health data for effective exchange	An improvement in service delivery and availability of reliable health data
Patient	Rahimi et al. (2012)	Chronic disease management	A framework representation to translate data into the desired quality outcome
Patient	Riano et al. (2012)	Chronic disease management	Developed a decision support tool for chronically ill patients
Patient	Romero-Tris et al. (2009)	A diagnostic guide for medical practitioners	A knowledge-based homecare model
Patient	Tiwari & Abraham (2020)	Monitor patients in real-time with IoT	Developed a quality assessment approach to analyze the quality of the proposed ontology model
Organizational	Dias et al. (2012)	Improve healthcare operational process	Reduction of the high failure rate of healthcare systems. Removal of waste to improve flow time. Improving healthcare operational processes.
Organizational	Ramadoss (2014)	Provide a systemic view of patient and patient care	Development of a knowledge-based case profile healthcare ontology
Organizational	Lasierra et al. (2014)	Improve healthcare resources management	Developed an ontology-driven solution that organizes and describes knowledge related to the usage of medical items
Organizational	Vyas & Pal (2012)	Decision support system	Development of an electronic healthcare system to improve healthcare services
Organizational	Spoladore & Pessot (2021)	Decision support system	Provided some reference insights for multiple ontology system integrations
Regional	Sunitha & Babu (2014)	Healthcare information system integration	Development of a centralized semantic knowledge base for healthcare
Regional	Cameron et al. (2015)	Mobile healthcare knowledge base	Discover the gaps in research and between research and practice
Regional	Duncan et al. (2015)	Healthcare information system integration	Development of a new ontology in a public health system
Regional	White et al. (2014)	Healthcare Quality Monitoring	Use of several ontologies for proper data analysis and integration

2.2.3 Tools for ontology modelling

Many tools have been created to assist with the implementation and integration of ontology models. Semantic-based languages are one type of tools for representing ontology models. Resource Description Framework (RDF) (Bicer et al., 2005) in conjunction with Web Ontology Language (OWL) (Bodenreider, 2004) is often regarded as a de facto standard (Dimitrieski et al., 2016) for semantic web and linked data technologies and serves as a foundation for defining healthcare ontologies. Additionally, eXtensible Markup Language (XML) technology and relational databases are also frequently utilized, largely due to the availability of good validation tools and support from major manufacturers.

Many languages focus on EHR data, its structure, and system implementation. For example, Health Level Seven International (HL7) is a non-profit organization with the goal of increasing the interoperability of healthcare information systems through the development of healthcare standards. Part of HL7 is the Clinical Document Architecture (CDA) document markup standard, which defines the structure and semantics of "clinical documents" for exchange between healthcare providers and patients. It employs XML to define documents such as discharge summary, imaging report, admission & physical, pathology report, and more.

HL7 has published the Fast Healthcare Interoperability Resources (FHIR) (www.hl7.org/fhir/), one of the latest developments in ontology language. This open standard enables new apps and legacy systems to better exchange data than previously. FHIR's strong focus on implementation and its simple implementation process provides a good foundation for data integration between different standards. In FHIR, basic data is described as resources. Various predefined and customized resources can be defined to describe real-world clinical and administrative data. This has led to its wide acceptance among major tech firms such as Apple, Microsoft, Google, Amazon, IBM, Oracle, and Salesforce.

The other type of tools are ontology editors. It is important to have good editing software in order to construct ontologies in an efficient and standard way. Ontology editors allow users to visually manipulate, inspect, browse, code, and maintain ontologies. Some of the most popular editors include Protégé, Swoop, Apollon, etc. Below, we discuss a few popular editors and their features.

Protégé (Noy et al., 2003; Tudorache et al., 2008; Sivakumar & Arivoli, 2011) is a free, open-source platform that provides users with a suite of tools to construct domain models and knowledge-base applications with ontologies. It supports the creation, visualization, and manipulation of ontologies in various languages, with OWL being the default. Its extensibility is one of the platform's key advantages. This allows for visualization, ontology merging, version management, inference, and remote collaboration.

Swoop (Kalyanpur et al, 2005 & 2006) is an open-source ontology editor, based on OWL, that provides validation, various syntax views and reasoning support. It also allows users to compare, edit and merge entities and relationships from multiple ontologies. To aid integration, Swoop has a deep learning-based search algorithm that combines entities based on keywords. It can also support plug-ins for collaborative annotation and importing external ontologies.

Apollo (Lee et al., 2009; Hogan et al., 2016) is a knowledge modelling application that enables users to create ontologies with basic primitives, such as classes, instances, functions, and relations. It uses a hierarchical structure for organizing ontologies, which can be inherited from other ontologies. However, Apollo does not include graph view, information extraction, or multi-user capabilities. Instead, it provides type consistency checking, storing ontologies as files, and the ability to import/export ontologies in various languages.

Despite the various tools available, their adoption in healthcare organizations has been slow. This is due to two main reasons. Firstly, the integration and exchange of data between systems implementing two different standards is time-consuming and labour-intensive. Secondly, these tools are mainly focused on EHR data. A set of predefined resources is provided to facilitate the integration of patient data, restricting its implementation to the patient level. For studies like healthcare resource management and healthcare quality monitoring, users must define customized resources. Even using the same tool, different resources can be created to describe the same thing, leading to incompatibilities between different ontology models created by the same tool. This can reduce the effectiveness of the data integration these tools provide.

2.2.4 Discussion

Based on the review above, we can identify three knowledge gaps: (1) a lack of a unified definition of ontology in the field of healthcare information systems; (2) repeated efforts required from both domain experts and information technology specialists when integrating ontology-based information systems; and (3) current ontology modelling tools not being able to ensure ontology model compatibility, particularly when dealing with data outside EHR. Of the three, the first is the most fundamental. It may influence the other two either directly or indirectly. Therefore, we recommend that future studies should have a more comprehensive understanding than existing studies based on a unified definition of ontology and ontology modelling in information systems.

2.3 Sustainability and resilience in healthcare systems

2.3.1 Concept of sustainability and resilience in healthcare systems

Recently, researchers in the healthcare sector have been paying attention to systematically considering sustainability and resilience through policy development and decision making. This lens promotes long-term thinking about the quality of healthcare, which considers the trajectory of indicators related to the domain to identify risks, build resilience, and ensure that policy choices are contributing to higher quality now and in the years to come, without sacrificing future generations. While this lens is intended to bring a long-term perspective to all dimensions, a subset of relevant dimensions, including social sustainability and system resilience, should be given priority when preparing for future health risks.

Sustainability is a term used mainly in ecology, with a specific meaning of "conserving an ecological balance by avoiding depletion of natural resources" (Oxford Dictionary of English, 2003). "Sustain" also means to support or maintain (Oxford Dictionary of English, 2003). In other words, sustainability is the capacity of systems or processes to maintain balance and endure. When applied to healthcare, the term "endure" is used to refer to the continuous provision of healthcare services to the public.

Resilience is defined as the ability to "withstand or recover quickly from difficult conditions" (Oxford Dictionary of English, 2003). In the ecological context, it refers to the capacity of a system to absorb disturbance, while maintaining its structure and viability. According to Folke (2006), individuals or systems must be prepared for any surprises or disturbances that may arise. In the healthcare context, resilience refers to the ability of a system to sustain or restore its performance in the event of one or multiple system failures (Alemzadeh, 2020).

Several studies have investigated the sustainability and resilience of healthcare systems (Vorsters & Van Damme, 2018; Achour & Price, 2010; Cristiano et al., 2021; Matin et al., 2022; Goodarzian et al., 2022). Vorsters & Van Damme (2018) assessed four scenarios of HPV (Human Papillomavirus) immunization programmes and analysed their sustainability and resilience. They found that the response to crises was slow due to a lack of political leadership and a crisis mitigation plan. To address this, they suggested proper monitoring of the programme. Cristiano et al. (2021) conducted a systems-thinking-based assessment of a Sudanese hospital with the aim of understanding its efficiency, resilience, and sustainability. They recommended larger, transdisciplinary efforts to optimise resources, including social and systems studies. Goodarzian et al. (2022) developed a healthcare supply network that incorporated sustainability and resiliency concepts. Simulation case studies showed that their network was resilient to changes in transportation costs, demand for medicines, hospital waste, and financial crises. Similarly, Matin et al. (2022) argued for the importance of considering sustainability and resilience in healthcare supply chain planning. They highlighted that during unexpected events such as natural and man-made disasters, a sustainable and resilient healthcare resource supply system is essential.

2.3.2 Discussion on the health system sustainability & resilience

Most of the existing work has treated sustainability and resilience as two distinct concepts. For example, Crowther et al. (2016) argued that resilience is an element of difficulty that is responded to either by holding steady or by quickly resuming a normal state. It differs from the definition of sustainability, such as an appropriate balance of economic, environmental, and social aspects of a supply-demand system (Goodarzian et al., 2022). Even for studies that explore both sustainability and resilience simultaneously (Cristiano et al., 2021; Matin et al., 2022; Goodarzian et al., 2022), no explanation of the relationship between the two has been provided.

Sustainability and resilience both serve the same goal: providing sufficient services. In the example of a healthcare system, it should provide sufficient services under both short-term rapid disruptions, such as disease outbreaks, and long-term significant trends, such as global warming. The capability to handle the short-term rapid disruptions is system resiliency, and the capability to handle the long-term significant trends is sustainability. These two capabilities are interdependent and should not be considered separately.

The United Nations' Sustainable Development Agenda for 2030 (2022) outlines three main pillars of sustainability: economic, environmental, and social. Most studies related to sustainability concentrate on the economic and environmental pillars. This review focuses on the social pillar, in particular on the issue of health equity, in response to the heightened awareness of Equity, Diversity, and Inclusion (EDI) in our society.

2.3.3 Health equity measurement

Matin et al. (2022) have pointed out that measuring system equity and resilience is a major challenge in healthcare systems. The concept of health encompasses both moral and legal elements. The primary aim of many healthcare systems is to ensure health equity among all populations, which is defined as the lack of systematic disparities in health across social, economic, geographical, power, and prestige status (Braveman, 2003). To achieve this, healthcare must be made accessible, and any socially unjust disparities within healthcare must be addressed (Asthana & Gibson, 2008).

When measuring health equity, researchers typically need to determine a set of variables and indices. Variables are usually specific to the study in question, while indices tend to be more general and can be adapted to various problems. For example, in the study of measuring fair allocation of human and material healthcare resources to people across regions in Ethiopia (Woldemichael et al., 2019), the authors used four variables including the annual outpatient visits per capita, the proportions of immunised children, and the under 5 child mortality rates, and infant mortality rates. For comparing those variables among regions, three indices, including the Theil L (θ_L), Theil T (θ_T) and Gini index (Gini) were calculated. The θ_L and θ_T can be calculated using the following mathematical expressions:

$$\theta_L = \frac{1}{n}\sum_{i=1}^{n}\frac{\log Y_i}{P_i} \quad \textbf{(2.1)}$$

$$\theta_T = \frac{1}{n}\sum_{i=1}^{n}\frac{P_i \log P_i}{Y_i} \quad \textbf{(2.2)}$$

where n represents the number of regions, P_i is the population proportion of the i^{th} region, and Y_i is the proportion of a given distribution of the i^{th} region. The Gini was calculated using the following mathematical equation:

$$Gini = 2\sum_{i=1}^{n} Y_i P_i R_i - \mu \quad \textbf{(2.3)}$$

where μ is the mean value of the overall distribution, n is the number of regions, Y_i is the value of a distribution in the i^{th} region, P_i is a region's population share and R_i is the relative rank of the i^{th} region. By using those variables & indices, the authors measured the inequity in healthcare workforce, infrastructure, and outcomes. It was discovered that Gini is an efficient means of recognizing regional inequity, though the limited number of regions could lead to an underestimate.

In this part of the review, we are focusing on the calculation of indices due to their wider usability in related studies. Gini, also known as the Gini coefficient, is one of the most commonly used approaches for the calculation of healthcare equity (Goddard, 2010; Hara, 2017; Wagner, 2009; Zhang, 2017; Smoyer-Tomic, 2004). It is used as a measure of statistical dispersion to represent income or wealth inequality within a nation or a social group (Gini, 1936). The Gini index is calculated as the ratio of the area between the perfect equality line and the Lorenz curve (A) divided by the total area under the perfect equality line (A + B), as shown in Figure 2.1. The Lorenz curve (Lorenz, 1905) has an abscissa is the cumulative normalized rank of income (or healthcare resource in our case) from the lowest to the highest (x), and an ordinate is the cumulative normalized income (or healthcare resource) from the lowest to the highest (y).

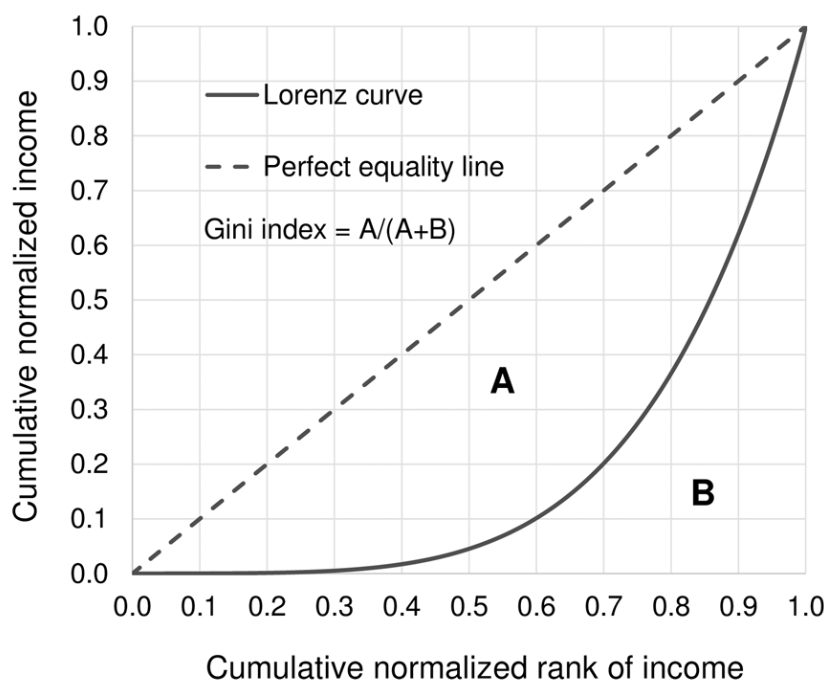

Figure 2.1 Lorenz cure and Gini index calculation (Sitthiyot & Holasut, 2020)

Table 2.2 Other commonly used indices for health equity calculation

Name	Formula	Features
Regression and Correlation Analysis (RCA) (Truelove 1993; Roeger et al., 2010)	$\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(Y_i-\hat{Y}_i\right)}$ Where Y is the observed variable while $\hat{Y}$ is the estimated variable from a regression	Suitable when there is a clear connection between variables under the interests, such as available resources, and needs such as population
Spatial Autocorrelation (SpA) (Smoyer-Tomic & Hewko, 2004; Bowen et al, 1995)	$\frac{n}{\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(Y_i-\hat{Y}_i)(Y_j-\hat{Y}_j)}{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}}$ Where Y is the observed variable while $\hat{Y}$ is the estimated variable from a regression, w is the spatial weights matrix which depends on the influence between two groups.	Suitable for spatial equity problems which influence between groups under investigation can be observed. For example, if two areas have a shared border or not.
Concentration Index (CI) (Witthayapipopsakul et al., 2019; Wagstaff et al., 2007; Gan et al., 2015)	$\frac{2}{N\mu}\sum_{i=1}^{n}h_i r_i-1-\frac{1}{N}$ where h_i is the resource variable, μ is its mean, and $r_i = i/N$ is the fractional rank of individual i in the living standards distribution, with i = 1 for the poorest and i = N for the richest	Depends only on the relationship between the resource variable and the rank of the need related factors and not on the value of the factors themselves.
Corrected Concentration Index (CCI) (Bonfrer et al., 2014)	$4\left[\sum_{k=1}^{K}\beta_k\bar{x}_k CI(x_k)+\sum_{j=1}^{J}\beta_j\bar{z}_j CI(z_j)+GC\right]$ with $\overline{x_k}$ and $\overline{z_j}$ representing the means of x_k, , need related variable, and z_j non-need related variable, respectively, and $CI(x_k)$ and $CI(z_j)$ are their concentration indices, GC is a residual term.	Suitable for a mix of need related variables and non-need related ones. Can be used with correlation analysis to identify the underlying drivers of inequity.
Atkinson Index (AtI) (De Maio, 2007; Sitthiyot, & Holasut, 2020)	$1-\left(\frac{1}{N}\sum_{i=1}^{n}\left(\frac{y_i}{\bar{y}}\right)^{1-\epsilon}\right)^{\frac{1}{1-\varepsilon}}, \varepsilon \neq 1$ $1-\frac{\prod_{i=1}^{N}\left(y_i^{\left(\frac{1}{N}\right)}\right)}{\bar{y}}, \varepsilon = 1$ where y_i denotes the individual variable, $\bar{y}$ denotes the average, N is the number of populations or groups, and ε is a sensitivity coefficient.	Has a sensitivity coefficient (ε) that varies in the weight given to inequity in different groups. As ε increases, more concern is given to the lower end of the health resource distribution. In practice, ε values of 0.5, 1, 1.5 or 2 are used.
Generalized Entropy (GE) index (Mussard, Seyte, and Terraza 2003; Dagum 1997)	$\frac{1}{\alpha(\alpha-1)}\left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i}{\bar{y}}\right)^{\alpha}-1\right]$ where y_i denotes the individual variable, $\bar{y}$ denotes the average, N is the number of populations or groups, and α is a sensitivity coefficient.	Has a sensitivity coefficient (α) that varies in the weight given to inequity in different groups. The more positive α (typically =−1, 0, 1 or 2) is, the more sensitive GE(α) is to inequity at the top of the resource distribution.
Robin Hood Index (RH) (Sohler et al, 2003; Omrani-Khoo et al., 2013)	$\frac{1}{2}\frac{\sum_{i=1}^{N}\lvert x_i-\bar{x}\rvert}{\sum_{i=1}^{N}x_i}$ where x_i denotes the individual variable, $\bar{x}$ denotes the average.	It measures the maximum vertical distance from the Lorenz curve to the 45° line of equity.

Other common indices are Regression and Correlation Analyses, Spatial Autocorrelation, Concentration Index, Corrected Concentration Index, the Atkinson Index, Generalized Entropy index, and Robin Hood Index. Their formula and explanations of parameters are given in Table 2.2.

RCA evaluates whether the distribution of resources is related to need. The higher the correlation, the more equitable the distribution. For example, if the number of patients per subsidised physician has a strong positive correlation with the number of physicians per district, subsidised physicians are distributed based on one measure of need. The issue lies in defining an appropriate correlation coefficient between them.

SpA pays special attention to the spatial properties of the problem. The results are highly affected by whether the areas under investigation are geographically close to each other. A positive SpA indicates that nearby areas have similar levels of the healthcare resource variable, while a negative SpA indicates that areas with high levels of the resource are adjacent to areas with low levels of the resource.

CI is defined based on concentration curves. These curves plot the cumulative percentage of the resource distribution variable against the cumulative percentage of the population, both ranked by need-related factors. The CI is then defined as twice the area between the concentration curve and the line of equality (the 45-degree line). A CI of zero indicates no inequality. A negative CI implies a disproportionate concentration of health resources among the poor, while a positive CI means the opposite.

CI was designed specifically to measure healthcare equality and was widely used in related studies.

However, researchers began recognizing its limitations. CI is dependent on the mean of the health resource variable, making comparison between CIs in regions with varying health levels difficult. Furthermore, CI is unsuitable for use with qualitative based health resource variables. To address these issues, Erreygers (2009) proposed the CCI, which is suitable for a combination of need related and non-need related factors. Positive CCI values indicate a disproportionate concentration of the resource among the wealthy, and negative values indicate the opposite.

Gini is popular in literature due to its ability to present the inequity of resource distribution with a single statistic value between 0 and 1. However, it has been found that a region with a lower Gini index does not always have a more equal distribution of resources than another region with a higher Gini index. This is due to their Lorenz curves intersecting, reflecting different resource distributions. To counter this limitation, Atkinson (2014) devised the social welfare-based index, AtI. This index uses a sensitivity parameter (ε) ranging from 0 to infinity. A lower parameter indicates that the researcher is unconcerned about the nature of resource distribution, whereas a higher parameter indicates that the researcher is more concerned about the lower end of the health resource distribution.

In order to circumvent the social welfare assessment, which is determined by the sensitivity parameter (ε) in AtI, an array of GE indices were employed as alternatives when the Lorenz curves of the two regions intersect. The parameter α impacts the sensitivity of the index to inequalities at the top of the distribution (Bellù and Liberati, 2006). This value is usually -1, 0, 1 or 2. GE(1) is often referred to as the Theil index (Conceição & Ferreira, 2000). The exact specification of the GE(α) index is contingent on the value of α, thus making it hard to contrast the resource inequity across disparate regions.

RH, or Hoover Index, is the maximum vertical distance from the Lorenz curve to the 45° line of equity (Kawachi I, Kennedy, 1997). It is interpreted as the proportion of resources that need to be transferred from those above the mean to those below the mean to achieve an equal distribution (Kondor, 1971). A higher RH value indicates a more unequal society, meaning a larger share of resources needs to be redistributed. Compared to the Atkinson and GE indexes, RH does not incorporate a sensitivity coefficient, which makes it easier to use.

2.3.4 Discussion on health equity measurement

In summary, there are three types of equity indices: correlation-based, concentration curve-based, and Lorenz curve-based. Correlation-based indices, comprising RCA and SpA, assume that certain independent factors, such as population, are correlated with a resource distribution variable, such as the number of physicians. Thus, the resource distribution variable can be estimated from the independent factors. The discrepancies between the estimated variable and the actually observed variable determine the equity indices; the larger the difference, the greater the disparity in resource distribution. For systems with a clear correlation between independent factors and the resource distribution variable, correlation-based indices are the optimal choice.

The second type of equity indices, including CI & CCI, are based on concentration curves. Those indices are related to the rank of the independent factors, rather than their value. These factors could be either need-based or non-need-based, making them suitable for measuring equity in healthcare.

The third type of equity indices, based on the Lorenz curve, comprises AI, GE, and RH. The Lorenz curve is determined only by the resource distribution variable and its rank, with no independent factors being considered. This feature makes them potentially more suitable for complex system analysis, where independent factors are hard to determine.

Most of the equity indicators reviewed originate from the economy, designed to measure the difference between reality and a perfect equality situation. Equality and equity are terms often used interchangeably, yet they have different meanings. Equality involves treating everyone the same, regardless of individual differences or circumstances. Equity, however, is the idea of fairness and providing people with what they need to be successful, considering individual differences and circumstances.

