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PICT-DPA: A Quality-Compliance Data Processing Architecture to Improve the Performance of Integrated Emergency Care Clinical Decision Support System

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Claremont, California

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Ruizhi Yu as fulfilling the scope and quality requirements for meriting the degree of Doctor of Philosophy in Information System and Technology.

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Abstract

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Emergency Care System (ECS) is a critical component of health care systems by providing acute resuscitation and life-saving care. As a time-sensitive care operation system, any delay and mistake in the decision-making of these EC functions can create additional risks of adverse events and clinical incidents. The Emergency Care Clinical Decision Support System (EC-CDSS) has proven to improve the quality of the aforementioned EC functions. However, the literature is scarce on how to implement and evaluate the EC-CDSS with regard to the improvement of PHOs, which is the ultimate goal of ECS. The reasons are twofold: 1) lack of clear connections between the implementation of EC-CDSS and PHOs because of unknown quality attributes; and 2) lack of clear identification of stakeholders and their decision processes. Both lead to the lack of a data processing architecture for an integrated EC-CDSS that can fulfill all quality attributes while satisfying all stakeholders' information needs with the goal of improving PHOs. This dissertation identified quality attributes (PICT: Performance of the decision support, Interoperability, Cost, and Timeliness) and stakeholders through a systematic literature review and designed a new data processing architecture of EC-CDSS, called PICT-DPA, through design science research. The PICT-DPA was evaluated by a prototype of integrated PICT-DPA EC-CDSS, called PICTEDS, and a semi-structured user interview. The evaluation results demonstrated that the PICT-DPA is able to improve the quality attributes of EC-CDSS while satisfying stakeholders' information needs. This dissertation made theoretical contributions to the identification of quality attributes (with related metrics) and stakeholders of EC-CDSS and the PICT Quality Attribute model that explains how EC-CDSSs may improve PHOs through the relationships between each quality attribute and PHOs. This dissertation also made practical contributions on how quality attributes with metrics and variable stakeholders could be able to guide the design, implementation, and evaluation of any EC-CDSS and how the data processing architecture is general enough to guide the design of other decision support systems with requirements of the similar quality attributes.

Knowledge

I would like to express my deepest gratitude to Professor Yan Li, Professor Samir Chatterjee, and Professor Manoj A. Thomas for their invaluable guidance and support throughout this dissertation process. Their insightful feedback and encouragement helped me to refine my ideas and produce a more rigorous and comprehensive study.

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Chapter 1 Introduction

1.1 Background

Acute conditions caused by injury and cardiovascular disease are the top global causes of mortality and morbidity in the population (Johnson et al., 2014; Mehmood, 2018; WHO, 2020). Unintentional injuries, which is already the main death reason among the youth population nowadays, accounts for nearly 5 million deaths per year (WHO, 2019). Among all kinds of injuries, motor vehicle crashes were estimated as the sixth-leading cause of death and third-highest cause of disability-adjusted life-years by 2020 (Hsia et al., 2010). In terms of cardiovascular disease, stroke has been the top three leading causes of death for approximately five decades (Johnson et al., 2014). As the world's biggest killers, stroke and ischemic heart disease were responsible for 27% of worldwide death from 2010 to 2019 (WHO, 2020). In the last decade of the United States (US), heart disease caused nearly 25% of death in the early 2010s (Johnson et al., 2014).

Emergency Care System (ECS) is a critical component of health care systems by providing acute resuscitation and life-saving care (Hsia et al., 2010; Moresky et al., 2019). It also serves as an important safety-net provider as an entry point to health care concerning injuries and cardiovascular disease progression (Hsia et al., 2010; Reynolds, 2017). ECS prevents millions of deaths and long-term disabilities from acute conditions each year (WHO, 2019; Reynolds, 2017). For example, it is estimated that up to 54% of annual deaths in low-income and middle-income countries (LMICs) could be addressed and up to 25% trauma-related mortality may be reduced by an efficient ECS (Moresky et al., 2019; Mehmood et al., 2018). A responsive ECS consists of multiple distributed emergency care (EC) functions based on system protocols as guidance to improve patient health outcomes (PHO) (Poulymenopoulou et al., 2011; Nadarajan et al., 2018; Mehmood, 2018; WHO, 2019). These functions are relevant to different types of stakeholders. For example, a dispatcher would decide to send appropriate on-scene care providers to patients based on dispatch protocols, and a triage officer would follow the triage protocols to make a decision on sending patients to the appropriate department of the hospital (WHO, 2018). As a time-sensitive care operation system, any delay and mistake in the decision-making of these EC functions can create additional risks of adverse events and clinical incidents (WHO, 2019; Bennett et al., 2016).

The implementation of EC Clinical Decision Support System (EC-CDSS) has proven to improve the quality of aforementioned EC functions (Bennett et al., 2016). The EC-CDSS is a computerized software system designed to support clinical decision-making on different EC functions in a limited time (Tcheng, 2017; WHO, 2019). It is intended to improve ECS services by enhancing clinical decision-making with targeted clinic knowledge, patient information and other health information (Tcheng, 2017). Like other CDSSs, EC-CDSSs can be classified as knowledge-based or algorithm-based (Berner, 2007). Knowledge-based systems would retrieve data to evaluate a set of literature-based, practice-based, or patient-directed rules (often as IF-THEN statements) from a prepopulated knowledge base and then produce recommendations. Algorithm-based systems, while still require a data source, leverage artificial intelligence, machine learning, or other statistical learning methods to produce recommendations. For example, knowledge-based EC-CDSSs have been able to accurately identify acute conditions in a few seconds and send alarm information to stakeholders for ECS system activation (Wen et al., 2008; Barcelos et al., 2015; Wang et al., 2016). Literature also demonstrated that algorithm-based EC-CDSSs have successfully supported on-scene providers' diagnosis and treatment (Wang et al., 2016; Valenzuela Espinoza et al., 2016; Albahri et al., 2019). Ultimately, the EC-CDSS should be designed to support the EC functions and improve the quality of life-saving care and PHOs (Lurie et al., 2013; Bianchi et al., 2015).

1.2 Definitions

1.2.1 Emergency Care System (ECS)

The Emergency Care System (ECS) is more than just medical care provided by healthcare professionals within or adjacent to the ambulance (Bashiri et al., 2019; Nadarajan et al., 2018). It refers to a system of emergency care provision from pre-hospital care (e.g., on-scene care before transport and intervention during transport) to in-hospital care (e.g.,facility-based care and medical/paramedical services) (Bashiri et al., 2019; Poulymenopoulou et al., 2011; Nadarajan et al., 2018). An ECS works like an integrated mechanism to address a wide range of time-sensitive acute conditions that are likely to result in morbidity or mortality if not addressed rapidly (Moresky et al., 2019; Reynolds et al., 2017).

1.2.2 Clinical Decision Support System (CDSS)

Computerized Clinical Decision Support Systems (CDSSs) are software programs designed to assist clinic decision-making by using data, medical knowledge, and analysis engine to generate patient-specific assessments or recommendations to health professionals (Sim et al., 2001). Osheroff et al. (2012) articulated a Five Rights Framework for CDSSs to improve clinic care processes and outcomes. The Five Rights Framework requires the design of CDSS to reflect the "what, who, how, where, and when" questions for the CDS intervention(s) (Osheroff et al., 2012). In other words, the CDSS must provide the right *information*, in the right *format*, to the right *people*, at the right *time*, with the right *methods* (Poulymenopoulou et al., 2011).

The information includes Electronic Health Records (EHR), physicians' professional knowledge, and other patient-specific data (HealthIT, 2018; Tcheng, 2017). The format means that the recommendations from CDSS should be understandable by the stakeholders (Kawtrakul et al., 2017; Rodriguez et al., 2005). For example, the CDSS should provide intervention protocols instead of a package of patient vital data and clinical records (Ciccone et al., 2020). The people refer to different stakeholders who would receive recommendations from the CDSSs, such as clinicians, physicians, nurses, clerical staff, allied health workers, and healthcare providers (WHO, 2018; HealthIT, 2018; Tcheng, 2017). The *time* means the time-point along the clinical workflow where CDSS can enhance decision-making (HealthIT, 2018). The *methods* are also called CDSS tools, which include *"*computerized alerts and reminders to care providers and patients; clinical guidelines; condition-specific order sets; focused patient data reports and summaries; documentation templates; diagnostic support*.*" (HealthIT, 2018).

1.2.3 Emergency Care Clinical Decision Support System (EC-CDSS)

Emergency Care Clinical Decision Support Systems (EC-CDSSs) are CDSSs designed in the context of ECS to ensure timely care for the acutely ill and injured (WHO, 2019). For example, it can send computerized alerts to dispatchers to active the ECS by identifying acute conditions in a short time (Wen et al., 2008; Tcheng, 2017), and support dispatchers by recommending appropriate ambulance with care providers and the target emergency department (ED) based on availability and capability of ambulances, care providers, and EDs (Latifi et al., 2007). An EC-CDSS may also provide diagnostic recommendations and clinical guidelines on interventions during patient transports and in the hospitals (Valenzuela Espinoza et al., 2016). While at the hospital, the EC-CDSS can automate patient reports and summaries with documentation templates for patient registration and provide triage recommendations to clerical staff (Crilly et al., 2011; Tian et al., 2014; Kyriacou et al., 2005; Kawtrakul et al., 2017).