In healthcare, equity is more suitable than equality because care should be tailored to the individual needs of the patient. For example, different care should be provided to someone with a mental health condition than to a person with a physical health condition. Furthermore, people with different backgrounds, cultures, and experiences require different approaches to care. Equity acknowledges these differences and ensures everyone receives the care they need. Given that most measurements are designed for equality, future studies should explore their usability in healthcare equity related applications.

2.3.5 Health system resilience measurement

Resilience Index (RI) (Liu et al., 2017; Retit et al., 2013), or resilience metric (Watson et al., 2014; Panteli et al., 2017), is a tool for measuring the resilience level of systems. A proper evaluation of resilience leads to effective and rational resilience enhancement strategies, such as advanced techniques to improve the resilience of infrastructure (Baghaee et al., 2019; Afshari et al., 2020; Raeispour et al., 2020). By using appropriate resilience measurement techniques, weak and strong areas of a system can be identified, allowing for the proposal of resilience enhancement strategies (Watson et al., 2014). However, quantifying resilience is difficult and requires a widely accepted metric and associated computation algorithm.

In the literature, there is no general agreement about the necessary capabilities, measurement method, and relation to desired outcomes for RIs. In the past, many reviews have classified RIs into categories that usually follow a certain hierarchy and contain multi-level sub-categories. For example, Raoufi et al. (2020) used a five-level hierarchy to classify RIs, resulting in over a dozen sub-categories at the lowest level. This makes the classification of an RI tedious and unnecessarily complicated. Therefore, instead of classifying RIs into categories, we developed a five-dimensional framework to describe any RI, as shown in Table 2.3. This framework does not require all dimensions to be applied to every RI. Rather, it provides insights into how a RI can be measured and what other angles can be considered. New RIs can be developed by using other choices from the same dimension, and/or adding another dimension.

Table 2.3 The five dimensions framework for RIs

Dimension	**Methods**
Research	Qualitative; Quantitative
Perspective	Subjective; Objective
Variable	Capacity; Outcome
Timing	Deterministic; Probability; Simulation
Calculation	Area under curve; Expected impact of disasters; Margin and sensitivity

Research is the first dimension. Two methods are typically used: qualitative and quantitative. Qualitative research, which tends to assess system resilience without numerical descriptors (Ungar, 2015; Sarre et al., 2014), is conducted through observation, interviews, focus groups, etc. (Mash et al., 2008; Witter et al., 2017; Raven et al., 2018; Brooke-Sumner et al., 2019; Thude et al., 2019). This type of research provides insight into resilience but lacks a quantitative value. Quantitative research, on the other hand, gathers quantifiable data to represent resilience (Paterson et al., 2014; Gizelis et al., 2017; Sochas et al., 2017; Kozuki et al., 2018; RayBennett et al., 2019). Its numerical nature makes it more suitable for system resilience measurement and comparison.

The second dimension of RI is perspective, which has two methods: objective and subjective. Objective methods are independent of judgement based on the subjects being evaluated (Cohen, Manion, & Morrison, 2002). In the context of resilience, objectivity refers to the range of steps in the measurement process, such as choosing definitions and frameworks, collecting data, and quantifying resilience. For example, most measurement toolkits rely on frameworks for resilience that are based on expert-elicitation or academic literature (Schipper & Langston, 2015). These approaches are largely objective, in that resilience is externally defined and those being measured have little or no say in determining what constitutes resilience. In contrast to objectivity, subjective methods take a different view. Rather than relying on external judgement, subjective approaches consider the individual in question to understand their own circumstances (Nguyen & James, 2013). Subjective resilience relates to an individual's cognitive abilities and their personal assessment of a system’s capabilities in responding to risk (Jones & Tanner, 2017). Subjective methods are usually conducted in the form of questionnaires or interviews (Béné, Al-Hassan, et al., 2016; Claire et al., 2017; Jones & Samman, 2016).

The third dimension is variable, with two methods: capacity and outcome. The capacity method, also referred to as functionality (Panteli et al., 2015; Landegren et al., 2016) or quality (Reed et al., 2009; Attoh-Okine et al., 2009), is the direct measurement of a system's resource. Examples of capacity RIs include the number of beds, available labour, and equipment. On the other hand, the outcome method focuses on the effect of the system on society, such as equity, the number of areas affected, and loss of life (Watson et al., 2014; Shinozuka et al., 2004). If the system is well understood, an outcome RI can be computed using capacity RIs.

Timing is the fourth dimension of RI. Three methods are typically used to measure resilience: deterministic, probabilistic, and simulation. The deterministic method is often used in empirical research, where researchers directly observe phenomena and measure them (Lei et al., 2018; Ji et al., 2017; Shao et al., 2017). As an example, Bruneau et al. (2003) proposed a static metric for measuring the resilience loss of a community to an earthquake, based on four aspects of the community before and after the earthquake. The probabilistic method accounts for the stochastic behavior of systems and uses the expected value or probability distribution of disruptions based on some intended disruption scenarios (Shinozuka et al., 2004; Johnson et al., 2020; Krishnamurthy et al., 2016; Chang & Shinozuka, 2004). This method is better suited to repeated disruption events like extreme weather. The simulation method forecasts system behavior using simulation models (Shinozuka et al., 2004; Carvalho et al., 2012; Panteli et al., 2015). Carvalho et al. (2012) used discrete event simulation to assess the resilience of a supply chain, by calculating the additional inventory required, as well as the extent of the disrupted transportation system under six different scenarios.

The last dimension is calculation. This dimension is only applicable to quantitative RIs, as it provides a quantitative means to assess resilience. RIs under this dimension usually compare system performances under two states: an initial state (the system's ideal performance) and a real state (the system's performance under disruption scenarios). The real state can be divided into three stages: absorb, where system performance declines due to disruptions; response, where from disruption stops until recovery starts; and recover, where a restoration strategy is in place to recover system performance. Many computational methods belong to this dimension, and here three of them are described in detail.

The **Area Under Curve** (Panteli et al., 2015; Bie et al., 2017; Li et al., 2017; Attoh-Okine et al., 2009) is a widely used method for measuring the difference between a system's performance under disruption and its ideal performance. This is represented by the area between the initial and real states. The **Composite Resilience Index** (Ayyub et al., 2014; Francis et al., 2014; Panteli et al., 2015) multiplies the recovering speed with the ratio of system performances in the real state to those in the initial state. The **Expected Impact of Disasters** (Panteli et al., 2015; Panteli et al., 2017; Ciapessoni et al., 2016) method compares a system's real performance with and without considering resilience strategies. The **Margin and Sensitivity** method (Landegren et al., 2016) uses a pair of two RIs to measure a system's resilience. This includes the initial drop in functionality and the time required to restore desired functionality. By considering disruption scenarios of increasing severity, a margin plot and a sensitivity plot are created. Different from the other methods, which are based on a given disruption scenario, the Margin and Sensitivity method investigates system resilience under different levels of disruption.

Most of the studies above focus on the areas of environmental science, ecology, and engineering. In the healthcare system, most of the work uses deterministic and qualitative RIs. Some have tried to improve the measurements by adding quantitative ones (Farley et al., 2017; Ammar et al., 2016; Fukuma et al., 2017). In 2016, Ammar et al. (2016) studied Lebanon's health system during a refugee crisis. They reported on the difficulty of not having a unified definition of health system resilience, indicating that "the literature lacks a rigorous and scientifically validated method for measuring and providing resilience in health systems." To address this, they decided to use an input-process-output model to measure the capacity of the health system and its performance.

In addition, subjective RIs are widely used in systems related to health workforce and community perspective (Falegnami et al., 2018; Patriarca et al., 2018; Raven et al., 2018; Cohen et al., 2019; Alonge et al., 2019; Andrew et al., 2016). Kruk et al. (2017) seek to assess multiple aspects of resilience, such as awareness, diversity, self-regulation, integration, and adaptability. Morse et al. (2021) proposed a framework for health workforce resilience, evaluating the state of the ill facing profound, devastating, and rapid life-threatening changes. This framework identifies protective, compensatory, and coping strategies that health workforce can use. This trend demonstrates that, in a complex system involving humans, both objective and subjective perspectives are necessary to gain a comprehensive understanding. As subjective RIs can reveal underlying human factors, they should be integrated with objective RIs in system resilience estimations.

2.3.6 Discussion on resilience measurement

From our reviews on resilience measurement, four things are worth mentioning. Firstly, approaches to measuring resilience are disparate, considering different types and classes. Compared to existing ways of classification, the five dimensions proposed in this work could better describe the characteristics of RIs and provide more inspiration for developing new ones. Secondly, most resilience measurements are made in the areas of environmental science, ecology, and engineering. Amongst these works, only those in engineering take a systematic view on the problem. Thirdly, most studies in engineering focus on the strategy of maximizing system capability in the event of disruptions. To complement this, system resilience optimization at the planning stage should also be investigated. Simulation-oriented RIs for planning are missing from the literature. Lastly, in the healthcare area, most of the existing work uses deterministic RIs. They focus on measuring system resilience before and after a disturbance. A systematic view is missing from the work.

In light of the reflections on Sections 2.3.4 and 2.3.6, we conclude that measurements of healthcare system sustainability and resilience remain novel. This is due to the recent recognition of their importance and the need to measure them, in order to identify areas for improvement. This is especially pertinent in the face of the unprecedented challenges posed by the pandemic.

In order to improve the measurements, several key steps can be taken. Firstly, definitions and indices should be developed more clearly, so that the system can be measured accurately and reliably. Secondly, a common framework for assessing sustainability and resilience should be established, allowing different healthcare systems to be compared and evaluated. Thirdly, healthcare systems' sustainability and resilience should be estimated at the planning stage, in order to identify and address areas of weakness earlier. Finally, more focus should be put on using data to inform decisions and strategies for improving healthcare systems, helping them to become more sustainable and resilient in the face of future challenges.

2.4 Resource allocation and scheduling

Healthcare optimization problems have attracted much attention in recent years in order to provide more appropriate services at a lower cost (Fei et al., 2010; Rais et al., 2011). Healthcare sectors, unlike most other industries, work around the clock. This prolonged and irregular work schedule can lead to job dissatisfaction and, consequently, can affect patient satisfaction. Additionally, the increasing population and population longevity have caused an increase in demand for medical services (Rais et al., 2011; Batun et al., 2013). The absence or shortage of healthcare, combined with higher demand, has put patients' lives at risk, raised infection rates, and caused overcrowding of patient flow (Oueida et al., 2020). As such, improved planning and scheduling of healthcare resources are vital in order to better address this problem. Such a system is important in reducing costs, increasing resilience, and enhancing accessibility to the healthcare system (Gupta et al., 2008). In this review, we will examine separately the modelling techniques for planning and scheduling problems and discuss the optimization algorithms that can be used to solve them.

2.4.1 Patient scheduling

The Patient Scheduling (PS) problem is a complex combinatorial problem (Bilgin et al., 2012) with the aim of scheduling patients in certain time slots to maximize management competency, patient comfort and safety, as well as enhance medical care in hospitals. This involves assigning patients to specific departments in a way that meets the patients' needs and respects all relevant medical restrictions. Usually, a centralized admission office is responsible for this assignment, though some hospitals do not have this and leave the admission responsibility to the various departments. PS can support decision makers at various levels, such as the long term (strategic level), mid-term (tactical level), and short-term (operational level) in healthcare institutes (Lusby et al., 2016), as explained in the following section.

Scheduling problem levels

At the strategic decision level, Robinson and Chen (2010) compared the performance of a pre-scheduled policy, which schedules patients in advance of their appointment days, with that of an open-access policy, which schedules patients on the same day they call for an appointment. Their numerical analysis assumed the number of appointments was given, the service time was deterministic, and the arrival of patients was punctual. Results indicated the open-access policy can significantly outperform the pre-scheduled policy in terms of patients' waiting time, doctors' idle time, and doctors' overtime. Dobson, Hasija, and Pinker (2011) also compared the two policies. They found that when there were a lot of urgent walk-in patients, the open-access policy performed better. The literature also discusses online and offline problems (Wang and Gupta 2011; Weiner et al. 2009; Kuiper et al. 2015). Kuiper et al. (2015) compared the two approaches and found the offline approach had better performance in reducing patient waiting time and staff idle time. The offline scheduling system collects patient requests electronically (e.g., via email or a web-based portal), then advises their appointment time using text messages, becoming more efficient with the use of personal mobile devices and instant messages.

At the tactical decision level, Klassen and Yoogalingam (2009) demonstrated that the most efficient pattern of appointment lengths was a plateau-dome structure, which breaks one day's schedule into three sections. In the first section (e.g., morning), appointment lengths increase over time, the middle section (e.g., afternoon) features the same appointment lengths, creating a plateau, and the last section sees appointment lengths decrease until the end of the day. They found that this pattern results in the least waste of capacity. Nguyen, Sivakumar, and Graves (2015) proposed a network flow model to determine the optimal allocated capacity based on different patient groups. Their study considered patients on their first visit and return visits, with differing appointment lengths. Zhou et al.'s (2019) work generalized this idea, taking into account uncertainties in patients' lengths of stay. They argued that when maximizing hospital revenue, it is important to allocate resources to multiple types of patients and uphold service equity.

At the operation decision level, there are two main streams of studies. One focuses on allocating clients (patients) to services and the other on determining the appointment time. Most studies on allocating patients assumed that all services are identical. For example, Zheng et al.'s (2015) study proposed an overbooking scheduling model. Their goal was to maximize the expected profit by optimizing the number of overbooked patients in multiple-provider clinics. Other studies used various factors to differentiate services. Balasubramanian et al. (2014) developed a model that factored in the importance of continuous care. Their study showed that significantly higher revenue was earned when a primary-care provider saw one of his/her own patients, as opposed to breaking the continuity of care. In determining the appointment time, Chakraborty et al. (2013) found that, compared with a slot scheduling method (slot time is predetermined), scheduling patients at any time in the consultation session can be more efficient. However, this is less attractive in practice as the resulting appointment time has no particular pattern, making it difficult for patients to follow. To address the same problem, Liu and Geng (2020) proposed an ordinal optimization strategy. Rather than controlling the appointment time directly, their approach was to determine the sequence in which a list of patients should be scheduled. This aimed to efficiently utilize the limited medical resources while still guaranteeing the quality of service for patients.

In practice, an outpatient scheduling approach usually covers two or three of the decision levels mentioned above. For example, Li et al. (2019) used an open-access policy (at the strategic decision level) to focus on appointment time optimization (at the operation decision level). From the literature, four remarks can be made. Firstly, offline scheduling is becoming more popular due to the accessibility of scheduling systems to patients via mobile phones. Secondly, scheduling models are often designed for a single type of scheduling policy. Thirdly, most studies consider only waiting time within healthcare units. Lastly, most of these studies have a single optimization objective.

Scheduling variables & constraints

In the past few decades, various scheduling methods have been developed to automate the search for an optimal schedule through different problem models. These models possess unique objective functions due to the distinctiveness of their problem definitions and healthcare systems. Examples of such objective functions are health equity and system resilience, as discussed in Section 3. Given that there are many versions of problem definitions and various problem variables, we attempt to identify commonalities between them by summarizing their types and corresponding constraints. The constraints can be applied to these variables as either hard or soft constraints (Hall et al., 2012). Hard constraints reject solutions that cause violations, while soft constraints tolerate the solution and add a penalty to the objective functions. Table 2.4 illustrates some principal variables and their typical constraints.

Table 2.4 Principal variables in PS problems and their typical constraints

Variable	Definition	Examples	Typical constraints
Patient need	Types of healthcare resources required	Gender, type of illness	Gender policy
Patient condition	Patient priority	Urgency level	Delay, waiting time
Length of treatment	Duration required for the treatment	Test duration; day of stay	(No direct constrain)
Resource specialty	Types of resource that meets patient needs	Type of treatment; levels of specialists	Patient-room suitability
Resource capacity	Amount of resources available	Number of beds, number of rooms	Overcrowd rate; idle room capacity
Resource cost	Capital and time required for consuming resource	Labour cost; material cost	Maximum overtime

The top three variables in Table 2.4 are related to patients, who require healthcare resources for a predetermined duration. "Patient need" describes the type of treatment needed and the patient's preferences; these preferences and needs can be met with varying levels of resources. For example, a patient who needs a bed may be assigned to a single, twin, or ward room. In some cases, constraints such as gender policies may be implemented to ensure that a room is shared only with same-gender patients (Ceschia et al., 2016). "Patient condition" indicates the urgency of the patient's situation. Patients with different urgency levels are usually treated with different plans and waiting time targets, which are often considered as constraints in some problems (Ceschia et al., 2012; Demeester et al., 2010; Kamran et al., 2018; Addis et al., 2016). Lastly, "length of treatment" describes the number of healthcare resources required by the patient. This variable is determined by data concluded from history or generated by researchers following set patterns, instead of relying on constraints.

The bottom three variables in Table 2.4 are related to resources, which provide healthcare services either a person or equipment. "Resource specialty" specifies the type of healthcare resource available and is closely related to patient needs. Constraints such as patient-room suitability could be implemented (Ceschia et al., 2012). "Resource capacity" describes the quantity of resources available and is often grouped by resource specialty (Demeester et al., 2010). Constraints related to resource capacity focus on the utilization rate, such as the maximum rate of idle patient rooms (Ceschia et al., 2016). Lastly, "resource cost" is frequently used to quantify the economical aspect of a scheduling problem; its related constraints include maximum overtime cost (Zhu et al., 2020) and total operation cost (Xiang et al., 2015).

2.4.2 Resource allocation

The Resource Allocation (RA) problem is the placement of a set of new facilities in an area of interest in order to minimize the transportation cost from facilities to customers, and to satisfy customer demand. It was first brought up by Cooper (1963) and has been widely adapted to solve problems in many areas, including hospitals, schools, warehouses, and industries. This review provides an overview of the most notable principal variations in this class of problems. To explain their roles in RA problems, a few examples are given that are considered as primary RA problem models. Table 2.5 shows general variable names, such as distance and flow, which are used in the discussion of RA problems. In actual healthcare applications, these variables could be replaced by, for example, travel time, transportation cost, or amount of samples to be tested. Furthermore, some practical applications in healthcare are described.

Table 2.5 Principal variables in RA problems and their example in healthcare applications

Variable	Definition	Example of variables in healthcare applications
d_{ij}	The distance between location i and j	travel time, transportation cost
f_{ij}	The flow between location i and j	number of patients, amount of test samples to be transported.
r_j	The requirement of demand point j	number of patients that need to be treated.
n	The total number of demand points	The total number of cities
qi	The capacity of the facility i	number of tests/operations can be performed every day
c_{ij}	The connection between facility i and demand point j	Patient-hospital assignment
m	The total number of facilities	The total number of hospitals
$\{X_i, Y_i\}$	Coordinates of the facility i	Location of hospital

A list of primary RA problem models is presented in Table 2.6 along with their respective objective functions and constraints. The **flow model**, in particular, focuses on determining the flow from facilities to demand points. Provided the locations, number of facilities, and demand points are known, the model seeks to minimize the cost of the flow, while satisfying the requirements of demand points and capacities of facilities. The base version of the model, as proposed by Balinski (1961), involves flow only from facilities to demand points, or only from demand points to facilities. Variations of the model, as suggested by Klibi et al. (2010) and Chorley et al. (2013), limit transportation capacity by restricting the maximum flow. Some extended flow models consider flow between demand points and between facilities (Arabani et al., 2012; Ojaghi et al., 2015). For instance, resources required by demand point B can be transported from facility I through demand point A. This extension increases the flexibility of the solutions and potentially enhances their efficiency.

Table 2.6 Primary RA problem models with their objective function and constraints in their base forms

Model name	**Objective function**	**Constraints**
Flow model	$\sum_{i=1}^{m}\sum_{j=1}^{n} d_{ij} f_{ij}$	$\sum_{j=1}^{n} f_{ij} \leq q_i$ $\sum_{i=1}^{m} f_{ij} \geq r_j$ $f_{ij} > 0$
Capacity model	$\sum_{i=1}^{m}\sum_{j=1}^{n} d_{ij} r_j c_{ij}$	$\sum_{i=1}^{m} c_{ij} \geq r_j$ $c_{ij} \in \{0,1\}$
Location model	$\sum_{j=1}^{n} r_j \sqrt{(X-x_j)^2 + \left(Y-y_j\right)^2}$	$\frac{N}{A}$

The **capacity model** (McAllister et al., 1976) assigns capacity to each facility when the number and location of facilities and requirements of demand points are given. The model decides the connections between facilities and demand points which consequently determines facility's capacity: $q_i = \sum_{j=1}^{n} c_{ij}\, r_j$. The base form model only considers discrete $c_{ij} \in \{0,1\}$. When $c_{ij} = 1$, it means that facility i supplies demand point j; and when $c_{ij} = 0$, it means that the supply does not exist. A natural extension (Tsou et al., 2005) to the base form is to consider continuous c_{ij} which ranges from 0 to 1.

The **location model** proposed by Kulin et al. (1962) seeks to determine how to best locate facilities in order to meet the predetermined requirements of demand points. The model's base form considers only a single centralized facility and assumes that the flows directed away from this central facility are known in advance. Furthermore, the model assumes that the travel costs are proportional to the linear distances between locations. The location model has two variations (McAllister et al., 1976, Scott, 1969): one considers the location of a facility in discrete space, and the other considers it in continuous space. It has been extended to consider more than one facility, with or without a predefined total number of facilities (Blanco et al., 2014). This extension has broader applications but is mathematically more challenging. In some studies (Roca-Rivada et al., 2011; Mittal et al., 2013), the model was further extended to include the addition of new facilities to an existing system. In this extension, the locations of some facilities are predetermined. A more sophisticated model (DeVerteuil, 2000) even considers changes in flows in the existing system as part of the cost.

Healthcare-related RA problems often require the combination of multiple primary problem models to accurately reflect the complex nature of healthcare resource planning. For example, Shariff et al. (2012) employed a model that combines the location and flow models, both of which feature discrete variables. This model was used to plan healthcare facilities in Malaysia, taking into account the limitations of facility capacity. Another example of a combined model is from Syam et al. (2012). They developed a combined model based on the location and capacity models, that optimized specialized healthcare services. In addition to the base models, the work added further constraints, such as multiple patient priority levels, multiple service level mandates by priority, and facility utilization targets by acuity. Zhang et al. (2016) also applied application specific constraints to their problem model, including a constraint on the total capacity, which should not exceed the population growth in the region.

Rahman and Smith (2000) categorized the RA models by their hierarchy into two types: single level models and multi-level models. Single-level models are used to determine the best locations for healthcare system facilities using a single model, as demonstrated by Zceylan et al. (2017), who optimized pharmacy warehouse locations to cover larger areas of pharmacies and hospitals.

Multi-level models involve problems with both upper and lower level facilities, such as in Şahin, Süral & Meral's work (2007), which includes a regional blood center (upper level), blood station, and mobile unit (lower level).

There are several limitations to existing models. Firstly, the spatial interaction between demanders and facilities is relatively simple; for instance, few models have employed realistic accessibility measurement when considering travel time, instead opting to calculate distance using coordinates and assuming the journey time is proportional to the distance, ignoring geographical limitations and the availability of public transportation. Secondly, models merely determine the location of facilities, without determining the number of resources to be allocated. This may result in a secondary step that limits optimization performance and lacks flexibility in implementation. Lastly, it does not account for the dynamic nature of resource availability, nor does it provide alternative solutions in the event of disturbances.

2.4.3 Optimization algorithm

PS and RA problems both utilize the same categories of optimization algorithms, as they often possess conflicting objectives. Complexities are caused by conflicting objectives, such as optimal efficiency, equity, resilience, and cost, which must be considered jointly (Mokarram et al., 2018; Ok et al., 2008). Therefore, this optimization can be characterized as a multi-objective optimization (MOO) problem, in which conflicting objectives must be optimized at the same time over a feasible set decided by constraint functions (Coello et al., 1999).

When solving MOO problems, one must consider a trade-off between objectives (Drummond et al., 2005; Levitin et al., 2006). This set of solutions that represents the best possible trade-off is called the Pareto optimal set. In other words, a solution is Pareto optimal if no other solution that is better or equal to all objectives. The set of function vectors generated by this set is referred to as the Pareto front (Yu et al., 1974). Finding the Pareto optimal set is a difficult task. Thus, many MOO algorithms have been developed to address this problem. We presented state-of-the-art algorithms by comparing their characteristics in three aspects: hyper-parameter control, solution selection, and new solution generation (Table 2.7). The comparison provides insights on choosing the proper type of algorithms for a specific optimization problem.

Table 2.7 State-of-the-art optimization algorithms with their characteristics

Algorithms	**New solution generation**	**Solution selection**	**Hyper-parameter control**	**Suitable problem**
Tabu search (TS)	Perturbing	Minimize objectives	Pre-determined	Continuous; avoid local minima
Genetic Algorithm (GA)	Combining & perturbing	Objectives & probability-based	Pre-determined	Discrete
Non-dominated Sorting Genetic Algorithm (NSGA)	Combining & perturbing	Non-dominated sorting	Pre-determined	Discrete; diverged pareto optimal set
Particle swarm optimization (PSO)	Combining & perturbing	Minimize objectives	Pre-determined	Continuous; large searching space
Simulated Annealing (SA)	Perturbing	Difference & probability-based	Iteration-based	Continuous; time sensitive

TS was designed to help with searching difficult regions of a search space and escaping local minima. It uses a move operator and a tabu list (Glover et al., 1989; Glover et al., 1990). The move operator generates candidate solutions by slightly perturbing a current solution. Then, these solutions are evaluated using a weighted sum of objective functions, and the one with the lowest sum is chosen for the next iteration. Additionally, the tabu list stores the most recent moves to prevent searching in those directions for a certain number of iterations. Lastly, hyper-parameters such as objective weights, perturbing variance, and number of recent moves are usually predetermined by researchers.

GA is a common heuristic algorithm used to solve engineering problems (Miettinen et al., 1999). It encourages the search toward the Pareto front while preserving the diversity of the population (Fonseca et al., 1998). New candidate solutions are generated through a process of combining and perturbing, called crossover and mutation, respectively. Crossover involves exchanging parts of solutions between two candidates, whereas mutation involves making random changes to one candidate. Candidate solutions are then selected through stochastic methods such as roulette-wheel selection and stochastic universal sampling, based on their objective functions and some random number (Konak et al., 2006). In GA, hyper-parameters, such as population size and crossover/mutation rate, are generally predetermined by researchers.

NSGA takes a different approach than GA. It uses Goldberg's non-dominated sorting procedure (Golberg et al., 1989; Deb et al., 2002) to select candidate solutions. In addition, NSGA uses a rank-based sorting procedure and a fitness sharing niching method to maintain sub-populations across the Pareto front (Brownlee et al., 2011). This adaptation makes NSGA and its variations, such as NSGA-II & NSGA-III (Deb et al., 2014; Jain et al., 2014), suitable for many MOO problems. The sorting procedure requires a hyper-parameter that is determined by researchers. The application of the NSGA-III algorithm is growing in various contexts, as pointed out by Tavana et al. (2016), due to its advantageous qualities.

PSO is similar to GAs in terms of their use of combining and perturbing to create new candidates, and their manipulation of a set of potential solutions. However, there is one major distinction: PSO combines existing solutions by adding them in a vectorized space, while GA treats solutions as a string and exchanges parts of them. This difference is based on the assumption that PSO is searching in a continuous solution space and GA operates in a discrete problem space. Particles, which are candidate solutions, move iteratively through the search space and improve the objective value based on a given quality measure (Hare et al., 2013). The quality measure and population size are researcher defined hyper-parameters. PSO includes a range of algorithms with similar characteristics such as the Whale Optimization Algorithm (Mirjalili et al., 2016a), the Polar Bear Algorithm (Połap et al., 2017), and the Dragonfly Algorithm (Mirjalili et al., 2016b). These algorithms have the potential to provide efficient results in comparative studies and form the basis for future work by the authors.

SA algorithm mimics the annealing process in material science (Kirkpatrick et al., 1983). Adapted in a multi-objective framework, it has a unique way of controlling hyper-parameters (Suman et al., 2006). Based on iterations and some acceptance criteria, SA uses an initial set of hyper-parameters to maximize efficiency, gradually tuning them for better effectiveness. This feature also enables SA to be combined with other algorithms, such as GA (Zhao et al., 2006; Mahfoud et al., 1995), PSO (Sudibyo et al., 2015), TS (Katsigiannis et al., 2012; Lin et al., 2016), etc., to control their own hyper-parameters. Since the first multi-objective SA proposed by Serafini (1994), several improved algorithms have been developed (Suppapitnarm & Parks, 1999; Ulungu & Teghem, 1999, Suman, 2005).

Overall, the choice of algorithm for solving a multi-objective optimization problem depends on the specific problem. For example, a RA problem can be presented in a continuous solution space, so PSO and SA may be more suitable, depending on the scale and application. Conversely, PS problems are often discrete, so GA or NSGA is more suitable. However, PS solutions are often represented as a sequence, which might not be compatible with solution combination steps such as crossover, implying that a new algorithm may need to be developed. Additionally, factors such as the number of objectives, variables, the type of constraints, and the complexity of the objective functions should be taken into consideration when choosing the algorithm.

2.4.4 Discussion

When solving an optimization problem such as PS or RA, one must carefully consider various factors, including the problem level, variables, constraints, and optimization algorithms. This review provides a guideline on how to make these choices. First, the problem level should be determined based on the complexity of the problem, the type of manageable resources, and the desired output. Second, variables and constraints should be chosen depending on the parameters of the problem and the desired output. For example, if the goal is to reduce the cost of resource distribution, the variables may include transportation costs and the flow between facilities, while the constraints may include time, budget, and facility capacity. Finally, the optimization algorithm, whether continuous or discrete, should be chosen based on the problem space. When the settings of hyper-parameters cannot be determined from expert knowledge, tuning methods such as SA could be considered to improve the algorithms' efficiency.

Based on the guideline, there are several potential opportunities for future studies. The first is to create a multiple objective scheduling method with a flexible scheduling policy. The second is to develop a comprehensive RA model, taking into account dynamics in patient demand, such as travel time, and changes in resource availability, such as manpower shortages and resource distributions. Lastly, a dedicated optimization algorithm specifically suitable for PS problems should be developed. PS problems often involve temporal, precedence, and resource constraints, which may not be manageable through conventional optimization algorithms.

2.5 Conclusion and future opportunities

In the post-pandemic era, an effective healthcare information system is essential for optimizing constrained healthcare resources. This system should have the capability to comprehensively capture all the data from the healthcare system, accurately and securely. It should also be able to assess system performance, and provide tools for operational management, such as resource and service allocation tools, and scheduling tools for sustainability and resilience.

In this review, three main topics surrounding healthcare information systems are discussed. The first topic is system modelling, for which we reviewed ontology-based system modelling methods and their applications in the healthcare sector. We noticed that the definition of ontology is still daunting, especially when it comes to information system modelling. This creates obstacles to communication among different ontology-based information systems. Therefore, a unified definition of ontology in the field of information systems is essential for advancing knowledge in this area. As for the applications, information system integration is often time-consuming due to the involvement of both domain experts and information technology specialists. This opens up the possibility of developing a modelling tool that integrates information systems using various ontology models with minimal effort from experts.

In the second topic, we explored the current implementation of equity and system resiliency in healthcare. We divided existing equity indices into three types: correlation-based, concentration curve-based, and Lorenz curve-based. Because most of these indices were designed to measure equality rather than equity, we believe that future research should investigate their applicability to healthcare equity and evaluate their performance. Furthermore, we proposed a five-dimensional classification for categorizing existing resilience related indices. Future studies could use this classification to develop new indices by exploring new variances in each dimension. With the development of equity and resilience related indices, a common framework should be established that allows comparisons among different healthcare systems. Additionally, it has been observed that most studies in healthcare utilize a deterministic approach to investigate system performance. With the advancement of data gathering and analysis, system performance can be evaluated in the planning stage. In the future, a systematic view of healthcare should be taken to identify and address areas of weakness before implementation.

In the third topic, we provided a comprehensive guideline on modelling the scheduling and allocation problems related to healthcare resource optimization. This guideline includes the main components of the problem models: problem level, variables, constraints, objective functions, and optimization algorithms. It compares the primary choices within each component and provides a detailed explanation of their applications. Consequently, one can use the guideline to create an ideal problem model with a suitable optimization algorithm for a specific optimization problem. The guideline also enables future opportunities for developing a comprehensive healthcare resource model that considers the dynamics of patients' demands and resource availabilities.

In the field of information systems, two buzzwords have become highly popular: digital twin and big data. They are both key elements of the digital transformation of the healthcare industry, with the potential to add value to the development of a resilient and sustainable healthcare system. Digital twin is a virtual model of a physical asset that can be used to simulate and predict the performance of physical assets. In healthcare, it can be utilized to simulate system status, evaluate its performance, and forecast the outcomes of various disruptions. This technology also has the potential to reduce risk, enhance patient outcomes, and streamline operations, making healthcare more efficient and cost-effective. Big data, on the other hand, is the use of large volumes of data to identify patterns and trends. This can be used to understand patients' needs and increase the equity of healthcare. It can also provide insights into how healthcare systems can be improved, such as in terms of cost-effectiveness and patient satisfaction. Based on both technologies, a list of opportunities to enhance healthcare information systems has been identified. These include: (1) identifying underserved communities and mapping out the best way to reach them with healthcare services; (2) monitoring patient health and providing better care through predictive analytics, allowing healthcare professionals to better anticipate and manage patient health outcomes; (3) providing healthcare providers with real-time data to inform decisions, thus improving the effectiveness of care; (4) streamlining processes, such as appointment scheduling and patient record management, resulting in improved efficiency; and (5) delivering patient-specific health information, allowing for more personalized care and improved patient engagement.

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Chapter 3
Ontology in the Modern Computer Era

This chapter presents the research for Objective 1, in short, to study the theory and methodology for ontology-based information system modelling. Based on the review in Chapter 2, it can be concluded that the definition of ontology in information system modelling is still daunting. This has created obstacles in communication and integration among different ontology-based information systems. Therefore, in this chapter, a unified definition of ontology is proposed, along with its modelling tools. The work was documented as a manuscript entitled "Ontology in the Modern Computer Era" submitted to Information Science in 2023 (under review).

Abstract

For decades, the concept of ontology has been daunting in literature. Many misconceptions exist regarding its definition. In this chapter, these confusions are cleared up. A unified definition and understanding of ontology is established, which also helps to distinguish ontology, work, and work domain. Indeed, prior to the emergence of the computer, ontology was primarily related to physics and philosophy, which does not have much terminology confusion. Now, in the era of modern computers and informatics, ontology is connected to the computer along with the computer's language or data (information and knowledge), which leads to confusion, as now ontology is across the human and computer. The fundamental reason for the confusion is the lack of understanding of this change, in particular the relationship between ontology and data model. This chapter

explores this relationship, which makes it possible to define the so-called data model of ontology (or ontology model for short), and further to define the data model of work and the data model of the work domain. Finally, this chapter examines data modelling techniques for ontology modelling, work modelling, and work domain modelling. Throughout this chapter, healthcare systems are used to facilitate discussions.

3.1 Introduction

Ontology is the branch of philosophy that deals with the nature of existence (Merriam Webster 2022), or a part of philosophy that studies what it means to exist (Collins 2022). Ontology is thus used to unify people's view of the physical world – its origin and meaning of existence. Ontology can be said to be foundational for the communication among humans. The emergence of the computer has changed the role of ontology from communication among humans to communication between humans and computers. Such ontology may be coined as computer ontology or data ontology. This chapter discusses the data ontology. Without much confusion, throughout this chapter, ontology and data ontology are used interchangeably.

Since the invention of the computer, different starting points for viewing ontology have emerged: original ontology and data ontology. Yet, even in the data ontology, one can see diverse definitions, as discussed in Section 2.2.1. Without a unified understanding and definition, it is hard to evaluate different products based on diverse understandings and definitions of ontology. This chapter attempts to provide a unified understanding and definition of ontology or data ontology. In addition, the data model of ontology is defined in relation to the data model of work and the data model of work domain. Finally, this chapter examines data modelling techniques for ontology modelling, work modelling, and work domain modelling. Throughout the chapter, healthcare data systems are used for illustration of our idea and for demonstration.

3.2 Common Confusions on Ontology

Many studies used ontology in data modelling but confused it with other terms such as work domain model (Cai et al. 2017; Lin, Zhang, and Watson 2001; Lin & Zhang 2004). For example, Sanderson, Chaplin, and Ratchev (2019) developed the so-called ontology model for an adaptive production system. The ontology model in their study represents a system's function, structure, and behaviour without their relationships. While the definition of the function, structure, and behaviour of a system is considered as work domain modelling in the work of (Cai et al., 2017). In the work of Wang et al. (2016), the ontology model was confused with the work domain model. The authors considered the ontology model and work domain model identical and thus used them interchangeably. A similar phenomenon can be found in the work of Singh et al. (2021), where the so-called ontology is used to build a work domain model for managing work databases.

There is, however, a common understanding of the role of ontology, i.e., sharing and integration of information within a system. For instance, Fern´andez-Cejas et al. (2022) proposed a methodology to create an ontology model that describes the key elements of a system, their characteristics, and the associations among them. The ontology they defined is the data ontology. The main problem with their study is that their definition of ontology misses the notion of semantics. According to Zhang (1994), semantics is a body of knowledge about the meaning of a symbolic representation that is created based on specific rules (syntactics) and in a specific context; the meaning is thus strongly context sensitive. The ontology model in Fern´andez-Cejas et al. (2022)'s work did not include the notion of context. Consequently, when communicating concepts as well as their relationships to different parties that are in different contexts, concepts with the same name may mean differently, and relationships among concepts may no longer make any sense.

The notion of contexts is not unfamiliar to computer specialists, though a comprehensive definition of this notion may refer to Zhang (1994), Zhang and Wang (2016) and Zhang, Wang, and Lin (2019), where for specific data (an entity or a relationship among entities), a context is a background that contributes to the meaning of the data along with the syntax of the data. Unfortunately, there is no study, to our best knowledge, that explicitly describes the notion of context along with an ontology model.

It is worth mentioning that the context here is different from the context-aware computing for ontology reasoning in the work of Wang et al. (2004) and Gu et al. (2020). In this study, context is a way of defining ontology and facilitating data integration across different sources. Context is used to specify the meaning and scope of both concepts and their relations in an ontology. Context-aware computing, on the other hand, is a way of selecting and presenting data based on the current situation of the user. Some examples of the activities include a tablet computer that switches the orientation of the screen with the user's current orientation and a phone that switches on the backlight when used in the dark. More details about context-aware computing and ontology reasoning can be found in Appendix A.

3.3 A Unified Definition of Ontology

The data ontology is a common understanding of a subject regardless of different computer or data languages, and its role is therefore to facilitate communication among humans and between the computer and human, and as such, to facilitate the integration of data (information and knowledge).

The ontology is analogous to a dictionary for human, a generalized dictionary for computers in this case. In the human dictionary, there are words along with their meanings and illustrations of their usage. In this generalized dictionary (or dictionary for computer), there are words and groups of words, among which relationships among words are a special type of groups, constructed by following specific syntactic or grammatical rules. Further, in the generalized dictionary or the ontology, the context is explicitly specified for any word and the relationship among words. The importance of context in defining the meaning of words and relationships cannot be overstated. For example, the word "fan" could be an instrument for producing a current of air in the context of a device. It could also mean an enthusiastic devotee in the context of a sport or an art.

The proposed definition of ontology is further built upon five ideas. The **first idea** is that knowledge in nature is an instance. The **second idea** is that information in nature is a class. As previously stated, information is a concept that can be generalized using a set of attributes. On the other hand, knowledge is unique, and it is specific to given concepts. For example, information such as patient and HCP (Healthcare Professional) are classes, that contain attributes such as name, sex, age, etc. Knowledge like how HCPs treat patients is very specific to an individual HCP and patient.

The **third idea** is related to so-called information relativity (IR). The notion of IR was first coined by Zhang (1994) and Li, Zhang, and Tso (2000) in describing a data repository. A data can be taken as a type, an attribute, a class, or an instance, depending on how the data is used. For example, "patient" is viewed as a class, which has an attribute called "diagnosis". However, "diagnosis" could be taken as a class if it represents a set of diagnosis variations or instances.

The **fourth idea** is that semantics are determined by context. As knowledge is very specific, a context is necessary to define situations that apply to the knowledge. For example, the knowledge "patients follow advice" should be applied only in the context "patients follow advice from HCPs".

The **fifth idea** is that constructs can be instances (knowledge), classes (information), and relationships. In this connection, Chen's (1976) definition of "entity" is expanded. In Chen's work, an instance is defined as a thing that can be distinctly identified. The concept of entity is expanded with the first four ideas above. Based on the notion of IR (the third idea), a class could also be a construct. It depends on using either an element's view or a system's view. Based on the notion of semantics (the fourth idea), a relationship could be a construct as well. For example, the relationship "marriage" can be viewed as an instance under a certain context.

3.4 Data Model in Big Data

Big Data enables organizations to evolve their decision-making processes from classic stationary data analysis (Abelló et al., 2013) (e.g., transactional) to situational data analysis (Löser et al., 2009) (e.g., social networks). These situational data often come in the form of data streams provided by third-party data providers (e.g., Twitter or Facebook). They use web services, or APIs (Application Programming Interface) to allow external data analysts to incorporate part of their data into big data analysis pipelines. Web services (Pautasso et al., 2008) offer providers flexible ways to share data, typically in unstructured or semi-structured forms, such as JSON (JavaScript Object Notation). However, this flexibility can be a disadvantage for analysts. Unlike machine-readable contracts from structured data, such as data from relational databases, data from web services typically do not publish such information. Consequently, analysts must carefully study the documentation and adapt their processes to the particular schema provided. In addition to the complexity imposed by web services, data providers frequently evolve their data formats. This necessitates that analysts must continually adapt their dependent processes to accommodate such changes.

Integrating an ever-evolving and heterogeneous set of data sources is a challenging problem, referred to as the data variety challenge (Horrocks et al. 2016). Traditional data integration techniques are unable to address this problem. A data model of ontology is one approach to dealing with it. It contributes to addressing the data variety challenge by providing a conceptual view of the data and assisting in the creation of a data model that facilitates data sharing and integration. Therefore, the data model of ontology (or ontology model, for short) becomes a key concept that needs to be defined. Before we discuss the ontology model, the concepts of data and data model should be discussed. According to Zhang (1994), data is a vehicle to carry information and/or knowledge. Information is concepts, e.g., the earth revolves around the sun. It is usually based on observation or interpretation. Knowledge is a causal relation among concepts, e.g., gravitational force causes an apple to fall. Knowledge is usually related to a purpose. For example, to explain why an apple falls to the ground.

A data model is a language for communication between humans and computers. For the purpose of being understood by computers and by humans, the data model naturally has two layers: a physical layer and a human layer. The data model at the physical layer is suitable for computers (i.e., the structure of the computer), and the data model at the human layer is suitable for humans, which is close to natural language. The human layer of the data model is also called the semantic data model.

A data model has a set of constructs and rules for the constructs (Wang et al., 2014; Ter Bekke, 1992; Yu et al., 2021). For instance, in the Entity-Relationship (E-R) data model (Chen, 1976, 2002), there are three core constructs: (1) Entity, (2) Attribute, and (3) Relationship. One rule is that a relationship connects two entities.

3.5 Ontology Model, Work Model, and Work Domain Model

Based on the definitions of ontology and data model, it can be concluded that a data model at the human layer is an ontology. In comparison, a data model at the physical layer is not an ontology, as it doesn't directly facilitate communications between humans. Therefore, we define **an ontology model as an ontology of a data model at the human layer**. The ontology model provides a set of constructs for humans to describe data (information and knowledge) in a computer system.

Under the definition of ontology model, we further define:

- Data model of work is a description of a work using a data model as its language.
- Data model of work domain is a description of the scope of a work by defining its components and variations of those components. An ontology model can be used as a language for the description.

The definition of data model of work domain is further explained by the following three understandings.

The **first understanding** is about the concept of work. Work is a human-machine system. To an automated system, the work is machine. To a human system, the work is human. Under the definition of a data model, such as a healthcare system, the work involves both humans and computers (machines).

The **second understanding** is about the concept of domain. Domain evolved from the concept of variables. If X is a variable, the domain of X defines its scope or bound, which means that X can only take values that are within the scope or bound. The domain D of X is thus {x1, x2, ….}. This then comes up with the description of the domain.

The **third understanding** is about the concept of work domain, which is the information that gives the scope or bounds of the work. In another word, a work has variations. For example, if a thing is a length of bed, say 200 mm, then it has variations from 180 mm to 240 mm. In this case, the domain of the length of the bed is 180–240 mm. In addition, a compound work has multiple primitive things. For example, a bed is a compound work that has primitive things, include length, weight, height, etc. The bed has variations, such as {s1, s2, ...}, and its primitive things have their own domains, such as the domain of length, the domain of weight, and so on.

The **fourth understanding** is that a compound work can be decomposed in different ways. For example, when we are investigating a healthcare call center, we can use FCBPSS (Function-Context-Behavior-Principle-State-Structure) (Zhang & Wang, 2016) to decompose the work, as shown in Figure 3.1. The work is decomposed into structure, state, behaviour, etc. The structures are patients, general public, healthcare professionals, and equipment. The states include the physical and mental states. The function is to plan healthcare resources according to demand. The behavior is the casual relationship among physical and mental states of people.