1.3 Research Motivations and Questions

The literature is scarce on how to implement and evaluate the EC-CDSS regarding the improvement of PHOs, which is the ultimate goal of ECS (Bennett et al., 2016). The reasons are twofold. First, the connection between the implementation of EC-CDSS and PHOs remains unclear. Most existing research describes the effectiveness of EC-CDSS without explaining how it improves PHOs. For example, Bennett et al. (2016) showed that an EC-CDSS could optimize test orders of emergency victims without exploring if optimized test orders would achieve better PHOs. Similarly, studies showed that EC-CDSSs can accelerate clinic interventions, such as taking blood culture (Valenzuela Espinoza et al., 2016) or wound cleansing (Wallis et al., 2016) without explaining how the improved intervention efficiency would result in the PHOs. The reason for such a research gap is the lack of a set of quality attributes and metrics for EC-CDSS in improving PHOs (Bennett et al., 2016). To the best of my knowledge, no research has identified the desired quality attributes and metrics for EC-CDSSs (Sariyer et al., 2018; Lytras et al., 2020).

Quality attributes are critical in system development because they establish requirements criteria that guide subsequent design, implementation, and testing activities (Bass et al. 2003). Metrics are also important because they can help evaluate quality attributes objectively. System quality (DeLone et al., 2003) and its related quality attributes are domain-specific, i.e., a different type of system would have a different set of quality attributes. This leads to a first research question: **what are quality attributes that have been considered in existing EC-CDSS, and which of these quality attributes are essential in improving PHOs?** Simply knowing a set of quality attributes for EC-CDSS is not sufficient in assessing if an EC-CDSS is successful in achieving its goals. Thus, the second research question is: **what are the metrics for these quality attributes so that the success of EC-CDSS can be measured?** With a set of clearly defined quality attributes and metrics, researchers will be able to investigate the relationships between quality attributes and the performance of EC-CDSS and their effectiveness on PHOs. Designers can also consider those quality attributes and metrics during the design, implementation, and evaluation lifecycle of the EC-CDSSs.

Second, although WHO (2018) summarized the stakeholders of different EC functions as human resources (e.g., dispatchers, healthcare providers, clerical staff, and allied health workers), research has yet to clearly define what are different stakeholders of EC-CDSSs (i.e., these who receive the recommendations and make clinical decisions) and their decision processes. It is the collective decision process among all stakeholders with the ECS workflow that ultimately would improve PHOs (Ji et al., 2021). For example, if a triage-related EC-CDSS only supports the triage decisions for triage officers without considering the priority level of patients (Tian et al., 2014), the on-facility care providers (physicians and nurses) may refuse to transport the patients they considered in need life-saving interventions. In another example, a dispatch-related EC-CDSS was designed to speed up dispatcher's routine with considering the appropriateness of dispatched ambulance and target hospital (Latifi et al., 2007), without the consideration of information needs of on-scene care providers. It could lead a patient to serious conditions if the on-scene care providers did not have the ability to provide appropriate interventions or the target hospital was not accessible. An integrative EC-CDSS should be able to satisfy information needs of all stakeholders. Thus, the third research question is: **who are stakeholders of EC-CDSSs, and what are their related information needs in the ECS process?**

These three research questions naturally lead to the need for a systematic literature review (SLR) of EC-CDSS literature, because it provides is "a means of evaluating and interpreting all available research relevant to a particular research question or topic area or phenomenon of interest" (Kitchenham, 2004). Chapter 2 of this proposal present the SLR and its result. More specifically, the SLR identifies four quality attributes of EC-CDSS: Performance of the decision support, Interoperability, Cost, and Timeliness (PICT). In addition, it identifies four stakeholders and related EC functions: dispatchers who activate the ECS and dispatch the on-scene care providers, on-scene care providers who provide life-saving interventions on the scene of acute conditions and during transportation, and on-facility care providers who provide treatment interventions in the facilities like emergency departments (EDs), and allied health workers who decide the triage.

More importantly, the SLR goes beyond synthesizing the EC-CDSS literature (i.e., answering "what" questions) towards theorizing, i.e., answering a fourth research question: **how can these quality attributes and metrics be used to guide the EC-CDSS design, implementation, and evaluation with the goal of improving PHOs?** The answer to this question is a PICT Quality Attribute model that describes how PICT may interact with EC functions and ultimately improve the PHOs.

The SLR also reveals that, while the existing literature offers various types of EC-CDSSs to improve the EC functions, a data processing architecture is missing for designing and implementing integrated EC-CDSSs that have all quality attributes while satisfy information needs of all stakeholders. The EC-CDSSs require the integration of massive data from disparate sources to generate the right *information*, in the right *format*, to the right *people*, at the right *time*, with the right *methods* (Poulymenopoulou et al., 2011). Traditional database management tools and processing architecture cannot be directly used to process the increasing amount of data from heterogeneous data sources while achieving all PICT quality attributes (Sariyer et al., 2018). Few studies have investigated databases designed specific for EC-CDSSs (Lin et al., 2004; Rasid et al., 2005; Omoogun et al., 2017). However, none includes a data processing architecture that enables all PICT quality attributes while satisfies all stakeholders' information needs. It is an important first step to design such a data processing architecture for an integrated EC-CDSS. This leads to the fifth research question: **how to design, implement, and evaluate a data processing architecture for an integrative EC-CDSS that has all quality attributes while satisfying all stakeholders' information needs with the goal of improving PHOs**?

The fifth research question will be answered through design science research (DSR) via the creation of innovative artifacts and thereby contributing new knowledge to the body of scientific evidence (Hevner & Chatterjee, 2010). The dissertation designs a new data processing architecture of EC-CDSS, called PICT-DPA, based on the quality attributes and stakeholders identified from the SLR. The dissertation hypothesizes that the PICT-DPA could support the improvement of PHOs through better EC functions when compared to non-PICT-DPA for EC-CDSSs. The design process will be guided by the design science research (DSR) process model introduced by Vaishnavi and Kuechle (2015). The design of PICT-DPA will depend on the kernel theory of the Emergency Care System (ECS) Framework (WHO, 2019), which is described in the next section.

1.4 Kernel Theory – WHO's ECS Framework

The kernel theory, also known as justificatory knowledge, is 'the underlying knowledge or theory from the natural or social or design sciences that gives a basis and explanation for the design' (Gregor and Jones, 2017). As the knowledge base of artifact, kernel theory is important for research rigor as it guides researchers on constructing and evaluating the artifact to assess progress toward the desired results (Gregor and Jones, 2017; Hevner, 2017; Hevner et al., 2004).

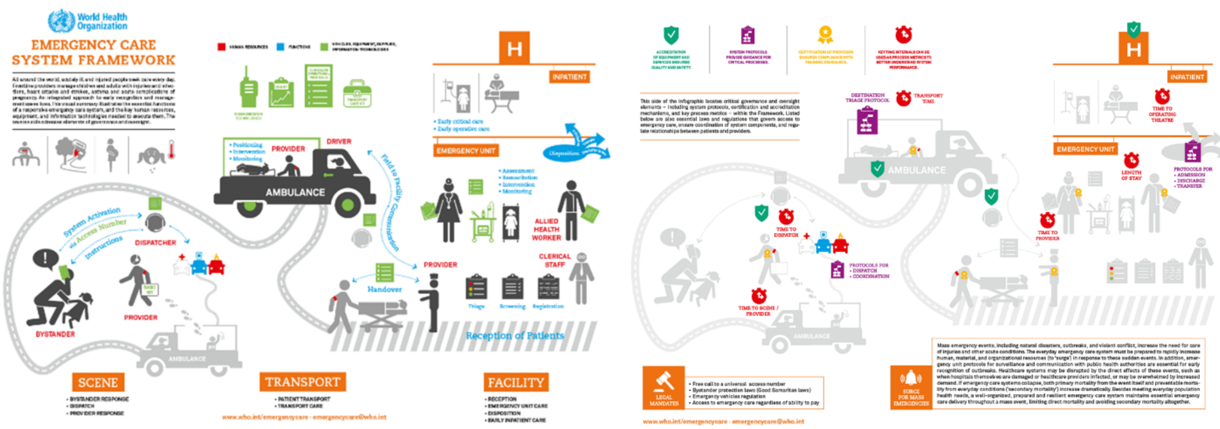


Figure 1. ECS Framework

This dissertation uses Emergency Care System (ECS) Framework (WHO, 2018) as the kernel theory, because it includes EC functions, stakeholders, and the data flow through these EC functions. Guided by the ECS Framework, the SLR synthesized all desired EC-CDSS quality attributes and related metrics for these EC functions and their related stakeholders. The data flow represented in ECS framework will further guide the design of required functionalities for the proposed data processing architecture.