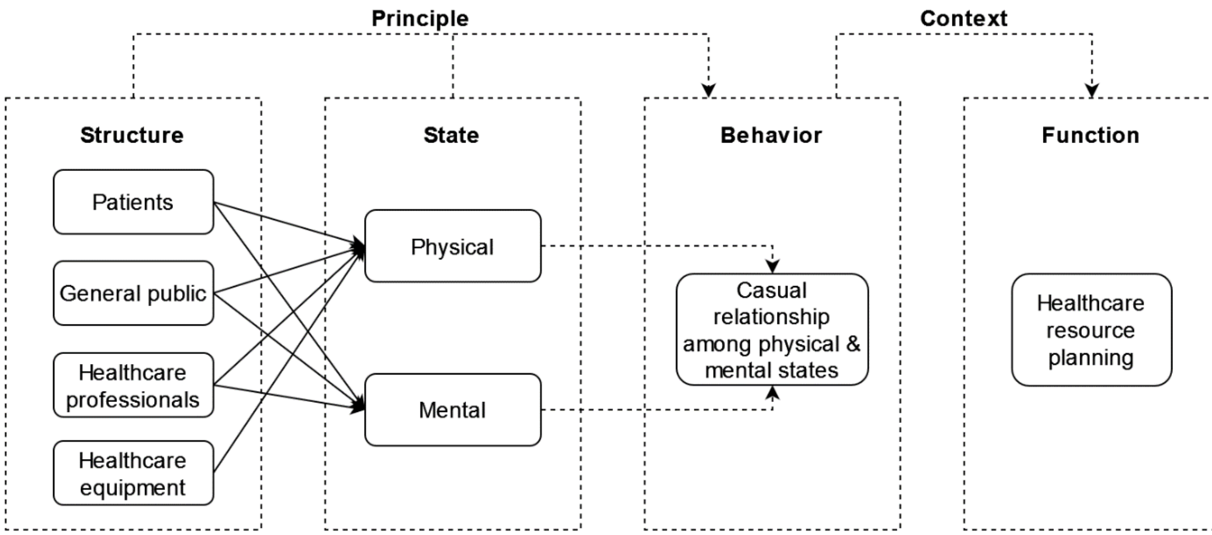

Figure 3.1 The structures are patients, general public, healthcare professionals and equipment.

3.6 Techniques for Ontology Modelling, Work Modelling, and Work Domain Modelling

Based on the requirements outlined in the working definition of ontology, we propose a set of ontology modelling tools as pre-defined constructs. Note that people may refer ontology modelling tools to modelling languages or editors that create ontology models. Those tools are for applying ontology models in people's mind into a written form. In contrast, our tools are for creating models at a conceptual level at where hierarchies and relationships among data are defined. This makes them very flexible in applications, where it can be incorporated into any existing languages such as OWL (Web Ontology Language) and used in any editor, such as Protégé (Noy et al. 2003). Compared to the existing modelling tools, which were formed by evolution and interaction, our tool was developed based on the so-called design thinking (Zhang & Wang, 2016).

Three ontology modelling constructs are proposed: (1) context-of, (2) mono-directional relationship, and (3) bi-directional relationship. The concept map of these blocks is shown in

Figure 3.2 and their semantics and notations are discussed in detail below.

(1) Context-of: The relation of concepts is constrained by its context. When the context changes, the relation has to change its behavior accordingly, although its concepts may never have changed. For example, in the context that patients have trust in a healthcare system, patients follow their HCP's advice, as shown in Figure 3.2. In the other context that patients have lost trust in a healthcare system, patients ignore their HCP's advice. Diagrammatically, we use a plain association with an unfilled circle at the receiver to denote it. Note that in the existing ontology representation, it is possible to replace context-of with constraints such as range or domain. However, the ontology model becomes more semantic by using an explicit construct as the context-of.

(2) Mono-directional relationship: Cause-effect relationships are directional relationships, such as a child of, take care of. We use a plain association with one arrow pointing at the receiver of the relationship, as shown as HCP belongs to a healthcare system in Figure 3.2.

(3) Bi-directional relationship: When it comes to presenting bi-directional relationships, such as equal to and co-related with, diagrammatically, current ontology approaches use two sets of mono-directional relationships. Such approaches are redundant and implicit. Instead, we use a plain association with arrows at both ends to denote it, as shown patient and HCP collaborate with each other, in Figure 3.2.

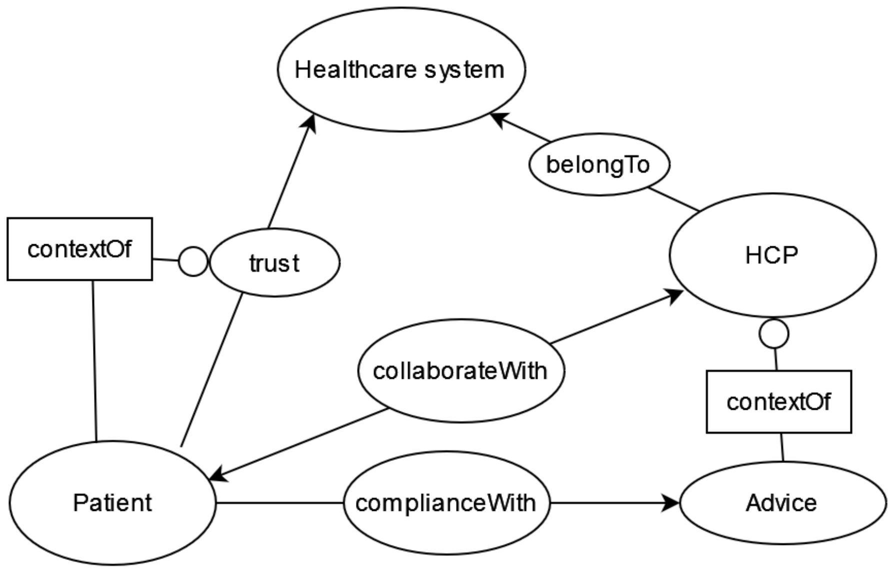

Figure 3.2 An example of ontology model for a healthcare system.

The ontology modelling constructs facilitate data integration among structured data and semi structured data. In a case of integrating doctor advice from two data sources, one can refer to the ontology model in Figure 3.2 and understand that the "Advice" data must be integrated together with "Patient" data, due to the mono-directional relationship "complianceWith". In addition, the construct "context-of" illustrates the necessity of referring to "HCP" data. Using this construct, "Advice" can be classified by the type of "HCP". Regardless of the data, structured or semi structured, the ontology model determines that "Patient" data and "HCP" data must be integrated alongside "Advice" data for a meaningful data analysis.

3.7 Conclusion

This chapter presents a working definition of ontology and its corresponding modelling tool. The purpose of this study is to clarify some of the most common confusions in ontology-related literature. Our definition of ontology is built on ideas about information, knowledge, information relativity, and context. Three ontology modelling constructs are proposed, including context-of, bi-directional relationship, and casual loop. Those constructs help build a more semantic ontology model compared to existing languages.

About ontology, data model and domain model, this study has the following conclusions: Ontology is for communication, such as a natural language for human. A data model is needed for human communication that involves computers, which describes the ontology of a work along with its domain. Data models facilitate the integration and analysis of data in the era of big data. They enable organizations to make informed decisions based on a comprehensive understanding of available information. Domain frameworks such as FCBPSS help describe a system along with its domain.

The following are the contributions of this chapter: (1) provision of a working definition of ontology, particularly from a relativistic standpoint; (2) elaboration of its distinct feature; (3) clarification of the definition of data model, and its relationship with working modelling and domain modelling; and (4) development of a new tool for modelling it, along with a discussion of the unique feature of this new tool as opposed to tools such as OWL.

In conclusion, the proposed definition of ontology clarifies its scope and applications. Featuring relativity, context view, and design thinking, the corresponding modelling tool can describe information and knowledge in a more semantic way.

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Chapter 4
Understanding resilience and sustainability of healthcare systems

4.1 Introduction

Section 2.3.2 pointed out that, even though sustainability and resilience are studied in healthcare system-related research, the connections between these two concepts have never been made clear. In short, resilience refers to a system's ability to handle short-term disruptions, while sustainability refers to a system's ability to maintain its performance over time. In this chapter, definitions of resilience and sustainability of healthcare systems, along with their connections, are discussed comprehensively, as per Objective 2. Additionally, privacy is examined using a set of design principles and a case study as an example to illustrate the application in healthcare. It is noted that the discussion in this chapter gives a background for the work presented in Chapter 5 and Chapter 6, respectively.

4.2 Definitions of resilience & sustainability of healthcare systems

Based on the previous discussion in Section 2.3.2, the proposed definitions of resilience and sustainability are revisited as follows:

- The resilience of a healthcare system is its ability to provide sufficient healthcare services or to meet its demands when facing unexpected short-term disruptions.

- The sustainability of a healthcare system is its ability to provide sufficient healthcare services to accommodate ever-changing demands in a long term.

Healthcare services encompass not only those that directly serve patients, but also those that support the service. For example, society's access to, acceptance of, and satisfaction with the services. The service demands extend beyond service provisions, demanding a socially and culturally compatible process (expecting that patients are free from anxiety, uncertainty, and fear). Examples of such demands are service accessibility, patient equity, and security in terms of protecting patient privacy. It is worth mentioning that both resilience and sustainability should be evaluated under constraints such as cost and time.

Based on the proposed definitions, the connections between the concepts of resilience and sustainability are concluded in the following:

1. Both concepts focus on a healthcare system’s abilities to provide sufficient healthcare services to meet demands, whether in short or long term.
2. The healthcare service could be jeopardised by either internal events, such as the lack of service supplies and rising demands, or external ones, such as natural disasters.
3. A certain event, like COVID-19, could have an impact on a healthcare system's sustainability and resilience at the same time.
4. Any procedures or actions that enhance one concept should consider how they can affect the other. The development of remote healthcare during COVID-19 (resilience), for instance, has an impact on how individuals obtain healthcare in the post-pandemic era (sustainability).

In the following of this chapter, we will use the security (i.e., protection of privacy) as an example of resilience to illustrate its application in HIS design. This work was published as Wenjun Lin et al. “Privacy, security and resilience in mobile healthcare applications” on Enterprise Information Systems in 2021, which is documented in Sections 4.3 and 4.4, respectively. It is noted that the subsequent chapters (Chapter 5, Chapter 6) present works to illustrate the application of both resilience and sustainability to healthcare operation management.

4.3 Design principles of the protection of patient privacy in HIS

4.3.1 Background

The provider-centric healthcare has been criticized for excessive waiting times. Patients have expressed dissatisfaction with the lack of availability of appointment slots and the inconvenience thus caused, particularly to patients requiring urgent care. Indeed, in emergency departments, this long waiting time can become a fatal issue. Thus, there is an urgent need to cope with the long waiting time in the Canadian healthcare system today.

Mobile applications, also known as “apps”, have seen rapid growth with the release of affordable smart devices (e.g., smartphones, tablet computers). Mobile systems are seen to provide a promising infrastructure to contribute to the reduction of patient waiting time, besides their essential promise in improving the efficiency and quality of healthcare services (Aceto, Persico, and Pescap´e 2020; Lancharoen, Suksawang, and Naenna 2020; Li et al. 2019).

However, mobile systems also raise additional concerns including security, privacy, usability, resilience, and so on (Hathaliya and Tanwar 2020; Al-Muhtadi et al. 2019). Since health information (e.g., phenomena, health conditions, and emergencies) is highly sensitive to patients in the Canadian healthcare system, any inappropriate disclosure of patients' health information may violate patient privacy (Liang et al. 2012; Rahmadika and Rhee 2018). Patients may also be concerned about tampering with their critical health data when it is stored on untrustworthy cloud servers (Zhou et al., 2013; Loft et al., 2021). In addition, the mobile device is usually operated in a wireless environment, and different devices have different hardware and operating systems (OSs), which may have compatibility issues and thus cause problems such as data loss and single points of failure (Tawalbeh et al. 2015).

To cope with the issues or problems above more effectively, we treat mobile apps, operating systems, databases, and their related communication services as a whole, termed the mobile network system (MNS) because they together affect the quality of healthcare services, including privacy protection. The infrastructure-substance (I-S) framework (Zhang and Lin 2010; Zhang and Van Luttervelt 2011; Zhang, Wang, and Lin 2019) along with a general modelling methodology for a system ontology (Zhang and Wang 2016; Wang et al. 2014; Cai et al. 2017) will be employed to build the MNS system for healthcare, in which an individual's privacy is protected in a resilient manner.

4.3.2 The I-S framework of MNS

According to the I-S framework, a general service system includes an infrastructure layer and a substance layer. In the MNS, the infrastructure layer includes computer terminals and backend, and the substance layer includes signal and data. Video, audio, messages, etc. are used to fulfill the system function and provide user data (both information and knowledge) (Zhang 1994). In another word, the infrastructure processes the substance and allocates the data (Figure 4.1). For example, a cellphone station and its related infrastructure transmit voice message flow between two mobile phones to fulfill the function of a real-time voice call.

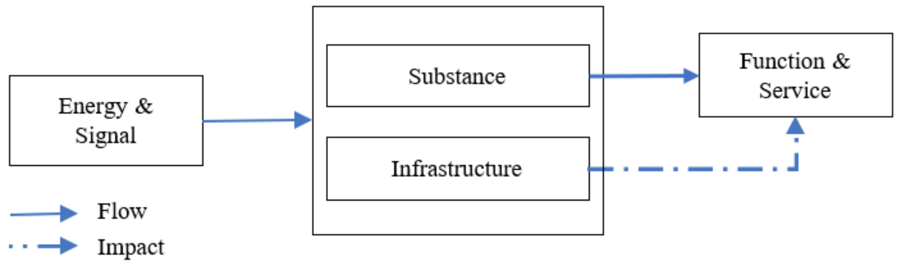

Figure 4.1 The I-S frameworks for MNS

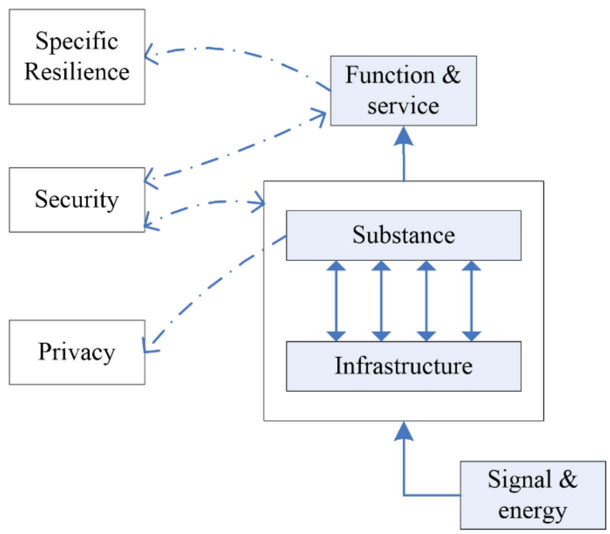

Figure 4.2 The I-S view of the relationship among Privacy, Security, and Resilience for MNS

Figure 4.2 The I-S view of the relationship among Privacy, Security, and Resilience for MNS illustrates the relationship of Privacy, Security, and Resilience (PSR) in the MNS from an I-S framework perspective. Privacy in MNS is related to the data that can be used to identify an individual entity; for example, a person, or a group, and the data owned by one entity should not be shared with another entity. Besides, security in this study is specific to the protection of privacy, which is stored in the substance system as data and processed by the infrastructure system. Therefore, security is one of the functions of a system (e.g., MNS). Further, the system's resilience means that once a system's security function is partially damaged, the system can recover it in an allowable time and at an allowable cost by itself. Finally, to make the MNS run, energy or power must be available, which is an external resource to a service system (e.g., MNS), as well as external signals (or data), which represent the semantics of privacy.

4.3.3 Design principles for security in MNS

Based on Figure 4.2, we discuss the design principles of MNS for security from three aspects: the infrastructure, substance, and energy. Further, the design principles are represented in the form of rules.

Infrastructure aspect:

Rule I-1: Fulfill the functional and constraint requirements with well evaluated, and widely accepted options.

Rule I-2: Evaluate and test new algorithms before implementation.

Rule I-3: Choose an adaptive app style based on the function and security requirements.

Rule I-4: Evaluate a platform, at local servers or clouds, with both security and functional requirements. As both service and data storage of mobile apps are moving toward the clouds, the security obligation needs to be transferred as well due to different cloud platforms having different service requirements.

Substance aspect:

Rule S-1: Identify and classify privacy information into two categories: attribute and relationship. The attributes refer to those that define an entity. The relationship refers to information that links one entity to another entity or others.

Rule S-2: Specify the responsibilities of users and systems to determine forms to enhance. There are two forms: legal binding and non-legal binding. Legal binding involves terms and conditions that require some effort to establish. Non-legal binding often depends on some preliminary understanding and evolves based on experience and best practices.

Rule S-3: Minimize the information required from users. More information has a higher cost of losing privacy information.

Rule S-4: Determine appropriate techniques and algorithms for the security of private information, for example, encryption and certificate verification.

Rule S-5: Plan for both data storage and data processing security strategies. There is a trade-off between data storage security and processing efficiency. Local storage has a higher degree of security but may have insufficient data processing power. While cloud storage may have advantages of data processing efficiency, but it might have a higher risk of a data breach.

Rule S-6: Balance among encryption, authentication, authorization, usability, storage strategy, encryption, and computational capability for an acceptable security expectation.

Rule S-7: Develop a life-time management strategy against privacy abuse. Besides the techniques, human and cultural factors need to be taken into considerations.

Energy aspect:

Rule E-1: Check the energy (e.g., battery or backup generator) level before running any critical process, like, heavy encryption, heavy algorithm calculation, or mass data transfer. The system should be designed to alert users of situations such as battery failure.

Rule E-2: Monitor the status of the energy source closely considering environmental factors such as battery temperature to facilitate a pro-active energy plan.

4.3.4 Design principles for resilient security in MNS

In MNS, resilience refers to the system's ability to keep the functions of the system at an acceptable level, subject to perturbations or mishaps. To provide resilience to the security functions designed based on the rules in Section 4.3.3, five design axioms are proposed in the following (notice: each of them is further further broken down into several rules for ease of use).

Axiom 1: Redundant resources for critical security components.

Resources for MNS include function, capacity, and infrastructure.

Rule R-1: Identify critical functions and design redundancy. For instance, data transportation is a crucial function for a mobile app. The tunnel for data transportation can be either 4G (4th Gen cellular network) or 2G (2nd Gen cellular network), and this forms a redundancy.

Rule R-2: Arrange the redundant capacity for the critical functions. Capacity refers to the availability of electricity, computation, storage, or bandwidth. Take data storage as an example. In addition to a remote database, redundancy of storage capacity would include a local database as a backup safeguard against data loss.

Rule R-3: Design redundant infrastructure for critical functions. Multiple back-end services are involved in a mobile app-based system. They include the clouds, web servers, database servers, and cellular telephone network equipment. Their redundancy is to ensure a reliable and robust service.

Axiom 2: Effective management of redundancy.

A resilient MNS needs to decide when and how to reconfigure a system for a lost function or replace a failed sector with redundant resources. In other words, a mechanism to manipulate the redundant resources is required.

Rule R-4: List the attributes, types, and availability status of redundant resources.

Rule R-5: Create clear instructions, like algorithm or management rules, about how and when to replace the resources as well as how to work with the re-configured system.

Axiom 3: Monitoring of system performance.

Rule R-6: Keep monitoring key system status that concerns security functions. For example, Mozilla introduced a web API, "navigator.battery", to enquire system's battery charge level and whether the device is charging. In this way, it is possible to decide whether or how to run a program regarding battery status. Further, necessary status information is recorded for forecasting system errors.

Axiom 4: Error forecasting and handling mechanism.

Mobile app errors are a combined result of design, coding, operation, and resource utilization. Suppose that an app has a low success rate in accessing a remote database due to uncontrollable factors. The remote database login operation should be treated as a separate procedure. By decoupling the login procedure, other functions can be operated with improved robustness.

Rule R-7: Forecast and locate possible vulnerabilities from algorithms, logical procedures, and the relationships between different system components.

Rule R-8: Countermeasures for error situations should be defined ahead of time.

Axiom 5: Software version control for system evolution.

Rule R-9: Update software, like a mobile app, as a countermeasure against external attacks. By updating, the old, vulnerable program is replaced by a new, robust one. To effectively manage the updates, a version control mechanism needs to be implemented in the app.

4.4 Case study

To explain how these design principles can be applied into the design of an MNS that processes healthcare information, a mobile app is demonstrated here. The app is developed for outpatients to make doctor appointments based on the previous work in the authors' group (Dai 2016). Functions are added in this work to improve the system's resilience and security. Note that although only one mobile app design is illustrated, the whole MNS system includes the needed software, OS, hardware, communication system, database, etc.

The app is developed on a laptop with Windows 10 OS. The primary development platform is Eclipse which is integrated with JDK (Java Development Kit) and Android SDK (Software Development Kit). The app is expected to operate in a wireless environment like 2G/4G or WiFi (Wireless Fidelity). On the same device, the Google Map android app is also required.

4.4.1 Conceptual design

The app is to help patients make doctor appointments based on their symptoms and available hospital resources in the area. The goal is to set up an appointment with the minimum patient waiting time at the hospital chosen by the patient. Figure 4.3 is the app's operational procedure. A patient should first register in the app with the healthcare information. The information is then transferred via the wireless connection and authenticated by a remote server, which is owned by the corresponding healthcare database management authority. Once the input information matches an entry in the healthcare database, a brief description of the symptom needs to be provided by the patient. With that, the app lets the patient choose from several candidate hospitals. After having received the decision, the app will again access the healthcare database for authentication and record the appointment. At the same time, a navigation option is initiated by OS through the Google Map navigation service.