According to the ECS Framework, the ECS is a sequential process with six time intervals in three phases. The first phase is SCENE with two related time intervals: Time to Dispatch and Time to Scene/Provider. At the SCENE, once a patient has an acute condition, the bystander will make an emergency call for the dispatcher to describe the acute conditions and activate the ECS process. The dispatcher will then give instructions on how to handle the acute condition while dispatching the ambulance with on-scene care providers. The time interval between this process is the Time to Dispatch. Three EC functions are related to this time interval: system activation, instructions, and dispatch. The flow of acute conditional data is from bystander to dispatcher and then to on-scene care providers in the ambulance. The Time to Scene/Provider is the duration for the on-scene provider to access and pick up the patient. There is no data flow related to this time interval.

The second phase is TRANSPORT with one time interval: Transport Time. During the TRANSPORT, the driver will transport the patient to the target hospital with an ambulance, while the on-scene care provider will perform interventions on the patient and monitor their life situation. Three EC functions are related to the Transport Time: intervention and monitoring provided by the on-scene care providers, ambulance location information reported by the drivers. The intervention data, patient situation data, and position data will be sent to on-facility care providers during this phase through the field to facility communication.

The third phase is FACILITY with three time intervals: Time to Provider, Length of Stay, and Time to Operating Theatre. During the Time to Provider, the on-scene care provider hands the patient over to the on-facility care provider with no data transmission requirements. For the Length of Stay in the FACILITY, the on-facility care provider works on additional assessment, resuscitation, intervention, and monitoring, followed by working with Allied Health Workers for triage and disposition. At the same time, the clerical staff screens and registers the patient. The Time to Operating Theatre is from the patient being registered and triaged till in the operating theatre. Table 1 summarizes phases, related time intervals, EC functions and stakeholders related to each time interval, and data flows.

Table 1. Summarized EC functions, Stakeholders, and data flows based on ECS Framework

Phases	Time intervals	EC Functions	Stakeholders	Data Flow
SCENE	Time to Dispatch	System Activation	Dispatcher	Acute condition data: bystander to dispatcher
		Instructions	Dispatcher; Bystander;	No data flow
		Dispatch	Dispatcher; On-scene Care Provider	Acute condition data: dispatcher to on-scene care providers
	Time to Scene/Provider	Access to Patient	On-Scene Provider	No data flow
TRANSPORT	Transport Time	Positioning	Driver; On-Facility Care Provider	Positioning data: driver to on-facility care provider
		Intervention Monitoring	On-Scene Care Provider	Acute condition data and operational data: on-scene care providers to on-facility care providers
FACILITY	Time to Provider	Handover	On-Scene Provider; On-Facility Provider	No data flow
	Length to Stay	Assessment Resuscitation Intervention Monitoring Triage	On-Facility Provider; Allied Health Workers	Acute condition data and triage data: on-facility care providers to allied health workers
		Screening Registration	Clerical Staff	No data flow
	Time to Operating Theatre	Disposition	Clerical Staff	No data flow because all data have already been in the system.

1.5 Significant of the research

This dissertation will make both theoretical and practical contributions. The first theoretical contribution is the identification of quality attributes and related metrics of EC-CDSS. This has not been done before. The second theoretical contribution is the quality attribute model summarized from the

SLR. The model can guide researchers or designers to design, implement, or evaluate the EC-CDSS with the focus of improving PHOs. Third, a system design requires a full understanding of constraints from the design context, which is a set of environmental features and conditions that determine the behavior of the system (Bashiri et al., 2019). The design context of PICT-DPA is a complex dynamic environment involving multiple EC functions with different stakeholders. The design process provides a better understanding of constraints and lays a foundation for more integrative EC-CDSSs designs in the future. The practical contribution is the proposed PICT-DPA, which can be used as a foundation to build integrated EC-CDSSs with better quality and performance. In addition, the PICT-DPA will be general enough to guide the design of other decision support systems that require similar quality attributes.

1.6 Outline

The remainder of the dissertation proposal is organized as follows. Chapter 2 provides a systematic literature review of EC-CDSS studies. The review identified quality attributes and metrics of EC-CDSS and summarized a quality attribute model explaining the relationship between quality attributes and PHOs. Chapter 3 describes the research methodology, including the reason to choose design science as the research methodology and the design process.

Chapter 2 Systematic Review

2.1 Methods

This systematic literature review follows the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) checklist and workflow for reporting reviews (Page et al., 2021), as described below.

2.1.1 Eligibility Criteria

This review includes all peer-reviewed studies investigating EC-CDSS from 2001 onwards when the start of the application of computer-based decision support for medicine (Ball & Berner, 1999). The review includes the studies concerning the implementations of EC-CDSSs and their improvement on either EC functions or PHOs. At last, the review only includes the studies reported in English. The eligibility criteria are summarized in Table 2.

Table 2. Inclusion and exclusion criteria

Criteria	Specified Criteria
Inclusion	Peer reviewed studies Studies reported implementation of EC-CDSSs Studies reported the improvement of EC functions or PHOs from EC-CDSSs Studies published from 2001 onwards
Exclusion	Studies published in a language other than English Studies reported CDSS in health domains other than ECS Studies reported EC-CDSS without the EC functions or PHOs Systematic reviewed studies of EC-CDSS Adoption studies of EC-CDSS

2.1.2 Information Source and Search Strategy

The information search sources used for this review include PubMed, IEEE, Science Direct, ACM Digital Library, and Wiley Online Library. In addition to these databases, backward-reference list checking was performed to identify additional studies. The following combination of keywords were used: ("*emergency health"* OR *"emergency healthcare"* OR "*emergency care") AND* ("*information* *technology*" OR "*telemedicine"* OR "*electronic health record* OR "*information systems"* OR *"clinical decision support" OR "decision support").*

2.1.3 Selection Process

The selection process of studies retrieved from the initial search included three iterative phases: (1) screening phase, where titles, abstracts, and keywords of articles were reviewed to exclude irrelevant ones based on the eligibility criteria; (2) eligibility phase, where the full-text of articles were reviewed to assess their relevancy to this study; and (3) backward-reference list checking, where phases 2 and 3 are repeated for eligible articles from phase 2.

2.1.4 Data Collection Process and Data Items

A data extraction form was created (see Table 3) based on research questions. The quality attributes of EC-CDSS are the data firstly extracted from the reviewed studies. The SLR summarized all EC-CDSSs with their functionalities and identified those functionalities as quality attributes if they can guide the design, implementation, and test of EC-CDSSs. It also reviewed how studies evaluated the EC-CDSSs based on quality attributes and identified the measurements as quality metrics if they can represent the quality attributes. In terms of stakeholders, the EC Functions that can be guided by possible EC-CDSSs and their related stakeholders were reviewed. At last, the SLR recorded the improvement of EC-CDSSs on EC functions and PHOs to discover the effectiveness of quality attributes and relationships within quality attributes.

Table 3. Data Extraction Form

Items	Descriptions
Quality Attributes	What are quality attributes that have been considered in the EC-CDSS?
Metrics	What metrics are used to measure and represent the quality attributes?
EC Functions	What EC Functions are supported by related EC-CDSS?
Stakeholders	Who implements related EC-CDSS on EC functions?
Relationships	Which quality attributes directly improve PHOs? Which quality attributes indirectly improve PHOs through EC functions? Are there any relationships between quality attributes?

2.1.5 Critical Appraisal

After the initial screening, two researchers conducted the second and third phases of the selection process separately. There were extensive discussions among researchers to resolve any disagreement in the selection process. The researchers then independently coded each selected article guided by the data extraction form. The results are discussed in the next section.

2.2 Result

The initial database search yielded a total of 968 articles. The review of title, abstract, and keywords excluded 509 articles. Language criteria excluded four articles reported in a non-English language. After the full-text review, only 27 articles were kept based on eligibility criteria. Another article was found by backward-reference list checking on kept articles (see Figure 2 for the flow diagram of screening process). Thus, the final review included 28 articles that are listed in Table 4.

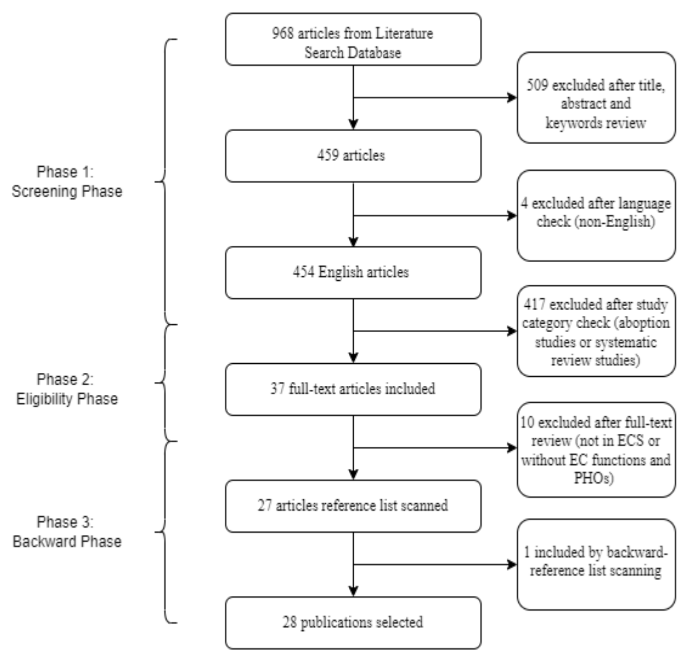


Figure 2 Flow Diagram of Screening Process

Table 4. List of articles

Index	Articles	Index	Articles	Index	Articles
1	(Yuan-Hsiang Lin et al., 2004)	11	(Anantharaman et al., 2001)	20	(Amouh et al., 2005)
2	(Rasid & Woodward, 2005)	12	(Ciccone et al., 2020)	21	(Kyriacou et al., 2005)