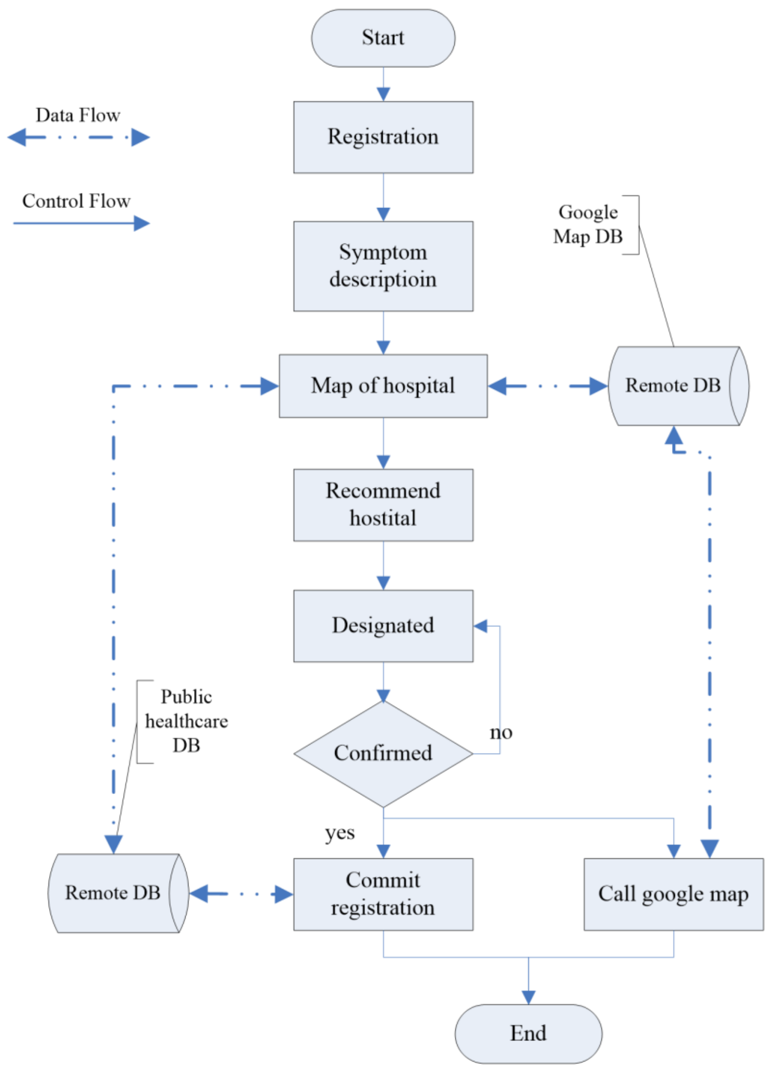

Figure 4.3 Program flow of the mobile app

4.4.2 Application of the design principles

Infrastructure aspect:

Application of Rule I-1 (choose matured options): AndroidManifest.xml is an entrance file to define the operational status and references for the app. First, set “allow-Backup” to “false” to avoid an unauthorized copy of the application data by enabling the USB debugging option. Second, set “Debuggable” to “false” to reduce the likelihood of stealing users’ login credentials or accessing data by bypassing an authentication process. Figure 4.4 is a program fragment intended to get the value of “Debuggable”.

```
public static boolean is ApkDebuggable(Context context)
try{
    ApplicatioinInfo info=context.getApplicationInfo();
    return(Info.flags&ApplicationInfo.FLAG_DEBUGGALBE)!=0;
}catch(Exception e){
}
return False;
}
```

Figure 4.4 Code for the value of the “Debuggable”

Besides, the Native Development Kit (NDK) is chosen to implement app’s codes in native C++ and C. These languages are extremely resistant to decompilation. This reduces the risk of source code disclosure, which could lead to an app crack. In our app, C++ was chosen with the NDK to realize crucial functions, like the login module in Figure 4.5 and the user registration module.

Application of Rule I-2 (choose an adaptive application style): A soft keyboard provides safe inputs for sensitive data in the process of login and registration. Users are required to input the password during those processes. There may be a risk of password leakage using a third-party input method. As a result, the app includes a custom keyboard. As illustrated in Figure 4.5, the randomly distributed keyboard ensures the security of password input.

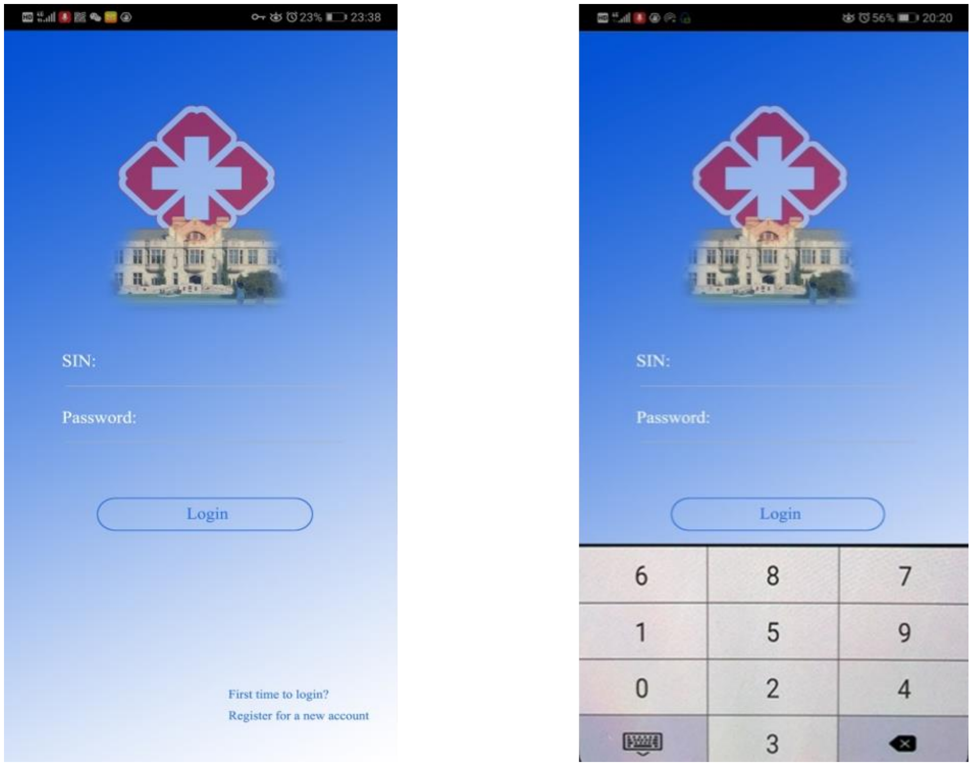

Figure 4.5 Screenshot of the app at login screen with (right) and without (left) a soft keyboard

Substance aspect:

Application of Rule S-1 (identify privacy information): Figure 4.6 shows an E-R model for patients and hospitals in the context of appointment registration. Patients' attributes, such as the patient's telephone Number (Tel.), name, address (Addr.), personal health number (No.) and personal geographical location (PGL) are captured. The attributes of the action (Register) include symptoms, time, and location that a patient requests an appointment. The last attribute is marked as registration geographical location (RGL). For hospitals, attributes such as hospital identity (ID), hospital geographical location (HGL) and address are identified.

Application of Rule S-3 (minimize information required): The PGL in Figure 4.6 is being monitored by the app when it is running. According to rule S-3, PGL should not be stored or transmitted because it is closely related to personal identity. In contrast, personal location information about registration (RGL in Figure 4.6) can be stored in local storage or transferred to remote servers and databases as evidence of registration. This helps to avoid potential issues like data compromise from transferring privacy data like the patient's location.

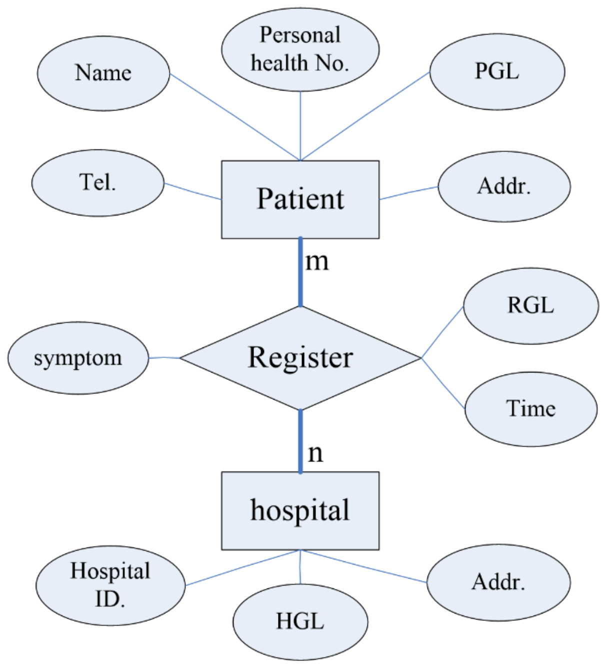

Figure 4.6 Entity Relationship between patients and hospitals

One of the most critical issues is what part of the location-related data should be transferred and stored to avoid compromising personal privacy. According to Rule S-3, PGL should not be stored or transferred as it is closely related to personal identity. By contrast, the personal location information regarding registration, i.e., RGL in Figure 4.6, can be stored either in local storage or transferred to a remote server and database, as evidence of registration.

Application of Rule S-5 (management for data storage, use and transfer): A choice among local storage, remote servers, and the clouds is made considering security, communication efficiency, and cost. For instance, patients' personal health numbers and symptom descriptions are stored locally. This avoids the risk of patients' private information being leaked from a centralized database.

Further, two management rules are established. First, only the data owner or device owner has access to the data, following the authentication strategy and technique. Data access should not be permitted without the owner's formal consent. Second, for the data stored remotely, tools such as the identity shielding technique are applied. This technique makes the breach of information through the data mining technique difficult.

Application of Rule S-6 (Authentication and certification): Authentications are established with the patients' health numbers and credentials like a password and fingerprint. When the app transfers the health number and credentials to the server, the communication is secured by the HTTPS (HyperText Transfer Protocol Secure) protocol. The protocol encrypted data with certifications. In the app, the public/private key pairs and certificates are managed by Keytool from JDK.

Energy aspect:
Application of Rule E-1 and E-2 (Energy monitoring): The OS's attribute "ACTION BATTERY CHANGED" is used to monitor the state of a system, in particular, the real-time battery charge level. The app can use this attribute to decide whether to disable some high-energy-consumption services, such as Google Maps navigation.

System resilience:
Application of Rule R-1 (Identify critical functions and design redundancy): Critical information such as patients' current geographic data, symptom descriptions, and the designated hospital have dual backups, i.e., one copy in a cloud database and one copy in a local database.

Application of Rule R-6 (Monitoring the state of the system function): The OS's "enableNetwork" method to monitor whether the Internet is connected or not. The result triggers the app to choose which redundant resource to use. For example, to load critical information from the local database when the Internet is not available.

Application of Rule R-7 (Error forecasting): Potential errors are estimated as follows: (1) an error occurs while requesting a database connection; (2) users forget login credentials; (3) the app fails to launch; and (4) there is insufficient power while performing a critical process.

4.5 Conclusion

In this chapter, resilience and sustainability are defined in terms of healthcare systems. The definitions provide details about the scope of services and demands. Based on the definitions, patient equity, service accessibility, and privacy security are used as examples of demands. In particular, the privacy protection is used to demonstrated how to consider resilience in HIS design. The patients' privacy will be compromised to a large extent if a system's security and resilience in security is not adequate. In general, the systematic consideration of the privacy protection is lacking in the development of a mobile app.

The main contribution of this study is advancing the understanding of privacy, privacy security, resilience in security, and their relationships. A set of mobile app-based system design principles are proposed for comprehensive privacy protections. Also, a mobile healthcare app is developed to demonstrate how to reduce patients' waiting time and keep their privacy protected using the design principles.

Several future endeavors may be carried out. (1) An analysis could be performed on the relationship between PSR and other attributes such as scalability, usability, and system performance. Analysis strategies for balancing those attributes in various implementation contexts could also be investigated. (2) A detailed guide for testing and evaluating PSR in mobile app-based systems could be developed. Once a system is developed, an applicable and affordable way is needed to test and evaluate all its attributes. (3) Human factors in PSR need attention, especially how cultural factors may affect its performance.

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Chapter 5
A Novel Scheduling Method for Reduction of Both Waiting Time and Travel Time of Patients

This chapter is an application of sustainability as patient accessibility in healthcare decision-making, as per Objective 3. It targets one of the gaps identified in Section 2.4.4, which calls for a multiple objective scheduling method with a flexible scheduling policy and a dedicated optimization algorithm for the method. This chapter was submitted as Wenjun Lin et al. "A Novel Scheduling Method for Reduction of Both Waiting Time and Travel Time of Patients to Visit Health Care Units in the Case of Mobile Communication. Enterprise Information Systems" to Enterprise Information Systems in 2022 (published).

Abstract

This chapter presents a novel encoding method that is suitable for various Genetic Algorithms (GA) for a multi-objective scheduling problem. The problem has two objectives: patient waiting time and patient travel time. The patient waiting time starts from the time that patients desire a healthcare service outside of healthcare units, e.g., in an office, to the time that the patients receive the service. Patient travel time refers to the amount of time patients spend travelling from their home to a healthcare facility. The motivation to define this new problem is the scheduling of patient tests (e.g., the COVID-19 test). Experiments were carried out based on generalized situations, and results demonstrated the effectiveness of the proposed encoding method and its corresponding GA.

The encoding method required 17% fewer optimization iterations compared to conventional methods. For specific examples in the experiments, the GA reduced the total waiting time by up to 58.2% and the travel time by up to 89.3%. There are two main contributions of this chapter: (1) a new scheduling problem that considers waiting time outside healthcare units and travel time to healthcare units, and (2) a novel encoding method for evolutionary computation algorithms, especially suitable for the scheduling problem.

5.1 Introduction

Long waiting time for appointments and extensive travel time are two of the major barriers for out-patients to access healthcare services (Allen et al. 2017; Ahmed et al. 2001; Leung et al. 2020). Outpatients must wait for hours or days before getting healthcare services in some regions and countries. Examples of such services are patient tests such as e.g., COVID-19 tests, imaging tests, colonoscopy examinations, etc. (Puzhko, 2017; Bobrovitz, Lasserson & Briggs, 2017; Gudivada, Philips, and Tabrizi, 2020). It has been found that excessive waiting time is an important reason for outpatient dissatisfaction (Clague et al,. 1997). Waiting time is a non-value-added time in the health service system (Barlow, 2002; Khanra et al., 2020); besides, a longer waiting time may complicate outcomes for patients (Kaushal et al., 2015; Zhuang et al., 2020; Zhan et al., 2021). During the ongoing Covid-19 pandemic, the waiting time problem has worsened, because of the reduced resources available for non-contagious patients (Jeffery et al., 2020). Elsewhere, the increase in non-value-added time may increase the total cost of a service or manufacturing organization significantly (Adeyemi, Ogbeyemi, and Zhang, 2021).

In addition, travel between a patient’s location (i.e., home, office, etc.) to a healthcare unit is an important factor for patients to access proper healthcare services. In the past, scheduling problems only considered patient wait time and overlooked patient travel time due to potential conflict between those two. Smith et al. (Smith et al., 2003; Pereira Detro et al., 2020) found that greater travel time for accessing services can result in a reduced number of physician visits, increased rates of attrition, and inadequate management of chronic conditions. Prolonged travel time is considered a major barrier to healthcare access. It doesn't only involve time consumption but is also related to cost, public transit availability and safety, vehicle access, etc. (Syed, Gerber, and Sharp, 2013). Although telemedicine can eliminate some of these problems (Sarivougioukas & Vagelatos, 2020), it can only be used in cases that do not require in-person physical examinations. Additional barriers to telemedicine are lack of appropriate equipment, or insufficient internet bandwidth.

The problem can be defined with the help of Figure 5.1. The scenario is as follows: there are multiple healthcare units in a region, and there are a few professionals (doctors, nurses) in different departments of one unit. Patients are looking to book healthcare services, e.g., COVID-19 testing, through phone calls or online (Lin et al., 2021; Wan & Chin, 2021). It is reasonable to assume that patients want to have short waiting time and short travel time. Waiting time in this study is defined as the interval between the time that a patient desires to have a healthcare service and the time the patient actually receives the service. When there is no immediate time slot available for the patient's desired time, the patient's appointment will be postponed to the next available one; as such, waiting time occurs. The travel time is defined as the time that a patient travels from a patient's location to a healthcare unit.

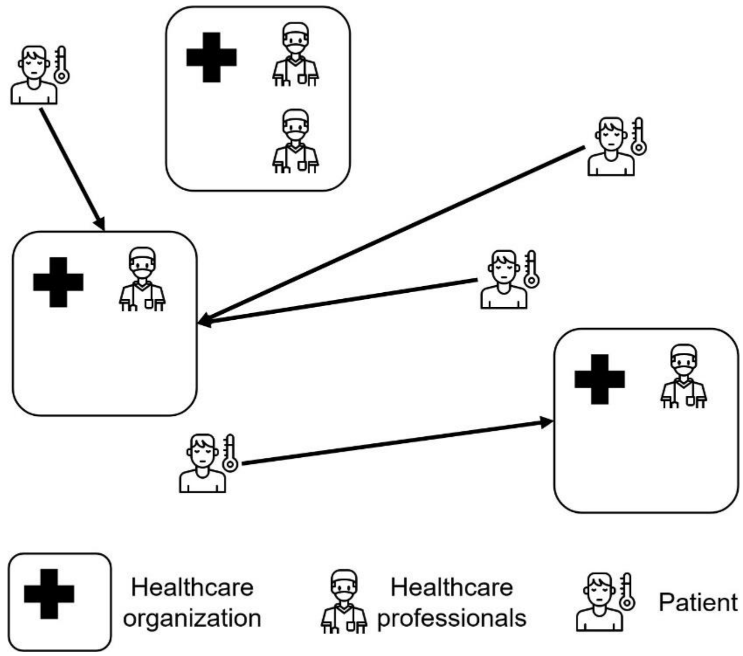

Figure 5.1 A general situation of the scheduling problem.

Studies in literature have largely been focused on reducing waiting time from the scheduled appointment time to the time that the appointment actually starts (Ahmadi-Javid, Jalali, and Klassen, 2017). To our knowledge, very little study has examined the issue of waiting time between when a patient requests an appointment and the scheduled appointment time. Moreover, there have been no studies that have investigated how to reduce both the waiting time and travel time simultaneously. During the COVID-19 pandemic period, remote scheduling with consideration of both travel time and waiting time is a sensible solution for scheduling COVID-19 testing. In this study, the problem is formulated as a multi-objective optimization problem and solved with a Genetic Algorithm (GA). In this connection, a novel encoding method, Discrete Event Encoding (DEE), is proposed for GA as well as any evolutionary computing algorithms. As an example, DEE is implemented as a part of Non-dominated Sorting Genetic Algorithm II (NSGA-II) in this study. The simulated experiment demonstrates the effectiveness of the proposed method. This chapter has two contributions. The first one is in the field of healthcare service management, specifically, a new problem has been defined and its mathematical model has been developed. The second contribution is in the field of GA, namely the novel encoding method, DEE, which can represent candidate solutions without causing violations of constraints or resource wastes. Further explanations are given in Section 5.2.2.

The remainder of this chapter is organized as follows. In Section 5.2, a literature review is provided on the problem of patient waiting time reduction and encoding methods used in multi-objective optimization algorithms. In Section 5.3, the model along with the algorithm for scheduling is presented. The performance of the algorithm is illustrated through simulated experiments in Section 5.4. Finally, Section 5.5 concludes the chapter with a discussion of future work.

5.2 Literature Review

5.2.1 The existing approaches to reduce patients waiting time

The outpatient scheduling problem has received attention from healthcare researchers and practitioners. Extensive reviews of appointment scheduling literature can be found in the study conducted by Cayirli and Veral (2003) and Ahmadi-Javid (2017). The approach can be divided into three levels: strategic, tactical, and operational (Ahmadi-Javid, Jalali, and Klassen, 2017). Strategic decisions are long-term decisions that determine the main structure of an outpatient appointment system. Tactical decisions are medium-term decisions related to how patients as a whole, are scheduled, or how groups of patients are processed. Operational decisions are short-term and are concerned with efficiently scheduling individual patients.

At the strategic decision level, Robinson and Chen (2010) compared the performance of the pre-scheduled policy, which schedules patients in advance of their appointment days, and the open-access policy, which schedules patients on the same day that they call for an appointment. In their study, the number of appointments was given, the service time was deterministic, and the arrival of patients was assumed to be punctual. Their numerical analysis revealed that the open-access policy can significantly out-perform the pre-scheduled policy in most cases including patients' waiting time, doctor's idle time, and doctor's overtime. Dobson, Hasija, and Pinker (2011) also compared a pre-scheduled policy with an open-access policy; they found that when there were a lot of urgent walk-in patients, the open-access policy performed better than the pre-scheduled policy. It is worth mentioning that both online (appointments are scheduled immediately upon their request) and offline (appointments are scheduled after a batch of requests has been received) problems have been studied in the literature, see (Wang & Gupta, 2011; Weiner et al., 2009). Indeed, the use of personal mobile devices, instant messages and notifications have made offline scheduling more efficient. The offline scheduling system collects patient requests electronically (e.g., via email or Web-based portal) first, and then advises their appointment time using text messages. Kuiper et al. (2015) compared the performance of the online and offline approaches and found that the offline approach had a better performance in terms of reducing the patient waiting time as well as staff idle time.

At the tactical decision level, Klassen and Yoogalingam (2009) showed that the best pattern of appointment lengths was a plateau-dome structure. The structure breaks one day's schedule into three sections. In the first section (e.g., morning), the appointment lengths increase over time. The appointment lengths of the middle section (e.g. afternoon) have the same, creating a plateau. The appointment lengths of the last section decrease until the end of the day. Their study found that this pattern results in the least waste of capacity. As opposed to these time-dependent appointment lengths, Nguyen, Sivakumar, and Graves (2015) proposed a network flow model to determine the optimal allocated capacity based on different groups. In their study, two patient groups with different appointment lengths were considered; they were patients on their first visit and return visits. In Zhou et al.'s work (2019), they generalized the idea of different appointment lengths and considered uncertainties in patients' lengths of stay. They raised the point that when managing for maximizing hospital revenue, it is important to allocate resources to multiple types of patients and uphold service equity. At the operation decision level, there are two main streams of studies. One focuses on allocating clients (patients) to services and the other on determining the appointment time. Most studies on allocating patients assumed that all services are identical. For example, Zheng et al.'s study (2015) proposed an overbooking scheduling model. Their goal is to maximize the expected profit by optimizing the number of overbooked patients in multiple-provider clinics. Other studies took some factors to differential services. Balasubramanian et al. (2014) developed a model that factorized the importance of continuous care. Their study showed that significantly higher revenue was earned when a primary-care provider saw one of his/her own patients compared to when the continuity of care was broken. In determining the appointment time, Chakraborty et al. (2013) found that, compared with a slot scheduling method (slot time is predetermined), scheduling patients at any time in the consultation session can be more efficient; however, it is less attractive in practice because the resulting appointment time has no particular pattern, which means difficulty for patients to follow. As an alternative way to determine the appointment time, Liu and Geng (2020) proposed an ordinal optimization strategy. Instead of directly controlling the appointment time, their approach was to determine the sequence, in which a list of patients should be scheduled. Their goal was to utilize the limited medical resources efficiently while ensuring the quality of service for clients.

Although each study in the above focuses on a specific decision level, an outpatient scheduling approach usually covers two or three of the decision levels above. For example, for a study that focuses on appointment time optimization (at the operation decision level), their scheduling approach used either a pre-scheduled or open-access policy (at the strategic decision level) (Li et al. 2019). From the literature above, three remarks are made. The first is that offline scheduling becomes more popular as scheduling systems are more accessible to patients via mobile phones. The second is that most studies only consider waiting time inside healthcare units. The third is that most of the studies above have only a single optimization objective.