3	(Wen et al., 2008)	13	(Latifi et al., 2007)	22	(Albahri et al., 2019)
4	(Omoogun et al., 2017)	14	(Poulymenopoulou et al., 2011)	23	(Hauenstein et al., 2006)
5	(Tartan & Ciflikli, 2018)	15	(Wallis et al., 2016)	24	(Lopez et al., 2019)
6	(Pal et al., 2017)	16	(Crilly et al., 2011)	25	(Wu et al., 2017)
7	(Sharma et al., 2017)	17	(Tian et al., 2014)	26	(Kawtrakul et al., 2017)
8	(Barcelos et al., 2015)	18	(Valenzuela Espinoza et al., 2016)	27	(Billhardt et al., 2014)
9	(Abo-Zahhad et al., 2014)	19	(Vidul et al., 2015)	28	(Preum et al., 2019)
10	(Wang et al., 2016)				

This SLR summarizes possible EC-CDSSs for four EC functions: system activation, dispatch, intervention, and triage. The system activation is to active the ECS process when a patient is in risky acute conditions by sending the alarm information (Tartan et al., 2018). The dispatch is to select and send the most appropriate ambulance to the patient (Kawtrakul et al., 2017). The intervention is to diagnose the symptoms and provide treatments (Valenzuela Espinoza et al., 2016). The triage is to register the patient and send the patient to the appropriate area of the ED (Anantharaman et al., 2001).

The models used to develop the EC-CDSSs are the knowledge-based threshold identification model and the algorithm-based machine learning model. The knowledge-based models were only recorded to support system activation by predetermining threshold ranges for abnormal vital data identification (Oresko et al., 2010). Once the monitored vital data crossed the pre-set limitations, the EC-CDSS can send the alarming information to related stakeholders to active the system (Rodriguez et al., 2005; Yuan-Hsiang Lin et al., 2004). The knowledge-based model can set up threshold on different types of vital data, including SpO2 (Yuan-Hsiang Lin et al., 2004), heartbeat (Chen et al., 2007; Tartan & Ciflikli, 2018), ECG wave (Wen et al., 2008), blood pressure (Lopez et al., 2019), and multiple vital data combinations (Omoogun et al., 2017; Abo-Zahhad et al., 2014; Wang et al., 2016).

The algorithm-based models were recorded to support all EC functions by training classification models based on patient vital data, historical electronic record (EHR) information, and other ECS operational data. In a ubiquitous system, the researchers applied an offline-trained Artificial Neural Networks (ANN) model to check the possible abnormal heartbeat that may trigger a stroke (Barcelos et al., 2015). The dispatch EC-CDSS trained the algorithm-based models based on patient vital data and status data from ambulances and hospitals to make decisions on the appropriate ambulance to dispatch and target hospital to transport (Poulymenopoulou et al., 2011; Wu et al., 2017). A cloud-based consultation system applied a total body surface area (TBSA) calculator based on image analysis technologies to calculate the TBSA and hence provided intervention suggestions (Wallis et al., 2016). At last, a risk-level localization triage (RLLT) was also an algorithm-based model for supporting the decision-making on triage (Albahri et al., 2019). Thus, unlike knowledge-based EC-CDSS that only working for system activation, the algorithm-based EC-CDSS can provide decision-support for all EC functions.

The SLR answers the first two research questions by identifying quality attributes (with related metrics) and stakeholders of each possible EC-CDSS. The final coding resulted in four core quality attributes (PICT) for EC-CDSSs (**P**erformance, **I**nteroperability, **C**ost, and **T**imeliness) and four core stakeholders (Dispatcher; On-scene care provider; On-facility care provider, and Allied health worker). The following sections describe the details of PICT, the relationships between PICT and EC functions (and possible PHOs), the intra-relationship within PICT, and the details of stakeholders.

2.2.1 Quality Attributes of EC-CDSS and associated metrics

The SLR identified PICT and their related metrics by exploring the characteristics of the knowledge- and algorithm-based models used to develop the EC-CDSSs. Table 5 lists the definition for the quality attributes, associated metrics, and mapping results. This section describes the details of each quality attribute and related metrics.

Table 5. Quality Attributes, Metrics, and Mapping Results (associated with Table 4.)

Quality Attribute	Quality Attribute Definition	Metric and its definition	Articles
Decision Support Performance	It is the ability of system to properly guide the users on specific EC event based on high quality guidance or recommendations produced by decision support algorithms (Hasan & Padman, 2006; Sutton et al., 2020)	Validity measures the extent to which the system can provide expected functions and document expected results (Damoiseaux-Volman et al., 2021).	[1, 3, 4, 8, 10]
		Reliability measures the consistency of a system, which is extent to which a system yields the same guidance or recommendations on repeated trials (Scott et al., 2019).	[18, 22, 24, 28]

Interoperability	It is the ability of the system to exchange and share information between different systems (Handler, 2004).	Number of heterogeneous data source measures how many different data sources being used to integrate data for decision-support (Amouh et al., 2005)	[9-10, 12-14, 16-23, 25-26, 28]
		Number of information exchange protocol/standards measures how many protocols or standards were used to integrate the heterogeneous data (Preum et al., 2019).	[9, 12, 14, 16-17, 20-21, 23]
Cost	The cost of infrastructure and data processing that required to compile evidence-based narrative guidelines (Jacob et al., 2017).	Cost of infrastructure measures how expensive to build an EC-CDSS based on required hardware and software (Valenzuela Espinoza et al., 2016)	[1, 7-8, 13, 18-19, 24, 25]
		Cost of data transmission measures amount of unnecessary data being transmitted into EC-CDSS (Rodriguez et al., 2005)	[3, 4, 9]
Timeliness	It is the ability of the system to reduce the end-to-end time required to respond an EC event in the ECS process.	*Data latency* is the time between the EC event and when the data is ready for analysis by the EC-CDSS (Hackathorn, 2002).	[1-11, 13, 15-20, 21-25, 27-28]
		Analysis latency is the time of initiating data analysis and delivering to the appropriate person (Hackathorn, 2002).	[1, 3-6, 8-10, 14, 15, 17, 18, 20, 22, 24, 25, 27, 28]

2.2.1.1 Decision Support Performance

The decision support performance measures the ability of CDSS to reduce errors in making decisions or providing recommendations on healthcare and treatment (Ji et al., 2021). In the context of ECS, the performance is rigorous that poor performance might result in incorrect identification of a patient's condition and or misleading recommendations, which in turn could lead patients to serious conditions or death in extreme cases (Preum et al., 2018; Omoogun et al., 2017). Most studies demonstrated the performance by measuring the validity and reliability, which are two core metrics of performance in general CDSS (Scott et al., 2019). Thus, we identified validity and reliability as the metrics of performance in EC-CDSS. The mapping result is shown in Table 4.

2.2.1.1.1 Validity

Validity measures the extent to which the system can provide expected functions and document expected results (Damoiseaux-Volman et al., 2021). Five studies measured the validity of knowledge-based models (n = 4) or algorithm-based models (n = 1) on abnormal vital data identification, of which four provided quantitative evidence.

Validity can be measured through different approaches but 'assessment of validity always requires the use of external standards' (Scott et al., 2019). Using the medSim 300 Patient Simulator, (Yuan-Hsiang Lin et al., 2004) achieved a less than 2% error rate in SpO and less than 2 bpm error in HR to demonstrate the accuracy of a pre-set thresholds ECG monitor. A 98.98% accuracy was achieved in an experimental evaluation study that used MIT/BIT Arrhythmia database on an ECG classification algorithm (Wen et al., 2008). (Barcelos et al., 2015) asked neurology experts to label the signs of a possible stroke during the development of an Artificial Neural Networks (ANN) model, so that the researchers were able to control the error rate to 0.02. At last, the results of a real-time patient monitoring system were compared with a reference signal generator and achieved less than 2% and 3% of error of pulse oximeter and pulse pate, respectively (Wang et al., 2016).

2.2.1.1.2 Reliability

Reliability measures the consistency of a system, which is the extent to which a system yields the same guidance or recommendations on repeated trials (Scott et al., 2019). Four studies measured the reliability of knowledge-based models (n = 1) or algorithm-based models (n = 3) on multiple EC functions, including system activation, intervention, and triage.

Based on the definition of reliability, the EC-CDSS should be able to provide consistent recommendations on related EC functions from multiple times of implementations. For example, a teleconsultant ambulance-embedded system was able to achieve a 100% success rate in identifying patients by calling out suspected acute stroke and a 94% success rate in providing related interventions by establishing the necessary teleconsultants (Valenzuela Espinoza et al., 2016). In addition, an integrated risk-level localization triage (RLLT) achieved 90% of consistency from the evaluation of six experts (Albahri et al., 2019). Also, a threshold-based abnormal identification system achieved a maximum +/- 5 points variations on similarity comparison (Lopez et al., 2019). Last, the NLP technique in an integrated CognitiveEMS system achieved almost zero false positives on the results of speech-to-text conversion for intervention (Preum et al., 2019).

2.2.1.2 Interoperability

Interoperability is another quality attribute that enables a large amount of multi-source data for better decision support by exchanging and integrating heterogeneous data to train the algorithm-based machine learning model (Omoogun et al., 2017; Handler, 2004). However, only integrating heterogeneous data doesn't mean interoperability. There is a difference between data integration and data exchange. Data integration is simply gathering heterogeneous data to support decision-making. On the other hand, data exchange means integrating and mapping heterogeneous data with variant formats into semantic standards and proprietary features on a specific data communication protocol or standard (Majeed et al., 2013). The result should be a new data set that is available for further analysis and decision-making. Thus, the systematic review identifies the number of heterogeneous data sources and the number of information exchange protocols/standards as the metrics to represent interoperability.

2.2.1.2.1 The number of heterogeneous data source

Heterogenous data means collecting data of different formats from different sources. Wearable Sensing Device (WSD), Emergency Care Systems (ECS), and Electronic History Records (EHR) are three data sources identified from selected articles. Wearable sensing device (WSD), which is integrated into wearable objects or directly with the body, continuously collect patients' vital data and send the data to healthcare providers for monitoring health and/or provide clinically relevant data for care (Mondal et al., 2020; Fang et al., 2017). Using WSD in an integrated system can continuously monitor without affecting the patient's daily routines and also make analyzed data available to be used on other platforms in cases where the patient is not within the location of his or her healthcare service provider or in cases of emergency (Omoogun et al., 2017). The sensors usually include a set of micro-electromechanical, biological, and chemical sensors often integrated with the electrocardiogram (ECG), electroencephalogram (EEG), and electromyogram (EMG) based sensing platforms. One of the most popular smart wearable sensors is the wristband/watch that collect data related to several health matrices including body temperature, heart rate, blood pressure, step counting, energy dissipation, etc. (Piwek et al., 2016). Other WSD include chest patch (i.e., PDA and Holter) for ambulatory cardiac monitoring like ECG (Tian et al., 2014; Oresko et al., 2010), ring for blood volume change and accelerometer, and shoes for ambulatory gait monitoring with pressure sensor (Dunn et al., 2018). The ECS data means any incident data collected through the ECS process, including clinical observations, medications administered, or procedures performed (Poulymenopoulou et al., 2011). An electronic health record (EHR) is a 'digital version of a patient's paper chart' that makes medical and treatment historical data available to authorized users (HealthIT, 2019). In EC-CDSS, the ECS data and EHR data are both for training the algorithm-based models. Sixteen studies provided evidence of integrating data from different heterogeneous sources [5, 12-13, 15-17,19-26, 28-29, 31]. Three heterogeneous data sources (WSD, ECS, and EHR) have four combinations to satisfy interoperability: WSD with ECS (n = 6), WSD with EHR (n = 1), ECS with EHR (n = 2), and all three data sources (n = 7).

The vital data from WSD have proven as a key data source for multiple predictive analyses to predict patient injury deterioration (Tian et al., 2014). Variable ECS optional data are mentioned in selected studies to facilitate patient intervention (diagnosis and treatment) during the ECS process. Six selected studies integrated these two data sources to develop multiple EC-CDSSs. For example, three studies collected WSD vital data and ECS data from ambulances to guide on-scene providers on interventions during transportation (Wang et al., 2016; Valenzuela Espinoza et al., 2016; Albahri et al., 2019). The other two selected studies made the same decisions on interventions and also sent them to on-facility providers in EDs or hospitals to help the preparation of the patient arrival (Latifi et al., 2007; Wu et al., 2017). Another selected study exchanged and integrated data from these two sources to make the decisions on triage through a dynamic triage-supporting model (Tian et al., 2014).

EHR is patient-centered records that 'make information available instantly and securely' for a broader view of patient care (HealthIT, 2019). Research has demonstrated that EHR can help predict patient-related workload and have a great potential in improving efficiency in the ED (Wang et al., 2021). One study exchanged and integrated WSD vital data and EHR data into a new database for furtherly analyzing and setting up the customized thresholds ranges (Abo-Zahhad et al., 2014). EHR data can also work together with ECS data. (Crilly et al., 2011) developed an EC-CDSS to make decisions on interventions in an ED environment by analyzing the linked-together data from the electronic Ambulance Report Form (eARF) and EHR. In another case, the ECS data (patient registration, entry of anamnesis data, test requests, nursing tasks, etc) and EHR data were exchanged and integrated to facilitate the cooperation between different systems in ECS (Amouh et al., 2005).

At last, seven studies used all three data sources for decision-making. For example, (Ciccone et al., 2020) created a database to store all sources of data (patient vital data, diseases records, and intervention outcomes) to assist the further analysis of meaningful and sustainable implementation. (Poulymenopoulou et al., 2011) used all sourced data to provide the patient-oriented information available for EMS authorization. (Hauenstein et al., 2006) developed a shared data model for emergency incidents to support data exchange between heterogeneous systems. At last, (Kawtrakul et al., 2017) created a collaborative model to support communication between different users.

As described above, only integrating heterogeneous data doesn't mean interoperability. In some cases of this metric, there was no data exchange between two heterogeneous data sources. For example, emergency doctors can prepare the intervention by analyzing patient vital data collected from WSD and real-time patient video collected from telemedicine tools used during the ECS process (Latifi et al., 2007). Information exchange protocol/standard is the key to integrating or exchanging heterogeneous data by standardizing different formats and semantic types (Majeed et al., 2013). Only data integration without data exchange can cause the homogeneity of an analytical product (Vidul et al., 2015). Thus, we furtherly explored how many data communication protocols or standards were used in selected studies.

2.2.1.2.2 The number of information exchange protocol/standard

The lack of a unique or common identifier to facilitate the data exchange and integration, highlighted by several studies, is the main challenge to interoperate the heterogeneous data within the proposed EC-CDSS system (Vidul A P et al., 2015; Crilly et al., 2011). Among the studies with heterogeneous data sources, only eight studies provided evidence of exchanging and sharing data based on data communication protocols/standards [9, 12, 14, 16-17, 20-21, 23].

Health Level Seven (HL7) is the most common protocol for electronic data exchange in the healthcare environment (HL7, 2016). (Poulymenopoulou et al., 2011) and (Kyriacou et al., 2005) created patient emergency personal healthcare records (EPHR) by exchanging vital data from WSD, on-scene care providers institutional records from ECS, and historical data from EHR through HL7. Also, (Tian et al., 2014) created a dynamic triage-supporting model based on exchanged vital data from WSD and hospital data from ECS through HL7. At last, (Amouh et al., 2005) created an integrated patient electronic record management system based on message-based integration by providing a software module implementing the HL/7 standard to support real-time ED management.

The other two studies created their protocols/standards to integrate and exchange the heterogeneous data. Medical Data Transmission Protocol is to pack the vital data from WSD and historical data from EHR into a package (Chen et al., 2007). (Crilly et al., 2011) developed a linking algorithm to match the data from ECS and EHR. Another service-oriented architecture addressed the interoperability challenges through a designed data exchange standard (Hauenstein et al., 2006). In addition, two studies created new databases and matched patient identification to map the data from different systems (Abo-Zahhad et al., 2014; Ciccone et al., 2020).

The information exchange protocols/standards were mostly used in the standardization of recorded data from different data sources. The recorded data means the data stored in a dataset or database for a while, including the patient normal vital data stored in the WSD, description data of hospitals or ambulances that were stored in the ECS database, or all EHR data. Another type of data is real-time data, which means the data that was collected in real-time, including the abnormal vital data collected by WSD or video data captured by ambulance during the ECS process. It is a challenge for studies to use protocols/standards to standardize both real-time data and recorded data. For example, (Latifi et al., 2007; Valenzuela Espinoza et al., 2016) separately analyzed the patient's situation using real-time abnormal vital data from WSD and real-time telemedicine video data from ECS. In addition, (Wang et al., 2016; Albahri et al., 2019) monitored the patients with their abnormal vital data and the rescuing operations data from ECS, and suggested intervention decisions without integrating both data. Using heterogeneous data without integration and exchange inhibits the substantial networks of different users (dispatcher, in-scene providers, and in-facility providers) to work together for providing high-quality emergency care (Latifi et al., 2007). Thus, the development of a data communication protocol/standard for integrating and exchanging real-time and recorded data should be under consideration.

2.2.1.3 Cost

Cost always goes hand-in-hand with complexity (Hevner & Chatterjee, 2012). Some well-satisfied EC-CDSS solutions, often commercial systems, are prohibitively expensive (Amouh et al., 2005). Although sophisticated technologies can reduce the cost of healthcare, the high cost of technologies is also a reason that prevents their application in ECS (Knickman & Kovner, 2015). Among selected articles, eleven studies decreased the cost of EC-CDSS with two avenues: to control the cost of infrastructure [1, 7-8, 13, 18-19, 24, 25] and to decrease the amount of data for processing [3, 4, 9]. We identified these two avenues as the two metrics to measure the cost.