When considering multiple objectives, e.g., maximizing revenue and resource utilization, the existing work often adds up those objectives with different weights. This type of optimization is useful as a tool which should provide decision-makers with insights into the nature of the problem, but usually cannot provide a set of alternative solutions that trade different objectives against each other (Savic 2002). On the contrary, in a multi-objective optimization problem with conflicting objectives, there is no single optimal solution. The interaction among different objectives gives rise to a set of compromised solutions. Investigating scheduling problems with multi-objectives captures more semantics of appointment booking and scheduling in practice (Castro & Petrovic, 2012). Therefore, our study is to address the scheduling problem using an offline scheduling strategy with multi-objectives.

5.2.2 The existing method for hospital scheduling problems

A typical hospital scheduling problem has the following characteristics: 1) schedule a given number of patients, 2) each appointment may take a different amount of time, 3) each appointment has to meet certain resource constraints. To maximize resource utilization, an optimal schedule needs to be found. This is an NP-hard problem (Yeh and Lin 2007) as the number of possible schedules grows exponentially if one attempts to exhaust all solutions. That is why researchers use Evolutionary Computation (EC) approaches and other approaches. EC is fundamental for evolutionary algorithms which includes Genetic Algorithms (GA) (Kramer, 2017; Mitchell, 1998), Genetic Programming (GP) (Kennedy and Eberhart 1995), Evolution Programming (EP) (Back, 1996), etc.

When applying an EC method such as GA, candidate solutions need to be encoded as an array of bits, called chromosomes. In the hospital scheduling problem, chromosomes can be either represented by a list of appointment times or a list of appointment indexes. Both encoding methods may cause violations of constraints after the crossover and mutation step. For example, when using a list of appointment times as a chromosome, time & space conflicts among appointments may happen due to the randomized nature of GA. Chromosomes with the violations need to be either discarded (Sulis et al., 2020) which causes a considerable waste of computation resources and reduces the algorithm's efficiency, or considered as a penalty when evaluating chromosomes (İnanç & Şenaras, 2020; Kaveh et al., 2020; Lin & Chou, 2020). The latter way may result in impractical results.

To avoid such constraint violations, many researchers (Roland et al., 2010; Vali-Siar, Gholami, and Ramezanian, 2018; Zhao, Chien & Gen, 2018; Hamid et al., 2020; Li & Chen, 2021) took a repair approach. The approach resolved violations of constraints by modifying candidate solutions based on given rules. For example, when duplicate appointments are found in a candidate solution. The repair step replaces the duplicate appointments with other ones from the previous generation of solutions. This made the new solutions very similar to the previous ones and diminished the benefits of evolution. Besides, this additional modification causes the results hard to converge

(Vali-Siar, Gholami, and Ramezanian, 2018; Zhao, Chien, and Gen, 2018). Alternatively, Rivera, et al. (2020) used a group of fixed-length containers to encode a solution. Each container had one or more appointments. At the crossover and mutation step, solution modification only happened at the container level. In this way, time conflict will be avoided. However, as the container length was fixed while the appointment length was not, there are gaps between appointments. Those gaps were considered as time waste, and they reduced resource usage.

In short, when applying traditional encoding methods on scheduling problems, violation of constraints happens in candidate solutions after mutation and crossover steps. To overcome this problem, researchers either used a repair step to fix the solutions, or added gap time in schedules to avoid the violation. The repair step is a waste of computational resources, and the gap time is a waste of healthcare resources. Our new encoding method, DEE, can naturally avoid the violation of constraints. DEE does not require any repair step or gap in schedules, and therefore does not cause any waste of resources. This method can be adapted for any EC algorithm which uses mutation or crossover steps in scheduling problems.

5.3 Scheduling Optimization Algorithm

5.3.1 Optimization Problem

The optimization problem has two objectives: (1) to minimize the patient waiting time, and (2) to minimize the patient travel time. Further, the following assumptions are applied:

(1) There are limited healthcare units in a region, which could offer similar services but are in different locations.

(2) Patients and healthcare professionals are punctual.

(3) The lengths of appointments vary among patients and are determined when patients request services.

(4) Patients do not know the appointment time or the healthcare location when they request a healthcare service. Instead, they will be notified of the time and the location with the length of time (θ) prior to their departure time.

5.3.2 Mathematical Model

A common scheduling method utilizes a first-come-first-serve strategy and schedules patients sequentially. Our scheduling algorithm optimizes a group of patients to achieve a better overall result in a scheduling system as opposed to the common strategy. We consider the following two scenarios: pre-scheduled scenario and open-access scenario. In the first scenario, scheduling for a group of patients within a pre-defined period of time is taken, where patients are not individually differentiated. After that, the schedule is kept unchanged. In the second scenario, patients are individually scheduled upon their requests being received.

Denote all patients' appointments in the system as $P = \{p_1, p_2, p_3, \dots, p_n\}$, where n is the number of appointments. The times when patients request their appointments are defined as R = $\{r_1, r_2, r_3, \dots, r_n\}$. Patients' preferred appointment times are denoted as $Y^r = \{y_1^r, y_2^r, y_3^r, \dots, y_n^r\}$, and the duration of appointments is denoted as A = $\{a_1, a_2, a_3, \dots, a_n\}$. Patients are given their initial scheduled appointment times as $Y^o = \{y_1^o, y_2^o, y_3^o, \dots, y_n^o\}$ using the basic scheduling method (as introduced in Section 3.2). Their optimized appointment time by the system is denoted as $Y^s = \{y_1^s, y_2^s, y_3^s, \dots, y_n^s\}$. Then, we have:

$$R \le Y^r \le Y^o \;\&\; R \le Y^r \le Y^s \tag{5.1}$$

Under the pre-scheduled scenario, the re-arrangeable patient appointments *Px* is:

$$Px = \{p_i | p_i \in P, s_j \geq y_i^0 \geq s_{j-1}\} \ (1 \leq i \leq n) \quad \textbf{(5.2)}$$

where y_i^0 is the time which patient p_i departures; s_j is the predefined time point to run the algorithm; s_{j-1} is the previous time point. For example, if the system groups all the patients within 24hrs and schedule time together, then s_{j-1} can be 8 pm on day 1, and s_j be 8 pm on day 2.

Under the open-access scenario the re-arrangeable patient appointments *Px* is:

$$Px = \{p_i | p_i \in P, y_i^0 \geq s'_j + \delta_{ik} + \theta\} \ (1 \leq i \leq n) \quad \textbf{(5.3)}$$

where s'_j is the time point when a patient requests an appointment, $s'_j \in R$; δ_{ik} is the time required for patient p_i to travel to healthcare unit k $(1 \leq k \leq m)$; θ is a predefined length of time, prior to patients' departure time, it determines the time the system confirms patients' appointments; *n* is the total number of healthcare units in the region/system.

There are two objective functions:

$$\text{OB-1: Min} \sum_{i=1}^{|Px|} \{y_i{}^s - y_i{}^r\} \ (1 \leq i \leq |Px|) \quad \textbf{(5.4)}$$

$$\text{OB-2: Min} \sum_{i=1}^{|Px|} \delta_{ik} \ (1 \leq i \leq |Px|) \quad \textbf{(5.5)}$$

where $|Px|$ is the number of re-arrangeable appointments. OB-1 is to minimize the total waiting time. The OB-2 is to minimize the total travel time.

The constraint of this problem is that there is no conflict in the scheduled time. It can be written as:

$\forall\, p_i, p_j \in Px, i \neq j,$

$if\ k_i = k_j, then$

$$[y_i - (y_j + a_j)] \times [(y_i + a_i) - y_j] \geq 0 \tag{5.6}$$

where k is the healthcare unit where a patient has an appointment. This constraint ensures that no overlap among appointments in the same healthcare unit. This creates a trade-off between appointment time and choice of healthcare units.

Here, we give the formal definition of the optimization problem as

$$\text{OB-1: Min} \sum_{i=1}^{h} \{y_i - r_i\} \ (1 \leq i \leq h)$$

$$\text{OB-2: Min} \sum_{i=1}^{h} \delta_{ik} \ (1 \leq i \leq h)$$

s.t

$\forall\, p_i, p_j \in Px, i \neq j,$

$if\ s_i = s_j, then$

$$[y_i - (y_j + a_j)] \times [(y_i + a_i) - y_j] \geq 0 \tag{5.7}$$

All notations used above are summarized in Table 5.1.

5.3.3 Algorithm

To solve the above multi-objective optimization problem, NSGA-II (Deb et al., 2002) was used in this study. NSGA-II is a well-known genetic algorithm, which is capable of fast sorting and elite searching for multi-objective solutions. Thus, it is ideal for our problem. To implement the genetic algorithm, a new encoding method, DEE, is proposed, in conjunction with the Discrete Event Simulation (DES) (Jun, Jacobson, and Swisher, 1999) to calculate the objectives' value of each chromosome. DES has the benefit of mimicking a scheduling process, while NSGA-II is effective in solution searching. Based on this understanding, we combined them based on the theory of engineering hybridization (Zhang, Ouyang, and Sun, 2010) and proposed a hybrid method called DEE-NSGA-II here. Its workflow is illustrated in Figure 5.2.

Table 5.1 Indices and parameters in the mathematical model

Symbol	**Explanation**
i,j	Appointment index
P	Total patient appointments
n	Number of total patient appointments
R	Time when patients request their appointments
A	Appointment durations
Y^r	Patients' preferred appointment time
Y^o	Initial scheduled appointment time
Y^s	Optimized appointment time
P_x	A subset of re-arrangeable appointments
s	Time points to run the algorithm
δ	Length of time required for patient to travel to a healthcare unit
θ	Length of time, prior to patients' departure time, it determines when the system confirms patients' appointments
m	Number of healthcare units
d	Healthcare professional assigned to an appointment

The optimization workflow of the DEE-NSGA-II follows a typical NSGA-II procedure. The method starts with a set of chromosomes that are generated using DEE. Each chromosome presents a candidate solution to the problem. The algorithm takes the population of chromosomes as parents and reproduces new chromosomes (i.e., offspring in a GA). The reproduction exchanges partial information between two chromosomes, called crossover, and makes minor changes, called mutation. Then, a subset of elite parents & offspring chromosomes are selected to reproduce the next generation of offspring. This process repeats for a given number of generations. Populations from newer generations are expected to perform better than ones from earlier generations as they are offspring from elite chromosomes. To identify those elites, NSGA-II uses the fast nondominated sorting and the crowding distance sorting to achieve a superior sorting speed and keep diversity among candidate chromosomes. More details on how each step in the NSGA-II can be found in (Deb et al., 2002). It is worth noting that applying the NSGA-II algorithm to the problem is not the main contribution of this work. There are many other multi-objective optimization algorithms that may be suitable for solving the problem. The NSGA-II is picked in this study to demonstrate the effectiveness of DEE, as explained below.

With the scheduling order (chromosome), the DES was used to evaluate the objective functions, step 2 in Figure 5.2. Details of this step are shown in Figure 5.3. For each appointment in the scheduling order, a group of healthcare units with the shortest waiting time available is identified. From this group, the healthcare unit with the shortest travel time is chosen. The process goes through all the appointments following the order. By summing up the waiting time and travel time of each appointment, the total patients' waiting time and travel time are calculated, which are the values of OB1 & OB2.

In applying NSGA-II or other multi-objective optimization algorithms, the most challenging part is the representation of candidate solutions (encoding methods). The candidate solution in a GA is typically encoded as a string consisting of N integer numbers (called chromosomes). Conventional encoding methods often require a repair step to resolve constraint violations from chromosomes. This additional step causes GA hard to converge. To overcome this inefficiency problem, we developed a new encoding method, DEE, which uses a scheduling order as a chromosome. Figure

5.4 shows an example of a scheduling order.

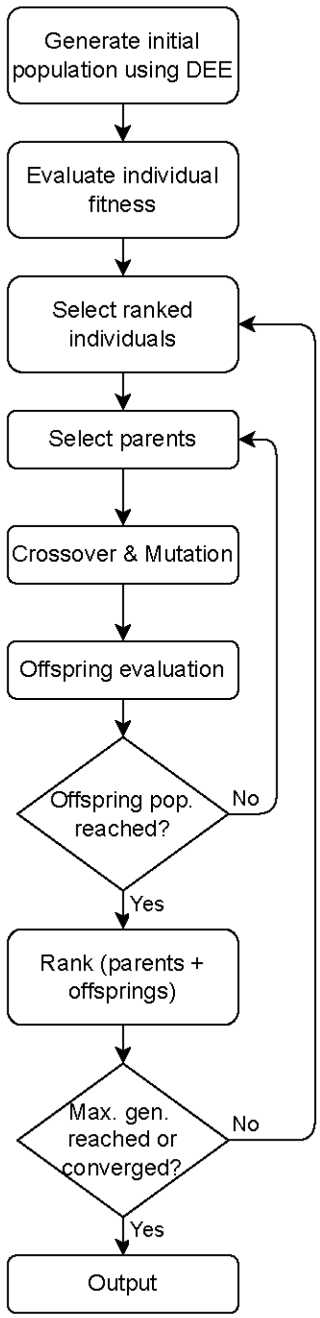

Figure 5.2 The optimization workflow of the DEE-NSGA-II.

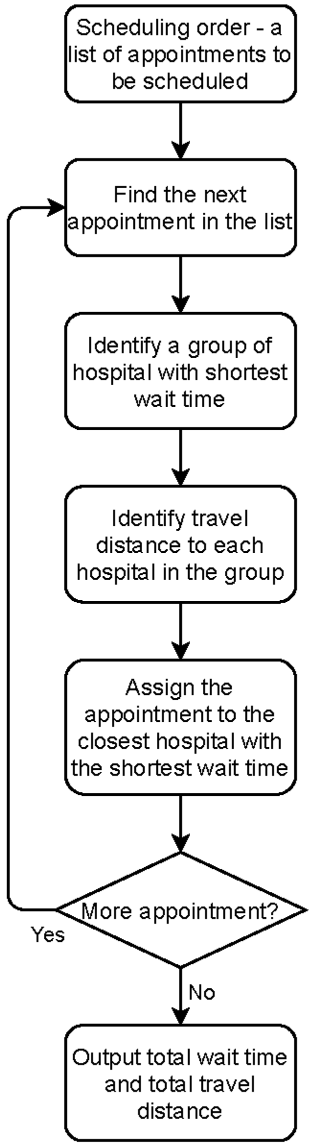

Figure 5.3 A flowchart of how the DES evaluates individual chromosomes.

3	3	1	1

Figure 5.4 An example of DEE encoded chromosomes.

In this example, the scheduling order of 4 appointments a, b, c, d in a queue is determined. The length of the chromosome is the number of appointments. Each digit in the chromosome represents the order in the current appointment queue. For example, the first number “3” means the third appointment in the current queue a, b, c, d. So, appointment c will be scheduled first and after that is removed from the appointment queue. The second number “3” means the 3rd appointment in the current appointment queue a, b, d. Therefore, appointment d is scheduled next and then removed from the queue. Similarly, the third number “1” means the 1st appointment in the current appointment queue a, b, which is appointment a. The fourth number “1” means appointment b, which is the 1st appointment in the remaining appointment b. One might notice that the last number in the representation will always be “1” as there is only one appointment in the queue. In summary, the chromosome in Figure 5.4 represents an appointment scheduling order as (c, d, a, b), and it only decides the order of appointments to be scheduled rather than the appointment time or location. This order will then be processed by the DES to guarantee the constraints in the optimization problem will not be violated.

5.4 Experiment

5.4.1 Experiment Data and Setting

In this section, we report two case studies to demonstrate how the proposed method works in a patient scheduling problem. In both cases, we used synthetic patient data to simulate realistic situations. The synthetic data was randomly generated to follow the rules in Table 5.2.

Table 5.2 Parameters used in generating synthetic patient appointment data

Parameters	**Value used in generating synthetic data**
Number of all appointments (n)	25~160, varies in each experiment.
Time of request appointments (R)	16~96 hrs, varies in each experiment.
Appointment length (A)	0.25~4 hrs, round up to the nearest quarter.
Patient travel time length (δ)	0~1 hr
number of healthcare units (m)	3
number of healthcare professional (q)	3

The proposed method is written in Python 3.6. The NSGA-II module is adopted from pymoo (Blank & Deb, 2020) and the DES module is developed by ourselves. pymoo is a python package for multi-objective optimization algorithms and is developed under the supervision of the original developer of the NSGA-II algorithm (Deb et al., 2002). Table 5.3 contains a list of parameters used in the proposed DEE-NSGA-II method.

The population size and the mutation probability are determined by the number of all appointments (n). The algorithm stops when there is no improvement (objective value changes < 0.0025) for g_s continuous generations, or the maximum generation (g_{max}) is reached. The Crossover & Mutation Distribution Index are the control parameters which are inversely proportional to the amount of perturbation in Crossover & Mutation. The smaller the value, the larger the perturbation and vice versa. A smaller value, thus, improves the resilience to premature convergence at the cost of a highly focused search. The default value of 10.0.

Table 5.3 List of parameters in the DES-NSGA-II method/model and their values

Parameters	**Values used in the experiments**
Population size	2 x n
Crossover rate	1
Crossover type	Simulated Binary Crossover
Crossover distribution index	3
Mutation probability	1/n
Mutation type	Polynomial Mutation
Mutation distribution index	3
Max. generation (g_max)	200
Termination criteria (g_s)	20

Two sets of hardware are used for the experiment. The cloud server is used for optimizing cases under the open-access scheduling scenario and the local desktop is for optimizing the pre-scheduled scenario.

- Local Desktop: Processor, Intel Core i5-7600K, Quad-Core, 3.8 GHz, Max Turbo @4.20 GHz. 16 GB RAM.
- Cloud Server (Compute Canada): Processor, Intel Xeon Platinum 8168, 32 Core 2.70GHz, Max Turbo @3.70 GHz. 64 GB RAM.

5.4.2 Case Studies

Two cases with simulation data were used in this study. The first is the pre-scheduled scenario, which schedules patients in advance of their appointment days, so all requests are optimized at the same time. The second is the open-access scheduling scenario, which schedules patients on the same day that they request an appointment. Compared to the open-access scheduling scenario, the pre-scheduled scenario has more appointments to be arranged and only runs once. It could take considerably less computational resources. However, it requires appointments to be made in advance and no changes to appointments can be made after the schedule is made. The open-access scheduling scenario, on the other hand, optimizes all appointments every time a new appointment is added or modified.

In the first case study, we compare DEE-NSGA-II to a baseline scheduling method and a GA using a conventional encoding method (GACE) that is adapted from literature (Vali-Siar, Gholami, and Ramezanian, 2018; Zhao, Chien, and Gen, 2018) using pre-scheduled scenarios. In terms of the total appointments (represented as patient numbers in Figure 5.5 & Figure 5.6, we used four different ones (12, 14, 18, 24). Under each number, 6 sets of synthetic appointment data were generated by following the rules in Table 5.2. Figure 5.5 shows the results for total waiting time, and Figure 5.6 shows the results for total travel time.

The baseline scheduling method schedules patients on a first-come-first-serve base strategy. Note that the same strategy was used in the DES to calculate optimization objectives. Details of this strategy were explained in Figure 5.3. The GACE schedule patients using the NSGA-II algorithm with an encoding method which represents a chromosome by a list of appointment indexes. Such an encoding method requires a repair step as explained in Section 5.2.2.

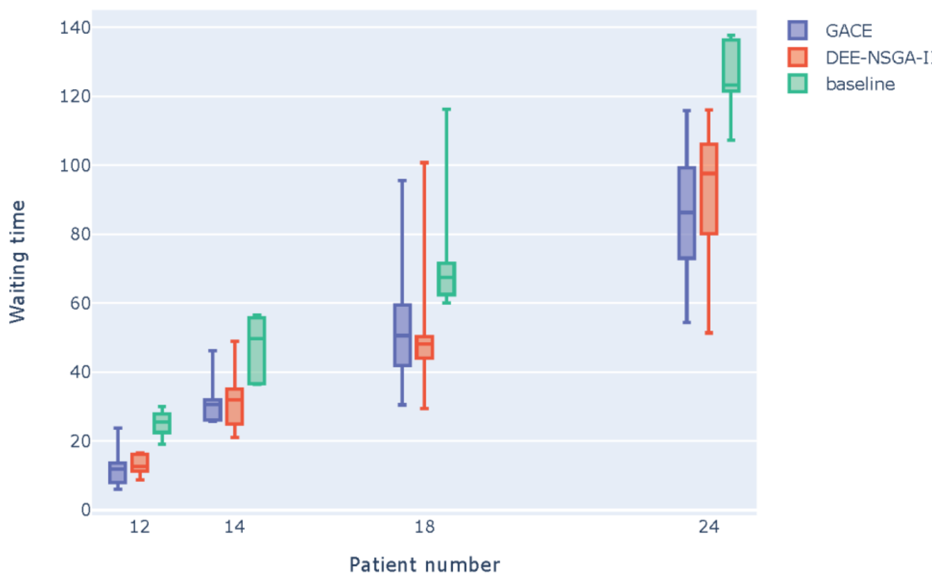

Figure 5.5 Comparing waiting time when pre-scheduling different sizes of patient groups.

Figure 5.5 shows the total waiting time of all patients in each group when under the pre-scheduled scenario. We see that results from DEE-NSGA-II and GACE are clearly better than the baseline. For example, when the patient number is 12, the total waiting time of the baseline method is 25.05 hours, while DEE-NSGA-II takes 13.0 hours and GACE takes 12.5 hours. That means 48.1% and 49.9% waiting time saving from DEE-NSGA-II and GACE, respectively. While the waiting time save is noticeable across all cases, it is worth noting that the rate of saving declines as the patient number grows. When the patient number increases to 18, the waiting time savings are 28.0% from DEE-NSGA-II and 26.2% from GACE.

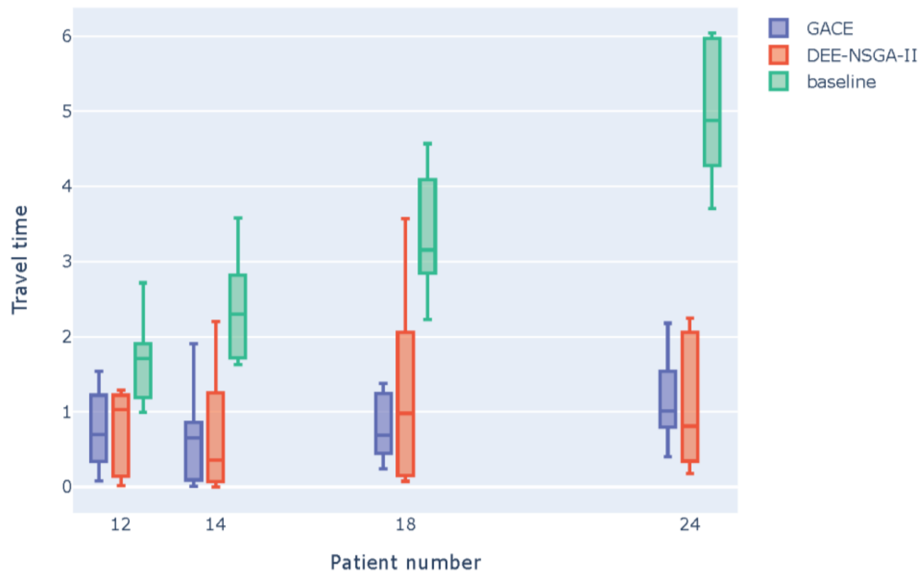

Figure 5.6 Comparing travel time when pre-scheduling different sizes of patient groups.