2.2.1.3.1 Cost of Infrastructure

Cost of infrastructure measures how expensive to build an EC-CDSS based on required hardware and software (Valenzuela Espinoza et al., 2016). It is usually cost-prohibitive to implement well-functional but expensive infrastructure for EC-CDSS (Wu et al., 2017). Thus, several studies demonstrated the budget-control EC-CDSS through either controlling the cost of hardware or software.

Four articles controlled the cost of hardware used for EC-CDSS. Barcelos (2015) chose an open-sourced platform to build EC-CDSS because of easy access and low cost. In another study, a 'plug-and-play' telemedicine artifact can reduce the cost on updating infrastructure of ambulance (Valenzuela Espinoza et al., 2016). The telemedicine or wearable psychological artifacts that promote doctor-patient remote communication can also decrease the cost of ambulance diversion by allowing self-control of patients' health and avoiding traveling to an ED (Lopez et al., 2019; Wu et al., 2017). Except for hardware, the cost of software can also be controlled by using advanced data processing techniques to provide high-performance data processing or wirelessly data transmitting (Yuan-Hsiang Lin et al., 2004; Sharma et al., 2017; Latifi et al., 2007).

2.2.1.3.2 Cost of Information Processing

Cost of data transmission measures amount of unnecessary data being transmitted into EC-CDSS (Rodriguez et al., 2005). Data transmission is usually costly and inefficient when a large amount of real-time data has to be transmitted (Rodriguez et al., 2005; Abo-Zahhad et al., 2014). In addition, it can also cause data latency if transmitting some normal vital data that might not be necessary for EC-CDSS (Abo-Zahhad et al., 2014). Multiple studies applied knowledge-based model as the filter to identify the abnormal vital data, which is necessary for further EC functions (i.e., system activation, intervention), and only transmit the abnormal vital data to control the cost of data transmission (Rodriguez et al., 2005; Chen et al., 2007; Wen et al., 2008; Omoogun et al., 2017; Abo-Zahhad et al., 2014).

However, the selected studies that mentioned the reduced cost neglect to provide quantitative evidence on how much the cost was reduced. This indicated that evidence related to cost reduction of EC-CDSS is insufficient. The generalizability of these many studies on this issue is problematic. As a result, why there is no quantitative evidence on cost reduction and how to record the cost are valuable research questions to be investigated in the future.

2.2.1.4 Timeliness

Timeliness refers to the ability to minimize any possible latency during the decision support process (Hackathorn, 2002). It is crucial for EC-CDSS because the EC-CDSS is a time-sensitive system that any latency in decision-making can prevent the ECS from delivering the necessary interventions in a limited time window for saving a patient's life (Barcelos et al., 2015). The latencies include data latency and analysis latency. The data latency refers to the latency of data being ready for analysis, and the analysis latency refers to the latency of initiating data analysis and delivering it to the appropriate user (Hackathorn, 2002).

2.2.1.4.1 Data Latency

In EC-CDSS, the data latency refers to the time of preparing data for making decisions on EC functions (e.g., identification of acute condition, dispatch of rescue teams, intervention, or triage) (Hackathorn, 2002). One reason for data latency is the poor data collection technology on vital signals of patients, like paper or manual data collection process during a phone call from bystanders or patients (Ciccone et al., 2020; Tian et al., 2014; Aboueljinane et al., 2013; WHO, 2018). Another reason is the store-and-forward data transmission model that prevents the user of EC-CDSS to access the ready data at any desired time (Tartan et al., 2018; Wen et al., 2008). The selected literature mentioned evidence of reducing the data latency in EC-CDSS through real-time technologies for data collection (n = 25) and data transmission (n = 18).

The Holter monitor was the first-generation data collection technology to monitor and record patient ECG data during everyday activities (Rodriguez et al., 2005). Instead of checking the heart rhythm rate in hospitals, two studies used Holter as a worn unit to constantly collect ECG data in real-time while the patients were outdoor on the move (Wen et al., 2008; Tartan & Ciflikli, 2018). WSD is another real-time data collection technology that is more flexible than Holter (Tian et al., 2014). The medical sensors implemented in the WSD can collect different kinds of physiological vital signs data, including temperature, heart rate, oxygen level, and so on (Omoogun et al., 2017). The last technology to faster the data collection is in-ambulance tools. It is to equip big sensors or instruments, such as CT scans, into the ambulance to monitor patients in real-time during transportation (Sharma et al., 2017). Unlike Holter or WSD, which can only collect patient vital data, in-ambulance tools can collect other ECS operational data in real-time. For example, the status of an ambulance (available, on-call, or not on duty) and location can assist the dispatch decision-making (Wu et al., 2017). In addition, an in-ambulance integrated system, like TeleStroke, can integrate the ECS operational data with EHR data (patient identity and demographics, clinical presentation, and medical history) while collecting vital data (Valenzuela Espinoza et al., 2016).

In terms of data transmission, many studies have utilized the real-time transmission model to reduce data latency. The real-time model enables EC-CDSS users to access the patient data immediately after the acquisition of specific EC functions (Wen et al., 2008; Abo-Zahhad et al., 2014; Lopez et al., 2019). For example, multiple studies used the real-time model to transmit the patient's abnormal vital data from WSD to the decision-making of system activation, so that alarm the users while there was an acute condition (Yuan-Hsiang Lin et al., 2004; Omoogun et al., 2017). In addition, the Mobile Stroke Treatment Unit (MSTU) was able to make decisions on the dispatch through patient vital data and ECS ambulance information immediately after receiving the alarm of acute condition (Sharma et al., 2017). Similarly, triage officers would make decisions on the triage based on the assistance of triage EC-CDSS immediately after receiving victim injury data (Tian et al., 2014).

Evidence from selected studies suggests that real-time data collection and transmission can decrease data latency. For instance, The HEAL system reduced the average data collection duration from 12 minutes to 90 seconds (Anantharaman et al., 2001). The Mobile Stroke Treatment Unit (MSTU) can compile and integrate all heterogeneous data in 8 minutes (Valenzuela Espinoza et al., 2016). Health Data Integration (HDI) software uses patients' demographic data to link their historical records in only 5 minutes (Crilly et al., 2011). The STREMS (an efficient smart real-time prehospital communication system for EMS) has proven to transmit emergency data (patient's vital data) to the hospital in less than 1.5s (Wu et al., 2017). A real-time patient monitoring system reported only 5 seconds as the average delay of transmission time (Wang et al., 2016). An e-Health prototype can compile multiple vital data from sensors in WSD and send them to the system in 23 seconds, ending by being visualized on a website in less than 2 minutes (Lopez et al., 2019). Collectively, these studies outline the critical role of real-time technology on data latency.

However, real-time data collection technologies (like multiple-sensor WSD, up-to-date vehicle electronics, or telecommunications technologies) were highly sophisticated and expensive (Pal et al., 2017; Vidul et al., 2015; Wu et al., 2017). In addition, fast data processing and transmission might require expensive equipment, a dedicated linking path, and skilled operators (Rasid & Woodward, 2005; Crilly et al., 2011). Thus, how to control the cost of these technologies to improve the EC-CDSS generation should be considered.

2.2.1.4.2 Analysis Latency

Analysis latency is the delay of data analysis initiation and decisions delivery to the appropriate user (Hackathorn, 2002). The analysis latency could lead patients into critical conditions if EC-CDSS could not make decisions on EC functions (system activation, dispatch, intervention, and triage) on time (Omoogun, 2017). It is a challenge to decrease analysis latency because analyzing a large amount of data is a time-consuming process (Barcelos et al., 2015). Thus, several studies had investigated real-time analysis to decrease the latency through either knowledge-based threshold limitation or algorithm-based machine learning classification.

The knowledge-based model used threshold limitations as rules to identify patient abnormal vital data in real-time (Sutton et al., 2020). (Wang et al., 2016) provided 40-second evidence as the average analysis time of blood pressure identification. The algorithm-based models had more evidence of decreasing the analysis delay. For example, the ANN-based ubiquitous system decreased the average duration of strokes identification to only 1.657 seconds (Barcelos et al., 2015). In addition, the STREMS used the EMS Patient Care Reporting (ePCR) system to decrease the analysis latency on acute condition identification and report development from a fixed 2-hour interval to 0.75 seconds on average (Wu et al., 2017). The algorithm-based dispatch systems decrease the analysis latency by automizing the assessment of a patient's injury, suitable EMTs, and resource situation of multiple hospitals in real-time (Poulymenopoulou et al., 2011; Wu et al., 2017). The TBSA, a system to calculate the burning area on the body surface, can automatically calculate the TBSA and provided treatment suggestions in real-time (Wallis et al., 2016). At last, the RLLT (risk-level localization triage) was implemented to improve the analysis latency for triage (Albahri et al., 2019).

To summarize, knowledge- and algorithm-based EC-CDSSs have both strengths and limitations based on the quality attributes. Knowledge-based EC-CDSSs can decrease the cost of information processing but only have high-quality performance on system activation. On the other hand, algorithm-based EC-CDSSs have high-quality performance on all EC functions but require more cost for model development. Thus, this systematic review will explore which quality attributes would directly improve the EC functions and PHOs and what are the intra-relationships between quality attributes. It could help us to look for a balance implementation of knowledge- and algorithm-based EC-CDSSs to achieve all quality attributes.

2.2.2 Relationship between qualitive attributes and ECS objectives

For the relationship extraction (see Table 3), the coding results were mapped into an association matrix (see Table 6). The rows are causes and the columns are results. For example, if a study stated any relationships between quality attributes and PHO, we include the article index into the specific quality attributes rows with the PHO column.

Table 6. The cause-and-effect matrix based on analytical tasks of the studies (associated with Table 4).

Properties	Performance	Interoperability	Cost	Timeliness	EC functions	PHO
Performance			[1, 5, 6, 7, 12]	[9, 11, 20]	[4-6, 8, 10, 12, 14-16, 21, 22, 27-28]	[14]
Interoperability	[5, 12, 15, 17, 20, 23, 24, 25, 26, 31]			[19, 26, 29, 31]		
Cost						
Timeliness					[3-4, 4-11, 13-16, 18, 21, 24-28]	[7, 13, 14]

2.2.2.1 Inter-relationship between quality attributes, ECS functions and PHO

Four articles mentioned the improvements of PHO, but none of them had enough evidence on a direct relationship between EC-CDSSs and PHOs. The evidence indicated the indirect improvement from EC-CDSSs to PHOs through the EC functions. For example, real-time technologies can provide faster decision-making of EC-CDSSs on several EC functions, thereby increasing the life-saving rate of patients (Sharma et al., 2017; Poulymenopoulou et al., 2012; Latifi et al., 2007). A triage-related EC-CDSS can save patient life through high-quality identification of patient acute condition and appropriate department for disposition (Latifi et al., 2007).

More literature provided evidence on the direct relationship between quality attributes and EC function. Thirteen articles had evidence of improving multiple EC functions through high-quality decisions made by high-performance EC-CDSSs. For example, the algorithm-based classification models can result in more accurate identification of acute conditions, thereby avoiding unnecessary system activation (Wen et al., 2008; Omoogun et al., 2017). The knowledge-based classification models can identify more precise abnormal data for rescue teams or physicians to assess the patients' acute conditions (Pal et al., 2017; Barcelos et al., 2015). The algorithm-based classification models can also guide the intervention by providing rescue teams or physicians the recommendations about who urgently needs medical treatment and what treatment would be appropriate (Wang et al., 2016; Poulymenopoulou et al., 2012; Amouh et al., 2005). In addition, the algorithm-based model with high validity can improve the triage function by analyzing the patient's risk level and survival probability (Tian et al., 2014; Albahri et al., 2019; Poulymenopoulou et al., 2012). At last, the algorithm-based model can also guide dispatch and registration by evaluating the patient's acute condition, ambulance situation, and hospital capability (Kyriacou et al., 2005; Billhardt et al., 2014; Preum et al., 2019).

In terms of timeliness, twenty-four articles applied real-time technologies to speed up the EC functions. A mHealth-based WSD with embedded biosensors can monitor and collect the patient vital data in real-time (Rasid & Woodward, 2005; Omoogun et al., 2017; Abo-Zahhad et al., 2014; Wang et al., 2016). Some articles added a classification model (either algorithm-based machine learning models or knowledge-based threshold limitations) in the WSDs to detect the abnormal vital data in real-time for acute condition identification (Omoogun et al., 2017; Abo-Zahhad et al., 2014; Wang et al., 2016). With these two technologies, EC-CDSS can activate the ECS process in real-time by sending the alarms to the users (ECS processer unit or hospital centers) immediately after identifying the high-risk acute conditions (Omoogun et al., 2017; Abo-Zahhad et al., 2014; Wang et al., 2016). The EC-CDSS can also shorten the dispatch time by providing dispatch-related decision support after real-time assessment of a patient's injury, suitable EMTs, and resource situation of multiple hospitals. (Poulymenopoulou et al., 2011; Wu et al., 2017; Albahri et al., 2019). At last, telemedicine technology can improve field-to-facility communication by transmitting the patient's data in either image or video format in real-time and having real-time video calls (Rasid & Woodward, 2005; Sharma et al., 2017; Anantharaman et al., 2001).

From selected studies, however, there is no evidence of direct improvement from interoperability and cost to EC functions. To explore the functionalities of these two quality attributes, we looked for if they have relationships with the other two quality attributes (performance and timeliness). The coming section describes the identified intra-relationships between quality attributes.

2.2.2.2 Intra-relationships within Quality Attributes of EC-CDSS

Based on selected articles, we found that the high-quality decision support performance can decrease the cost of information processing in EC-CDSSs, as mentioned in section 3.1.4, through only abnormal data transmission. The high-quality performance can also improve the timeliness of EC-CDSS. The accurate identification of abnormal vital data can reduce the analysis latency of making decisions on interventions (diagnosis and treatment) by having less data as input to the analysis process (Pal et al., 2017). In addition, a WSD with an embedded ECG identifier improved data delay by saving the time spent on gathering normal vital data (Tian et al., 2014; Barcelos et al., 2015).

In terms of interoperability, several pieces of evidence indicated the effectiveness of interoperability on both timeliness and performance. An integrated multi-sourced database allows EC-CDSS to access the heterogeneous data within a short time (Crilly et al., 2011; Hauenstein et al., 2006). In addition, the integrated database also speeds up the decision-making process of EC-CDSS by developing and delivering reports or recommendations in real-time (Kawtrakul et al., 2017; Preum et al., 2019). On the other hand, ten reviewed studies showed quantitative evidence of the improvement of performance from interoperability. EC-CDSS can provide more valid and reliable suggested decisions on multiple EC functions by using patient vital data from WSD, ECS operational data, and medical history data from EHR (Ciccone et al., 2020; Amouh et al., 2005). These EC functions include case injury/ illness accessing and triaging (Poulymenopoulou et al., 2011; Tian et al., 2014), selection of the most appropriate treatment procedures (Kyriacou et al., 2005; Poulymenopoulou et al., 2011), or selection of the most appropriate ambulance and hospital types (Albahri et al., 2019; Poulymenopoulou et al., 2011). For example, the CT scan had a 98% accuracy of radiological diagnosis with assistance from WSD data (Latifi et al., 2007). In addition, (Albahri et al., 2019) analyzed WSD data and ECS data for a better hospital selection.

2.2.3 Stakeholders of EC-CDSSs

The SLR identified EC functions guided by decision support from EC-CDSSs and related stakeholders of EC-CDSSs by analyzing who make the decision based on decision support from EC-CDSSs. Table 7 lists stakeholders, the EC functions they operate, related methods of EC-CDSSs, and mapping results. This section describes the details of each stakeholder and how they benefit from the EC-CDSSs.

Table 7. Stakeholders of EC-CDSSs for related EC Functions (associated with Table 4)

Stakeholders	EC Functions	EC-CDSSs	Articles
Dispatcher	System Activation	knowledge- and algorithm-based models	[1, 3-5, 8-10, 22, 24]
	Dispatch	algorithm-based models	[13, 14, 25]
On-scene care provider	Intervention	algorithm-based models	[2-5, 7, 9-11, 13-15, 18-20, 25, 28]
On-facility care provider	Intervention	algorithm-based models	
Allied health worker	Triage	algorithm-based models	[13, 14, 17, 18, 20, 22, 25]

The dispatcher is the stakeholder of both knowledge- and algorithm-based EC-CDSSs providing system activation decision-support. Without decision support from system activation EC-CDSSs, the dispatcher has to evaluate the acute condition information provided by emergency calls or alarming data from WSDs and then to determine whether or not the ECS services needed to be activated (Aboueljinane et al., 2013). It is hard for the dispatcher to make the decision based on the unclear information from emergency calls because of either fraudulent or prank calls, or insufficient descriptions of the acute condition from bystander (Su et al., 2002). The system activation EC-CDSSs timely provide high performance decision support to a dispatcher by computerizing the process of patient vital data collection acute condition identification. For example, a pre-set threshold ECG monitor or ECG classification algorithm sends alarming information about a patient with emergency cardiovascular disease to help the dispatcher active the ECS process (Khalemsky et al., 2017; Yuan-Hsiang Lin et al., 2004; Wen et al., 2008).

The dispatcher is also the stakeholder of algorithm-based EC-CDSSs providing dispatch decision support. The responsibility of a dispatcher related to dispatch is to timely deploys an appropriate ambulance with an appropriate on-scene care provider rescue team to the scene based on (i.e., one that can provide all necessary services and equipment) based on the case's injury or illness (Poulymenopoulou et al., 2011). It is an information-consuming process that requires the dispatcher to have full knowledge of the patient's geolocation, the severe level of an acute condition, the availability of a rescue team and ambulance, and the capability of the target ED (Aboueljinane et al., 2013). It is also a time-consuming process that requires the dispatcher to integrate and analyze all information to decide on an appropriate rescue team and ED (Su et al., 2002). In general, ECS provides two kinds of on-scene care providers with two levels of life support. Basic Life Support (BLS) provides basic medical care such as bleeding control, basic airway support, oxygen delivery, and patient stabilization. Advanced Life Support (ALS) requires more highly skilled paramedics who can provide higher-level care such as the interpretation of the patient's heart rhythm, administration of drugs, complex airway support, and other therapies (Wu et al., 2017). The dispatcher has to decide the level of on-scene care providers based on the acute condition. In addition, the dispatcher also needs to decide the destination ED in the best hospital. The evidence indicated that TAH (time of arrival of the patient at the hospital) and the availability of the ED play key roles in the selection of the best EDs (Albahri et al., 2019). It is hard for a dispatcher to avoid erroneous decision-making within a short time (Aboueljinane et al., 2013). The dispatch EC-CDSSs can provide decision support to a dispatcher with appropriate on-scene care providers and destination EDs. For example, an intelligent algorithm-based model incorporates heterogeneous data for selecting the most appropriate on-scene care providers, ambulances, and EDs (Poulymenopoulou et al., 2012; Wu et al., 2017).