Figure 5.6 shows the total travel time of all patients in each group when under the prescheduled scenario. The effectiveness of both DEE-NSGA-II and GACE on travel time reduction has been demonstrated. In the baseline method, total travel time increases as more patients are scheduled. In contrast, both DEE-NSGA-II and GACE can keep the total travel time low in all cases. The total travel time from DEE-NSGA-II and GACE ranges from 0.7 to 1.0 hour, while the baseline travel time increases from 1.7 hours to 5.0 hours. Compared to the baseline method, the DEE-NSGA-II and GACE reduced 53.7% & 55.3% of travel time respectively when the patient number is 12. When the patient number is 24, the travel time saving is 78.3% from DEE-NSGA-II and 76.7% from GACE.

Figure 5.7 shows the number of GA optimization iterations (generations) for DEE-NSGA-II and

GACE to converge when the patient number is 12. The termination criteria in this study are either reaching the max generation (200) or there is no significant change (<0.0025) in objective value in the last 20 generations. On average, GACE takes 130 generations to converge. On the other hand, DEE-NSGA-II requires 108 generations, 17.0% less than GACE. This result supports our claim that our new encoding method DEE has a better convergence rate compared to conventional encoding methods.

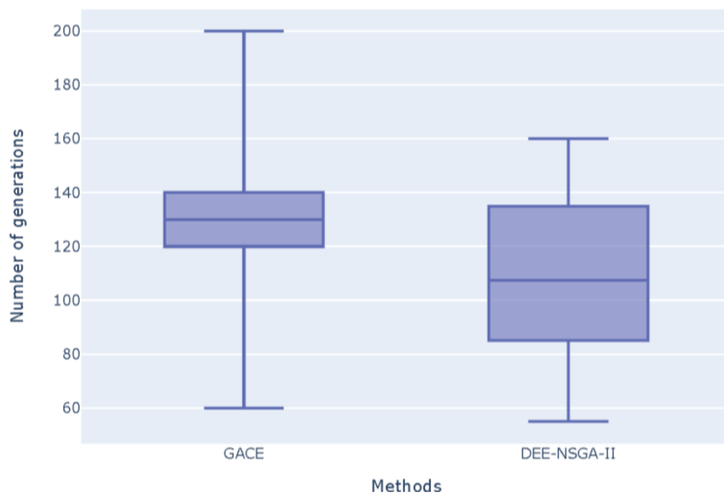

Figure 5.7 Number of generation for DEE-NSGA-II and GACE to converge.

In the second case study, we illustrate one open-access scheduling scenario by comparing DEE-NSGA-II to the baseline method. 10 sets of synthetic patient data were used (25 patients). Figure 5.8 shows the results for total patient waiting time from baseline and the optimization algorithm using open-access scheduling. The results from 10 sets of data show an average of 58.2% waiting time savings. Figure 5.9 shows the results for total patient travel time from baseline and the optimization algorithm using open access scheduling. The results from 6 sets of data show an average of 89.3% travel time reduction.

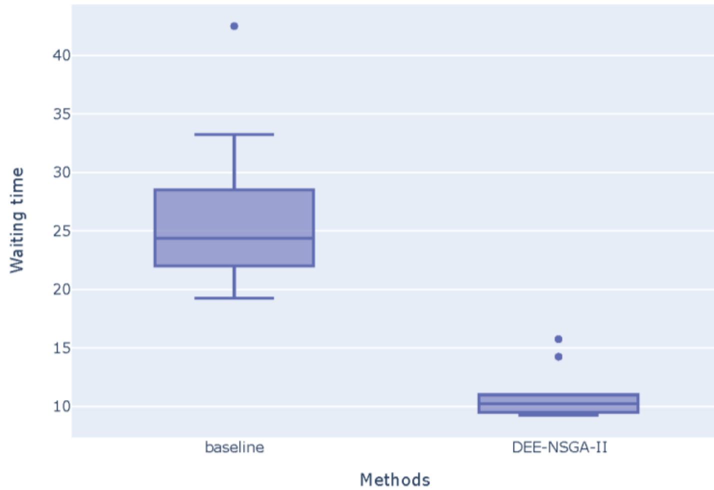

Figure 5.8 Comparing patient waiting time using open-access scheduling.

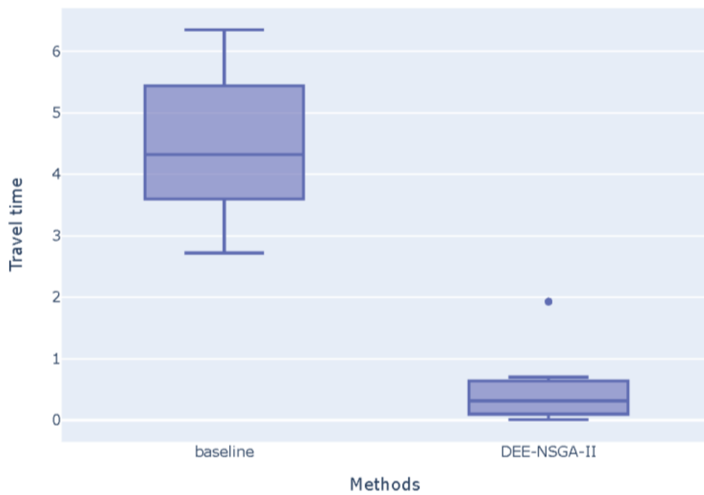

Figure 5.9 Comparing patient travel time using open-access scheduling.

5.4.3 Results and Discussion

From the above case studies, we found that DEE-NSGA-II is effective for both prescheduling and open-access scheduling. In the first case study, the effectiveness of both DEE-NSGA-II and GACE has been demonstrated. Both algorithms can save 26% to 49% of total waiting time. When achieving very similar results, DEE-NSGA-II requires 17% less iterations to converge than GACE. This result illustrates the benefits of our novel encoding method, DEE. In the second case study, DEE-NSGA-II saved 58.2% waiting time and 89.3% travel time compared to the baseline method.

Further, the total waiting time from DEE-NSGA-II is more consistent among 10 sets of test data. The standard deviation of the waiting time from DEE-NSGA-II is 2.1 hours while the one from the baseline method is 6.6 hours.

Compared to the waiting time improvement from DEE-NSGA-II, the travel time was reduced more significantly as the patient number grew. We believe that this is partially due to there being only three healthcare units in the case studies. This makes travel time optimizations simpler than waiting time optimizations. The significant travel time reduction also justifies the importance of optimizing travel time in addition to waiting time.

When comparing results from the pre-scheduling and the open-access scheduling, we found that DEE-NSGA-II is suitable for both cases and achieves noticeable time reductions. For example, it achieves 26.8% shorter waiting time and 78.3% shorter travel time when patient number = 24 in pre-scheduling cases. In comparison, it reduces 58.2% the waiting time and 89.3% the travel time in open-access cases. DEE-NSGA-II shows better results in the open-access cases. This advantage may be appreciated as open-access scheduling was found to be more useful in practice. Some reports show that online scheduling has a positive effect on reducing patients' no-show rates (Dobson, Hasija, and Pinker 2011).

5.5 Conclusion

Outpatient waiting time is a source of dissatisfaction with healthcare quality, lost productivity for individual patients, as well as increased risk of the deteriorated condition of patients. In addition, long travel time decreases the chance for patients to receive quality healthcare. To deal with both waiting time and travel time, we defined the problem as an optimization problem and proposed an optimization model. To solve the model, we proposed a novel encoding method for DEE-NSGA-II. The DEE-NSGA-II algorithm schedules patients to a health unit based on their locations and desired time. It minimizes patients' waiting time outside healthcare units, and their travel time to the units. To illustrate its performance, two case studies were conducted. The results showed that the algorithm is effective for the pre-scheduling scenario and the open-access scenario. Both waiting time and travel time were significantly reduced compared to a traditional first-come-first-service scheduling system. The results also showed the advantage of the novel encoding method when compared to the conventional encoding methods.

The contributions of this study are highlighted as follows. First, this study investigated a new problem which is to reduce travel time of patients in addition to waiting time. Travel time optimization was often omitted in existing studies, despite its impact on healthcare accessibility. To solve these two conflicting objectives, a mathematical model is formulated and implemented in two case studies. The results from the case studies showed its promising benefits in reducing travel time significantly. In addition, different from the existing work which combines multiple objectives into one, our method can be applied to more realistic problems and identify a wider range of alternatives to be selected by decision makers. Second, a new encoding method, DEE, is developed to represent a candidate solution in GA. It avoids violation of constraints when generating new candidate solutions, and its application is demonstrated through DEE-NSGA-II. DEE can be useful for solving other types of patient scheduling problems with different objectives, e.g., optimizing patient surgical waiting time while considering patients' mental status, risk of disease deterioration, etc. Furthermore, it can also be used in a category of single objective and multiple objectives GA such as BRKGA (Gonçalves & Resende, 2011), R-NSGA-III (Vesikar, Deb, and Blank, 2018), MOEA/D (Zhang & Li, 2007), etc. Potentially, the encoding method can be adapted to other evolutionary algorithms, which perform genetic operations on candidate solutions. Examples include Swarm Optimization Algorithms (Cuevas, Fausto, and González 2020), Evolution Strategy (Knowles & Corne, 2000), and Differential Evolution (Price, 2013).

There are a few limitations of this study that could be addressed in the future. For example, a more sophisticated case study with complex settings could be conducted. It should consider patients' & healthcare professionals' delays, patients' priorities due to their symptoms & deteriorations, hospital preferences, and their changes of locations. Those considerations could be modelled either as additional optimization objectives or as constraints. The other limitation is that the algorithm efficiency was not investigated. Based on the case studies, we noticed that the genetic algorithm is computationally expensive. In this study, the algorithm was only adapted for proof of concept and its efficiency is not a focus. We will further investigate it in the future by adapting or developing a more complicated optimization algorithm. Lastly, the implementation of the scheduling method was not discussed. Future studies could investigate how to fit our multi-objective scheduling method into an existing patient scheduling system.

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Chapter 6

An optimization model for resource allocation with consideration of the equity, efficiency, and resilience

This chapter is an application of sustainability and resilience as patient equity in healthcare decision-making. The discussion in Section 2.4.4 identified a need for a comprehensive resource allocation model that considers dynamics in patient demand, such as travel time, and in service availability, such as manpower shortages and resource distributions. This need is fulfilled by the research for Objective 4 of this thesis. This chapter was submitted as Wenjun Lin et al. "An optimization model for resource allocation with consideration of the equity, efficiency, and resilience of a healthcare system" to the International Journal of Intelligent Systems in 2023 (under review).

Abstract

Healthcare resource allocation is crucial for the quality of a public healthcare system, especially resilience and equity. Conventional resource allocation methods primarily focus on efficiency, which tends to result in resources being concentrated in a geographical center. This result is especially harmful in the situation where healthcare facilities may experience unexpected shutdowns (due to logistical challenges and human resource shortages). As a result, access to healthcare services in rural areas is extremely difficult. In this chapter, we develop a multi-objective optimization model for representing healthcare facilities and resources along with their

allocations with consideration of (1) healthcare equity, (2) resilience, and (3) efficiency of service delivery. For healthcare equity, three different indicators were implemented in the model. The effects of these indicators on service delivery quality were investigated using a case study involving the allocation of COVID-19 test sites in Saskatchewan (Canada). The results obtained with our model show that by considering system resilience, the allocation plan can reduce testing days by up to 92% in the event that one test site is shut down. In practice, the model served as a tool for the healthcare resources manager to allocate the COVID-19 test sites as well as other healthcare resources such as antiviral medications, intensive care unit beds, and ventilators. It may be apparent that the methodology for building such a model can be used for any type of resource. Therefore, the study has a generalized implication for the resource allocation problem. The study reported in this chapter is perhaps the first to consider equity and resilience together in a healthcare resource allocation problem.

6.1 Introduction

The worldwide outbreak of the COVID-19 pandemic and its far-reaching impacts have significantly highlighted the need for improved rational planning of healthcare resources (Kang et al., 2020). However, the conventional distribution of healthcare services often does not provide equal accessibility to all (Polzin et al., 2014). In Canada, for example, healthcare delivery often fails to address social and health inequities that lead to health disparities among specific populations, especially Indigenous and rural communities (Nader et al., 2017).

Unlike other resource allocation problems that focus on cost minimization, healthcare decision-makers face complex challenges when deciding where to locate healthcare facilities and how to distribute capacity. One challenge is related to healthcare accessibility. Healthcare accessibility is significantly dispersed across different locations (Langford et al., 2016), which causes spatial inequity. The other challenge is system resilience. While resilience is a core concept in disaster risk reduction, its application to healthcare systems is relatively new. It has been defined broadly as institutions' and health actors' capacities to prepare for, recover from, and absorb crises, while maintaining core functions (Kruk et al., 2015). The pandemic has caused logistical complications, supply shortages, and healthcare professional burnout. It is essential to have a resilient healthcare system that can effectively adapt in response to dynamic situations while still serving the acute care needs of their communities.

In this chapter, we use a multi-objective selection model to optimize these three criteria: efficiency, equity, and system resilience. The model determines the optimal locations of healthcare facilities and resource allocations for each facility. Multiple objective evaluation methods of equity and system resilience were adapted and implemented. Their performances were demonstrated in a case study that is for COVID-19 test site allocation in the province of Saskatchewan, Canada. This study's contributions are fourfold. First, it is one of the first studies to consider system resilience at the stage of resource allocation. Second, it compared different methods of evaluating equity. Their pros and cons are explained through the case study. Third, the model optimizes facility locations and resources in each facility at the same time. Fourth, it can serve as a guide to the authorities in determining the locations of the COVID-19 test sites as well as other scarce healthcare resources.

The remaining part of the chapter is organized as follows. In Section 6.2, we discuss literature related to healthcare equity, system resilience, and their applications in healthcare resource allocation problems. In Section 6.3, the model and the optimization algorithm are presented. In

Section 6.4, we present the case study and interpret the results. Section 6.5 presents the conclusion and discusses the limitations.

6.2 Literature Review

As a tool to optimize resources, location-allocation models have been around for a long time (Drezner & Hamacher, 2004). The classical models also include the p-median model, the maximal covering location model, the location set covering model, and the p-center model (Owen & Daskin, 1998). Taking the maximal covering model as an example, it deals with the coverage of demanders within a certain radius of each facility (Murray, 2016). Demanders are places where people demand services from facilities. The model aims to maximize coverage within the limited capacity of facilities available. Another example is the location set covering model, which is designated to achieve full coverage using the least number of facilities (García-Palomares et al., 2012).

There are a few limitations with the classical models (Wang, 2012). First, they fail to address complicated situations such as equity issues or partial system failure. Most of the existing allocation models only address efficiency-oriented objectives. Second, the assumptions of the spatial interaction between demanders and facilities in these models are relatively simple. Few models, for example, have used realistic accessibility measurements when determining how long it takes users to reach facilities. Third, those models only determine facility location without taking the amount of resources to be allocated into account. The optimal amount usually requires a secondary model. The two-step process limited its optimization performance and lacked flexibility in implementing the optimization solution.

Aiming to address the equity issue, Wang and Tang (2013) initiated a maximal accessibility equity

(MAE) model. The MAE model quantifies the equity of the configuration of facilities as the standard deviation (SD) of travel time to different facilities. The optimal solution would minimize the SD. The result suggested that to achieve better equity in accessibility, additional supplies are needed in less-central locations.

SD has been applied as an equity measurement in a few more studies. Tao et al. (2014) applied the maximal equity model to find the optimal configuration of residential facilities. Similarly, Wang et al. (2015) used a similar method to select newly added facility locations rather than reallocating resources at existing locations. Like the classical models, two studies used a two-step procedure, with the first step being to optimize the locations of facilities, and the second step being to optimize the respective sizes of the facilities. Most recently, Dai et al. (2019) used SD as an equity measurement to optimize educational opportunities.

In addition, Rong et al. (2020) used the GINI index (Gini, 1936) to represent equity in their studies of the spatial accessibility of medical treatment in the main urban area of Zhengzhou, China. By using an improved potential model and an Internet map navigation service, their study identified imbalances in the medical facilities and services on the outskirts of the city. This is one of a few studies of healthcare equity using GINI (Schoen et al., 2000; Liu, 2014; Braveman, 2006). Both SD and GINI are quite popular in the measurement of healthcare equity. However, the advantages and disadvantages of the two measures are still not clear, which can cause difficulties in their applications.

To date, few studies have paid attention to the resilience of the whole system when optimizing locations of resources (Qin et al., 2022; Wang & Liu, 2019; Alemzadeh et al., 2020). The focus of these studies is on the strategy of maximizing system capability in the event that one or multiple parts of the system fail. For example, to maximize the effect of SOPs (soft open points) on the boost of the resilience of the power distribution network, Qin et al. (2022) proposed a mixed integer non-linear optimization problem to schedule the siting and sizing of SOPs based on a multi-stage elastic mechanical model. A particle swarm algorithm is used to optimize the control strategies of SOP to obtain the maximum power system capability. Compared to regaining the capability of a system, where resources have already been allocated, system resilience optimizations at the resource allocation stage have less constraints. Therefore, the present study attempts to incorporate resilience into resource allocation for accessibility and efficiency.

6.3 Methodology

6.3.1 Optimization Problem

In this study, we investigate a resource allocation problem that chooses multiple locations in a region to set up healthcare facilities and to determine the distribution of resources among facilities. The problem has three objectives: (1) to maximize the region's overall efficiency in utilizing the resources, (2) to maximize healthcare equity among patients from different parts of the region, and (3) to maximize system resilience so its performance won't degrade dramatically in the event of a partial system failure.

The problem has the following assumptions:

1) There are a limited number of locations to be chosen. Each location offers the same services.
2) Travel time is the main barrier to accessing healthcare.
3) Patients use the same method of transportation, i.e., driving.
4) Patients always choose the closest facility.

5) A partial system failure means that one facility is shut down, and its resources is unavailable.
6) Upon the system failure, patients will go to the next closest facility which still operates.
7) There is a booking system for patients to access to facilities (Lin et al., 2022), which is expected to ensure the facility will not be overwhelmed.

6.3.2 Evaluation of system efficiency

We evaluate system efficiency with the maximum number of testing days (NTD) before all test demands are met. The NTD is calculated by

$$NTD = max\left\{i \in \{1,2,\dots,m\}: \frac{w_i}{c_i}\right\} \quad \textbf{(6.1)}$$

where m is the number of facilities, w is the healthcare demand and c is the capacity of each facility. The healthcare demand is determined by its nearby community population, assuming every community will always visit its closest facility.

6.3.3 Evaluation of equity

Multiple methods of evaluating equity from the literature are adapted for comparison in this study. The first one is the Gini index (GINI), also known as the Gini coefficient, which is a measure of statistical dispersion to represent income inequality or wealth inequality within a nation or a social group (Gini, 1936). The Gini index is widely used to evaluate the equality and equity in the accessibility to public service facilities (Lyon, Li, and Gastwirth, 2017; Christopoulos et al., 2017; Rong et al., 2020). The Gini coefficient is approximated by

$$GINI = 1 - \sum_{k=1}^{n} (W_k - W_{k-1})(T_k + T_{k-1}) \quad \textbf{(6.2)}$$

where W_k is the weight which can be the cumulative ratio of population, or healthcare demands required in each community, $k = 0 \ldots \ldots n$, $W_0 = 0$, $W_n = 1$; T_k denotes the cumulative ratio of accessibility, such as travel time required to access healthcare, $k = 0 \ldots \ldots n$, $T_0 = 0$, $T_n = 1$; n is the total number of communities in a region. The value of the Gini coefficient ranges from 0 to 1. According to the international standard of the Gini coefficient classification (Shu & Xiong, 2018), the Gini coefficient values of 0–0.2, 0.2–0.3, 0.3–0.4, 0.4–0.5 and 0.5–1 are, respectively, expressed as absolute equity, comparative equity, relative rationality, poor equity, and great disparity.

The second method to evaluate the equity is SD, which is a statistic that measures the dispersion of a dataset relative to its mean, and SD is calculated by:

$$SD = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^2} \quad \textbf{(6.3)}$$

where x_i is the accessibility in each community, such as travel time required to access healthcare, $i = 0 \ldots n$; μ is the mean of x; n is the total number of communities in a region.

The third method to evaluate the equity is ratio over a threshold (ROT). The ROT uses a threshold to determine inequity in accessing healthcare and is calculated by:

$$ROT = \frac{1}{n} |\{i \in \{1,2, \ldots, n\}: x_i \geq t\}| \quad \textbf{(6.4)}$$

where x is the accessibility; n is the total number of communities; t is the threshold, such as the maximum travel time that can be tolerated. Note that in SD as well as ROT, community populations are not included, which means that each community, regardless of its size, is treated equally.

6.3.4 Evaluation of system resilience

We incorporate the evaluation of resilience into the calculation of each objective. Instead of assuming that no failure occurs, and every healthcare facility can be accessed by any community, we consider the possibility that any facility may be shut down. In these cases, the resources of the failed facility cannot be utilized, and all demands are directed to nearby other facilities. The resilience of the system is determined by the difference of its performance with one facility shut down and without any facility shut down. A high resilience indicates that there is very minimum difference in performance, while a low resilience implies a high difference.

Two types of performances are used in this study, efficiency and equity. The efficiency is represented by the longest NTD among all cases, as follows:

$$NTD' = max\left\{i \in \{1,2,\dots,m\}, j \in \{1,2,\dots,m\}: \frac{w_{ij}}{c_i}, i \neq j\right\} \qquad \textbf{(6.5)}$$

where w_{ij} is the demand that is allocated to facility i in the event that facility j is closed; c_i is the capacity of facility i.

Similarly, the equity becomes:

$$E' = f(i \in \{1,2,\dots,m\}, j \in \{1,2,\dots,m\}: w_{ij}, i \neq j) \qquad \textbf{(6.6)}$$

where f is one of the equity evaluation methods presented in Section 6.3.3; w_{ij} is the demand that is allocated to facility *i* in the event that facility *j* is closed.

6.3.5 Optimization algorithm

The SMS-EMOA (hypervolume metric selection - evolutionary multi-objective optimisation algorithms) is used in this study for the multi-objective optimization problem. The algorithm is well-suited for Pareto optimization with two and three objectives, and found to outperform other established techniques (Beume, 2007).

The SMS-EMOA algorithm has a similar process as other evolutionary algorithms. As explained in Table 6.1, the algorithm starts with an initial population of μ individuals, and a new individual is generated by randomized variation operators. The new individual will become a member of the next population, if replacing another individual leads to a higher quality of the population with respect to the hypervolume metric. The reduce step is further explained in Table 6.2. First, the merged population $P_t \cup \{q_{t+1}\}$ is denoted as Q. It is divided into v layers $\{R_1, \ldots, R_v\}$ using fast-nondominated-sorting (Deb, 2002). The least ranked front is R_v and from this front, an individual is removed in the selection step to shrink the size of the population from $t + 1$ to t.

Table 6.1 SMS-EMOA algorithm

1: $P_0 \leftarrow$ init() // Initialise random population of μ individuals
2: $t \leftarrow 0$
3: **repeat**
4: $q_{t+1} \leftarrow$ generate(P_t) // generate offspring by variation
5: $q_{t+1} \leftarrow$ Reduce($P_t \cup \{q_{t+1}\}$) // select μ best individuals
6: $t \leftarrow t + 1$
7: **until** termination condition fulfilled

Table 6.2 Details of the reduce step

Input: Q
Output: Q
$\{R_1, ..., R_v\} \leftarrow$ fast-nondominated-sort(Q) //all v non-dominated fronts of Q
$r \leftarrow argmin_{s \in R_v}[\Delta\phi(s, R_v)]$ //detect element $s \in R_v$ with lowest $\Delta\phi(s, R_v)$
$Q \leftarrow (Q\ \{r\})$ //eliminate detected element
return Q

A distinct feature of the SMS-EMOA is that it is well-suited for approximating Pareto sets with a small number of individuals. This is often desired in practice. Therefore, the SMS-EMOA algorithm was selected for this study. It is noted, however, that our problem model can be solved by other multi-objective algorithms, and the choice of algorithm should not affect the results of optimization.

6.4 Case study

6.4.1 Case description

The study area, the province of Saskatchewan, is one of the Prairie provinces in Canada. Saskatchewan shares its borders with Alberta to the west, the Northwest Territories to the north, Manitoba to the east and the United States to the south. The province has a total population of 1,132,505, approximately 34% live in rural areas (Statistics Canada, 2021), which is defined as living in areas with less than 1000 residents and/or where the access to key amenities is greater than 5 km (Statistics Canada, 2008). Residents living in rural areas are often less affluent, older, and have limited access to health services (Litman, 2003; Starkey, Ellis, Hine, and Ternell, 2002; Statistics Canada, 2008).

In the early 2022, the Saskatchewan Health Authority (SHA) sets-up multiple COVID-19 test sites for the general public. However, many residents, especially those from remote communities, faced difficulties in accessing the tests (CBC, 2022). Therefore, SHA sought an optimal planning tool for allocating critical healthcare resources, such as the test sites and test kits at each site. The major barriers, in this case, are the availability of test kits and the long travel time to test sites. Therefore, we used travel time as the main way to evaluate equity in Saskatchewan. For different regions, the indicators should be adaptive to their specific accessibility barriers (Allen & Farber, 2019, Kaasalainen, 2012; Williams, 2011; Nagarajan, 2004).

6.4.2 Data source

Two parts of data are considered in our optimization model, community population and travel time between communities. The population data was retrieved from the website of the government of Saskatchewan (2022). The data includes 15 cities, 149 towns, and 273 villages, 437 in total. Broder cities, including Flin Flon and Lloydminster are excluded. Note that in this study, only communities that have a population greater than 2000 are considered a candidate for allocating test sites. A smaller community may not necessarily have adequate human resources and infrastructures to facilitate the site. This results in 32 communities which are close to the actual number of healthcare centers in the province (Abrametz, 2016). More population statistics are listed in Table 6.3.

Table 6.3 Population distribution among communities in Saskatchewan

Population	< 500	501 - 1000	1001 - 2000	2001-10000	10000+
Numbers of communities	298	68	39	21	11

Data regarding travel time were obtained via the google map Distance Matrix API (https://developers.google.com/maps/documentation/distance-matrix/overview) using the Python scripting language based on the average distance of travel time between two communities. The choice of route along with its duration is based on the road network and average time-independent traffic conditions. The route that takes the shortest time was chosen. The optimal travel routes along with travel time were generated by setting driving as the travel mode.

6.4.3 Implementation

The proposed method is written in Python 3.10. The SMS-EMOA model is adopted from pymoo 0.6.0 (Blank and Deb 2020), a python package for multi-objective optimization algorithms. Table 6.4 contains a list of parameters used in the SMS-EMOA model. The algorithm terminates when there is no improvement (objective value changes less than 0.0025) over g_s continuous generations, or when the maximum generation (g_{max}) is reached. A local laptop is used for the optimization with an Intel Core i5-10210U, Quad-Core, 1.6 GHz, Max Turbo @4.20 GHz. 16 GB RAM.

Table 6.4 List of parameters in the SMS-EMOA model and their values

Parameters	**Values used in the experiments**
Population size	100
Crossover rate	0.5
Crossover type	Simulated Binary Crossover
Mutation probability	0.9
Mutation type	Polynomial Mutation
Max. generation (g_{max})	200
Termination criterion (g_s)	20

6.4.4 Results

Two experiments were carried in this study. The first one is to examine three types of equity evaluation methods, GINI, SD, and ROT, and compare their impact on optimization results. Details on the equity evaluation methods were presented in Section 6.3.3. In this experiment, four optimizations were carried out. The first one serves as a baseline that has only one optimization objective which is to minimize the NTD. The other three optimizations used NTD as the first optimization objective and three equity evaluation methods as the second objective, respectively. In each optimization, the top five results are used for comparison. In particular, we are interested in the number of test sites (NTS) chosen, the standard deviation of the test capacity distribution (TCD), and NTD. In this experiment, we assume that 1% of the population needs to be tested, and we have the capacity to perform 8800 tests (~1% of the population) every day. In the calculation of ROT, we used a threshold of 120 minutes of travel time. The results of the experiment can be found in Table 6.5.

Table 6.5 Experiment 1: Comparisons of equity evaluation methods with a baseline and GINI, SD, ROT

	Baseline	**GINI**	**SD**	**ROT**
Objective 1	minimize testing days	minimize testing days	minimize testing days	minimize testing days
Objective 2	-	minimize GINI	minimize SD	minimize ROT
NTS	4	7.2	19.8	11.2
TCD	0.102	0.094	0.075	0.091
NTD	0.999	1.004	1.03	1.01

The baseline optimization illustrated a conventional optimization that only focuses on efficiency. Compared to the baseline, we found that GINI achieved a similar NTD but improved the diversity of test capacity. By optimizing GINI, TCD decreased by 11% at a cost of 80% more test sites. SD emphasizes diversifying test capacity. Optimizing SD results in a 31% lower TCD but 180% higher test site numbers when compared to the baseline. ROT reached a middle ground compared with the other two methods. ROT achieved a balance among NTS, TCD, and NTD.

The second experiment considers system resilience and examines its impact on results. The method of resilience evaluation was discussed in Section 6.3.4. In this experiment, we compared cases, where system resilience is included in the optimization, with cases, where resilience of system is excluded. In the cases where one test site shuts down, the system's NTD and equity will increase. However, a system with better resilience should expect a less amount of increase. In this experiment, we also assume that 1% of the population needs to be tested and the province has a capacity to perform 8800 tests (~1% of the population) every day. The results of the experiment can be found in Table 6.6.

Table 6.6 Experiment 2: Consideration of system resilience in optimizing system equity

	Equity	**NTD**
GINI without resilience	0.206	7.805
GINI with resilience	0.159	1.84
SD without resilience	0.569	29.6
SD with resilience	0.595	1.92
ROT without resilience	0.692	11.66
ROT with resilience	0.462	1.89

The results show that considering system resilience will dramatically improve the system's performance in the event that a test site shuts down. Under all three equity measurements, we found that NTD increased significantly when a shutdown happened. For example, when SD is implemented, the NTD increased to 29.6 days, a 28-fold increase from the case without shutdowns. In comparison, when system resilience was considered in the optimizations, the NTD only increased marginally. On the other hand, the change in equity is less significant compared to NTD. In the case of GINI and ROT, better (smaller) equity values were still achieved if system resilience was considered. Note that the equity values from GINI, SD, and ROT cannot be directly compared as they are not on the same scale.

6.4.5 Discussion

In the case study, the importance of considering equity and system resilience in healthcare planning has been demonstrated. Among the three methods of evaluating equity, GINI was found to be more focused on efficiency. GINI used the least amount of additional resources to enhance equity. This result could make GINI more practical and easier to be adopted by decision-makers. This unique characteristic may be because GINI is focused on an equal distribution rather than an absolute value. For example, when applying GINI to travel time, a solution where most communities must drive a long time might seem adequate. By looking at the GINI alone, our study got a score of 0.159, which means absolute equity according to the international standard (Shu and Xiong, 2018). However, the GINI score does not mean that no further effort is required to improve its equity.

Besides, we found that SD is the most impactful evaluation method. SD and GINI are both widely used in measuring data spread. However, they have three key differences. First, SD does not consider weights such as population. Second, SD retains the scale of data, while GINI has no measurement unit. Third, SD judges statistical dispersion through different lenses. GINI reaches its maximum value for a non-negative dataset if the dataset contains one positive and the rest are zeros. SD reaches its maximum if half the data lives at the extreme maximum and the other half registers at the extreme minimum. Those differences may contribute to the impact on optimization results and make SD potentially more focused on improving equity.

The third method, ROT, is quite straightforward and was able to achieve a middle ground between GINI and SD. That makes ROT a convenient way to evaluate equity. ROT also takes the least computational resource among the three methods and might be suitable for larger-scale calculations. One drawbacks of ROT are that its value depends on a threshold. The threshold is set up by experience and should be adjusted case by case. This means that an expert may need to be consulted.

The second experiment illustrated the importance of considering system resilience at the allocation stage. Optimizing objectives in the case of partial failure could help a system to recover under a minimal period. People in post-pandemic societies have a better understanding of how unexpected events can degrade system performance. Supply chain disruptions such as the 2021 Suez Canal obstruction (Gambrell, 2021) remind everyone of the importance of diverse critical resources. The resilience measurement in this study has improved our understanding of system resilience in resource allocation.

6.5 Conclusion

In this study, we investigated the resource allocation problem with consideration of efficiency, equity, and system resilience at the same time. An optimization problem model was developed to solve the problem. The effectiveness of the model was illustrated through a case study that optimized COVID-19 test sites in Saskatchewan, Canada. This study has made four contributions: (1) it has demonstrated the importance of considering system resilience in healthcare resource allocation; (2) it has compared three methods to evaluate equity and provided insights based on the case study; (3) it has provided a model that determines healthcare facility locations and resources in each location at the same time; and (4) it has provided decision-makers a guide in planning critical healthcare resources such as COVID-19 test kits, intensive care unit beds, ventilators, and so on.

There are several limitations to this study. First, only one site shutdown is considered when evaluating the system's resilience. In a more complicated region where more facilities are allocated, the shutdown of two or more facilities might need to be considered. Therefore, the resilience evaluation needs to be adapted accordingly. Second, equity is only demonstrated through spatial accessibility in this study. However, equity is multi-dimensional. In practice, regardless of the type of equity chosen, its performance needs to be further investigated through collaboration with local communities. Third, the cost of setting up facilities is not considered. In the case study, the cost of the test site is insignificant as it reuses existing facilities. For other applications, the facility cost should be considered as a constraint or another objective.

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Chapter 7
Conclusions and future work

7.1 Conclusions

This thesis was aimed to improve the process of HIS decision-making based on the advanced understanding of ontology modelling, system resiliency and social sustainability. In the current literature, “ontology”, “resilience” and “sustainability” are three buzzwords. However, their concepts lacked clarity, adversely affecting their development and applications. Thus, the main motivation of the study presented in this thesis was to thoroughly comprehend these concepts in order to develop a more solid theory. According to this thesis, all research objectives have been achieved. The conclusions pertain to these objectives can be drawn as follows:

(1) Regarding Objective 1 (studying the theory of ontology in data and developing a deep model for constructing HIS): By clearly defining the scope and application of an ontology, a data model with rich semantics and simple data integration may be produced.

(2) Regarding Objective 2 (advancing our understanding of healthcare system resiliency and social sustainability): Resiliency and sustainability are two closely related concepts. Any procedures or actions that enhance one concept should consider how they can affect the other. In addition, the recommended design principles can also considerably improve the resilience and sustainability of a healthcare system.

(3) Regarding Objective 3 (development of a methodology for scheduling with multiple objectives): A scheduling problem may be made more patient-accessible by carefully considering both efficiency and patients' experiences, as well as by using an innovative optimization technique.

(4) Regarding Objective 4 (development of a methodology for resource allocation with multiple objectives): The simultaneous optimization of efficiency, sustainability, and resilience at the system design stage is made possible by a systematic evaluation method for all three criteria. This method also enables effective resource allocations and site selections for healthcare facilities.

7.2 Contribution

The contributions of the thesis can be summarized as follows:

Scientifically, this thesis has expanded our scientific understanding of ontology and data modelling for HIS improvements, as well as our comprehension of the healthcare system's resilience and sustainability.

Technologically and methodologically, the thesis has advanced the state of knowledge for system modelling and decision-making. This thesis takes a system perspective to study the properties of healthcare systems. Three ideas in this thesis can be generalized and applied to other properties of other systems, namely the ontology-based data modelling method, the multi-objective optimization models, and the algorithms for solving the models.

7.3 Limitations and Future Work

Some further studies that may be needed to improve the thesis are given as follows:

First, the ontology modelling tools developed are only for data integration at the conceptual level. To solve the practical problem that people face in the integration of data, an external-level application needs to be developed and demonstrated in a few case studies. The findings of the case studies would in turn help with the development of modelling tools at the conceptual level.

Second, in a patient scheduling problem, patients' and healthcare professionals' delays, patients' priorities due to their symptoms and deteriorations, patients' healthcare preferences, and their changes of locations should all be considered to be more encompassing. Those considerations could be modelled either as additional optimization objectives or as constraints. They may cause some performance issues with the genetic algorithm adopted. Further investigation of the algorithm may therefore be required to improve its efficiency and effectiveness on complicated optimization problems.

Third, in this study, equity was only shown to exist in a resource allocation dilemma through spatial accessibility. However, in reality, equity has many different aspects. It is important to take into account how each person prefers their healthcare in relation to their culture, social standing, and wealth. These factors depend on an extensive data collection and integration system, which echoes the requirement for a data integration application.

APPENDIX A: ONTOLOGY REASONING

Ontology reasoning is a powerful technique for data integration, as it is supposed to infer new knowledge from existing ontologies as well as their data (both information and knowledge) sources. Yet, ontology reasoning still faces some challenges and has some limitations, especially when dealing with applications involving heterogeneous and dynamic data. In this appendix, ontology reasoning for data integration is explained with a close examination of its features and limitations, focusing on OWL as a standard language for representing ontologies (Grau et al., 2008), and SWRL (Semantic Web Rule Language) as a language that allows the expression of rules (Horrocks et al., 2004).

OWL constructs

OWL is an ontology language that provides a rich set of constructs to define classes, properties, individuals, and their relationships. OWL is based on the RDF and extends the RDF Schema (RDFS) (Brickley et al., 1998) with more expressive features. OWL is designed to support the Semantic Web, which aims to make web resources more understandable and interoperable for humans and machines.

OWL's main constructs can be divided into three categories: class expressions, property expressions, individual expressions. Class expressions are used to define complex classes of individuals based on logical conditions. Property expressions are used to define properties that relate individuals or data values. Individual expressions are used to define facts about the identity of individuals.

Some examples of class expressions are:

- intersectionOf: defines a class as the intersection of two or more other classes.
- unionOf: defines a class as the aggregation of two or more other classes.
- complementOf: defines a class contains exactly those individuals that do not belong to another class.
- oneOf: defines a class as an enumeration of specific individuals.
- subClassOf: defines a class as a subclass of another class.
- equivalentClass: defines two classes as equivalent.
- disjointWith: defines two classes have no common individuals.

Some examples of property expressions are:

- subPropertyOf: defines a property as a sub-property of another property.
- equivalentProperty: defines two properties as equivalent.
- inverseOf: defines a property as the inverse of another property.
- FunctionalProperty: defines a property as functional, meaning that an individual can have at most one value for that property.
- TransitiveProperty: defines a property as transitive, meaning that if an individual x has that property with y, and y has that property with z, then x also has that property with z.

Some examples of individual expressions are:

- sameAs: defines an individual is the same as another individual.
- differentFrom: defines an individual is different from another individual.

- AllDifferent: defines a list of individuals that are all different from each other.

OWL has some limitations in terms of expressiveness and decidability. For example, OWL cannot express arbitrary cardinality constraints on properties, such as "every person has exactly two parents". OWL also cannot guarantee that reasoning over an ontology will always terminate and produce a correct answer. To address these limitations, OWL has different dialects or profiles that trade off expressiveness and decidability. For example, OWL Lite is less expressive but more decidable than OWL DL (Description Logic), which is less expressive but more decidable than OWL Full.

OWL reasoning

Common reasoning tasks with OWL include classifying individuals into classes, inferring their properties and checking their identity or equivalence. For example, if an OWL defines that a person is a sub-class of a mammal, and that John is an instance of a person, then a reasoner can infer that John is also an instance of a mammal. OWL reasoning can be applied on data integration in various scenarios, such as schema matching, query rewriting, data fusion, and data validation (Marchetti et al., 2008). Schema matching is the process of finding correspondences between the elements of different data sources based on their semantic similarity. Query rewriting is the process of reformulating a query over a global schema (which may be an ontology) into queries over local schemas of data sources. Data fusion is the process of combining data from multiple sources into a consistent and coherent representation. Data validation is the process of checking the consistency and quality of data against an ontology.

SWRL reasoning

SWRL is a language that allows expressing rules that combine the expressive power of OWL with the procedural capabilities of Horn logic (Mcnulty, 1977). SWRL is closely related to OWL, as it uses the same syntax and vocabulary to represent classes, properties, individuals, and data types. In addition, SWRL uses variables to express more complex relationships and constraints that are not possible in OWL alone.

The syntax of SWRL is based on the notation of first-order logic with variables, predicates, and logical connectives. A SWRL rule consists of an antecedent (or body) and a consequent (or head), separated by an implication sign (→). The antecedent and the consequent are conjunctions of atoms, which can be either class atoms, property atoms, data range atoms, built-in atoms, or same/different atoms. A class atom has the form C(x), where C is an OWL class and x is either a variable or an individual. A property atom has the form P(x,y), where P is an OWL property and x and y are either variables or individuals. A data range atom has the form D(x), where D is an OWL data range and x is either a variable or a literal. A built-in atom has the form op(x_1,...,x_n), where op is a predefined or user-defined operation and x_1,...,x_n are either variables or literals. For example, the following SWRL rule states that if a person works at a university and supervises a student, then that person is a professor of that student:

worksAt(?x,?y) ^ University(?y) ^ supervises(?x,?z) ^ Student(?z) → professorOf(?x,?z)

SWRL reasoning can be done by using a reasoner (reasoning engine) that supports SWRL rules, such as Bossam (Jang et al., 2004) and Pellet (Sirin et al., 2007). It is worth mentioning that SWRL reasoning differs from OWL reasoning in several aspects. First, SWRL reasoning can express more complex and fine-grained knowledge than OWL reasoning and can capture domain-specific rules that are not easily modeled by OWL constructs. Second, SWRL reasoning is more computationally expensive than OWL reasoning and may not guarantee completeness or decidability of the inference process. Third, SWRL reasoning may introduce inconsistencies or conflicts with the OWL axioms, and therefore, expressions written with SWRL require careful design and validation.

Context reasoning

One challenge for OWL reasoning and SWRL reasoning is to cope with the dynamic and evolving nature of data sources (Halpin & Jayes, 2010). Data sources may provide different information depending on the context or situation of the query. For example, a person's location may vary depending on the time of day or the device used to access the data source. Therefore, context reasoning is used to handle temporal and contextual aspects of data sources.

The idea of context reasoning (Wang et al., 2004) is developed from context-aware computing techniques. Context-aware computing is a field that studies how to adapt software systems to the changing environment and user preferences. Context can be defined as any information that can be used to characterize the situation of an entity (e.g., a person, a place, an object). Context reasoning focuses on how to infer implicit or high-level context from explicit or low-level context using ontologies and rules. For example, if an ontology defines that one is at home if one is within a certain distance from one’s home address, then a context reasoner can use one’s location to infer that if the person is at home.

Context reasoning can enhance ontology reasoning for data integration by providing more relevant and accurate information for queries. For example, if a user wants to find nearby restaurants based on their current location and preferences, then a context reasoner can filter and rank the results based on the distance, availability, and ratings of the restaurants. However, context reasoning meets some new challenges and complexities for ontology reasoning, such as how to model and represent the context in ontologies, how to deal with incomplete or imprecise context information, how to resolve conflicts or inconsistencies between different contexts or sources, and how to update context information in real time. It is noted that the definition of imprecise information can be found in Cai et al. (2017), where imprecise information can be vague information, uncertain information, and missing information.

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APPENDIX B: LIST OF PUBLICATIONS

Under Review:

1. **Lin, W.,** Yan, Y., Babyn P., & Zhang, W. (2022). Ontology in the Modern Computer Era. Information Science.
2. **Lin, W.,** Yan, Y., Babyn P., & Zhang, W. (2022). Ontology-based resilient and sustainable resource allocation and scheduling in healthcare systems: a review. Enterprise Information Systems.
3. **Lin, W.,** Yan, Y., Babyn P., & Zhang, W. (2022). An optimization model for resource allocation with consideration of the equity, efficiency, and resilience of a healthcare system. International Journal of Intelligent Systems.
4. Han, B., Ogbeyemi, A., **Lin, W.**, Lu X., & Zhang, W. (2022). A New Definition along with its Measure of the Robustness of Algorithms for Optimal Processes. IEEE Transactions on Systems, Man and Cybernetics: Systems.

Published

5. **Lin, W.**, Babyn, P., Yan, Y., Zhang, W. (2023). A Novel Scheduling Method for Reduction of Both Waiting Time and Travel Time of Patients to Visit Health Care Units in the Case of Mobile Communication. Enterprise Information Systems, 2188124, DOI: 0.1080/17517575.2023.2188124.
6. **Lin, W.,** Xu, M., He, J., & Zhang, W. (2021). Privacy, security and resilience in mobile healthcare applications. Enterprise Information Systems, 1-15, DOI: 10.1080/17517575.2021.1939896.

7. Yu, H. Y., Ogbeyemi, A., **Lin, W. J.,** He, J., Sun, W., & Zhang, W. J. (2021). A semantic model for enterprise application integration in the era of data explosion and globalisation. Enterprise Information Systems, 1-23, DOI: 10.1080/17517575.2021.1989495.

8. Ogbeyemi, A., **Lin, W.**, Zhang, F., & Zhang, W. (2021). Human factors among workers in a small manufacturing enterprise: a case study. Enterprise Information Systems, 15(6), 888-908, DOI: 10.1080/17517575.2020.1829076.

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