The on-scene and on-facility care providers are both stakeholders of the intervention. The on-scene care provider provides basic or advanced life support services during transportation, while the on-facility care provider (i.e., physicians and nurses) provides diagnosis and treatment in EDs (Valenzuela Espinoza et al., 2016). The algorithm-based intervention EC-CDSS could facilitate both care providers by speeding up the decision duration. For example, the STREMS (an efficient smart real-time prehospital communication system) can collect and analyze patient vital data in real-time, which is beneficial to on-scene care providers in intervention decision-making during patient transportation (Wu et al., 2017). Also, a 24/7 In-Ambulance Telemedicine for Acute Stroke project speed up in-hospital processes for stroke diagnosis and treatment for in-facility care provider by automatically generating and sending the decision-support report (Valenzuela Espinoza et al., 2016).

The last stakeholder is allied health workers, specifically the triage officer from the SLR. The triage officer decides on a transportation priority level for the patient and appropriate target hospitals based on the patient survival curve (the computed probabilities of survival at a certain point of time) (Tian et al., 2014; Kishore et al., 2010). Multiple algorithm-based EC-CDSS can benefit triage officers with reliable decisions in a short time. For example, an integrated risk-level localization triage (RLLT) provides triage decisions with 90% of consistency in real-time (Albahri et al., 2019). A dynamic triage-supporting model exchanges and integrates data from different sources through the HL7 protocol (Health Level Seven) to make the decisions on triage (Tian et al., 2014).

2.3 Discussion

The evidence from the literature leads to a quality attribute model that represents the relationship between EC-CDSS quality attribute, ECS operations, and PHOs (see Figure 3). The model lists PICT with related metrics and explains the causal order from PICT to EC functions and PHOs.

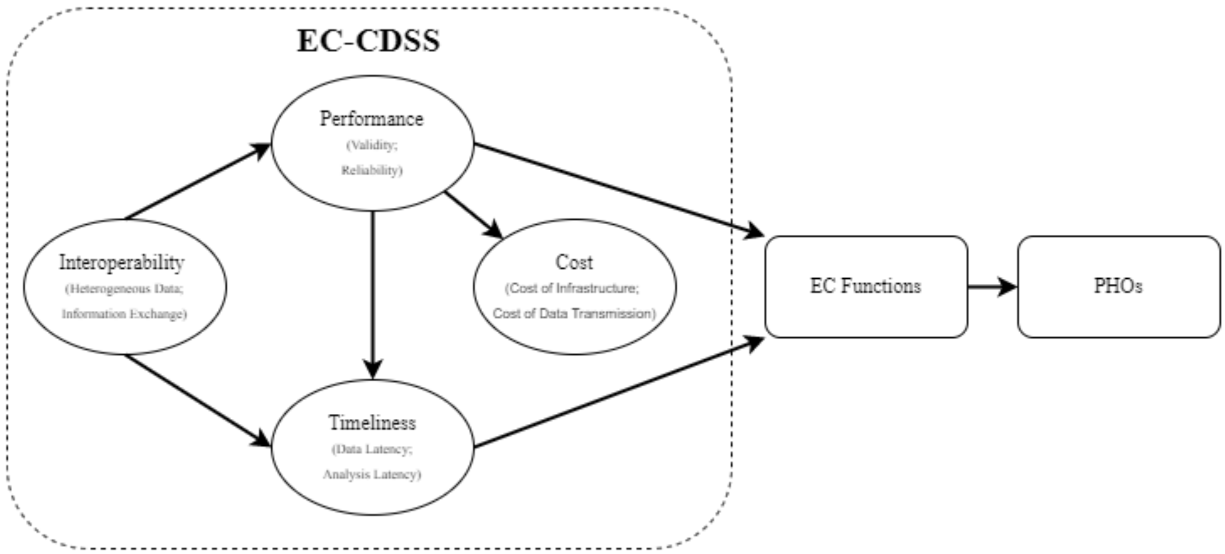


Figure 3. PICT Quality Attribute Model

As shown in Figure 3, interoperability can lead to performance and timeliness. Decision support performance can furtherly lead to cost and timeliness. Both performance and timeliness can directly improve the EC functions, thereby improving the PHOs.

2.3.1 Interoperability to Decision Support Performance/Timeliness

Interoperability refers to the 'provision for two or more systems to share and use information' (Stephanie et al., 2020). In EC-CDSS, interoperability means the integration of vital data from WSD, EHR, and ECS to train the algorithm-based models that used in multiple EC-CDSSs. Interoperability can improve the performance by providing sufficient data for training and developing better predictive algorithm-based models (Wang et al., 2021). Training algorithm-based models require historical input features and outcomes, which can only be provided by EHR data (Jiang et al., 2021). For example, a patient's acute conditions and medication history can work together with intervention behaviors (e.g., medication and dosage) to support the decision-making of intervention and triage (Wang et al., 2021; Tian et al., 2014). Historical ECG data recorded in Holter tools and medication history from EHR can work together with acute conditions to predict emergency cardiovascular disease (Rodriguez et al., 2005). In terms of timeliness, interoperability can reduce data latency of EC-CDSS by using the recorded data in the database, instead of collecting the historical data from original source in real-time (Crilly et al., 2011; Hauenstein et al., 2006). For example, an EC-CDSS can save time on a CT scan if the patient had a recorded CT image stored in the database (Wang et al., 2021). Thus, interoperability is treated as a required element of EC-CDSS (Brailer, 2005).

These documented positive effects of interoperability make it a required quality attribute of EC-CDSS. It is plausible to assume that interoperability can affect performance and timeliness positively. Analyzing data in an integrated way has proven to drastically improve patient quality of care and clinical outcome (Helgheim et al., 2019). Large-scale data enables researchers to use them as multi-dimensional features for building predictive models of health and behavior (Hicks et al., 2019). From the ECS perspective, vital data and laboratory tests are informative to predict mortality among high-risk ED patients (Li et al., 2021). In addition, using stored heterogeneous data or automatically applying algorithm-based models can save analysis time (Helgheim et al., 2019; Wang et al., 2021). According to the above evidence, interoperability has the potential to improve performance and timeliness.

However, fulfilling interoperability in EC-CDSS is facing challenges. The first challenge is the lack of standards of data exchange between multiple heterogeneous sources (He et al., 2021). The lack of commonly accepted terminologies and ontologies between different data systems for intelligence interfaces makes data exchange and interoperation hard to achieve (Jaspers et al., 2011; Sutton et al., 2020). Another challenge is the technical skills related to the design of optimal data models that support a diverse variety of data and the design of web services that support the information needs of each system (Hauenstein et al., 2006). The last challenge is the lack of trust between owners and users of heterogeneous healthcare data (Abu-elezz et al., 2020). A third-party Health Information Exchange (HIE) platform could effectively and efficiently share the EHR data among different health care information systems (Kawtrakul et al., 2017). However, the security of patients' personal data inhibits the implementation of HIE (Abu-elezz et al., 2020). These arguments show that EC-CDSS designers need to consider some practical challenges like data exchange and interoperation protocols/standards and security issue while fulfilling the interoperability.

2.3.2 Decision Support Performance to Timeliness/Cost

The decision support performance has been viewed as the most important feature in the quality of EC-CDSS (Ji et al., 2021). It could improve the timeliness and cost of EC-CDSS through reliable (the degree to which a measure is not afflicted by random errors) and valid (the extent to which a score truly denotes a concept) decision-making (Alkhawaja et al., 2020).

For example, a pre-trained algorithm-based arrhythmia identifier can alarm the emergency in real-time (Rodriguez et al., 2005; Oresko, 2010). Great performance diagnostic EC-CDSS can facilitate timely suggestions on intervention for patients with acute conditions (Wang et al., 2016). In addition, a machine learning model predicting the hospitalization of ED patients can save the time for a patient to be hospitalized by early identification (De Hond et al., 2021). The possible mechanism for performance to improve timeliness is the decreased man-hours required to analyze the data and make the decisions (Greenbaum et al., 2019). The progressing and updating information technologies can also increase the execution speed of the algorithm-based models (Oresko et al., 2010).

From a cost perspective, the knowledge-based abnormal data identification decreases the cost of information processing by preventing the EC-CDSSs from processing unnecessary normal vital data for further decision-making (Chen et al., 2007; Wen et al., 2008; Omoogun et al., 2017; Abo-Zahhad et al., 2014). It is expensive to process and analyzes a large amount of data (Crilly et al., 2011; Rodriguez et al., 2005). Also, the pre-trained algorithm-based models only need abnormal vital data as inputs to be applied for decision-making (Chen et al., 2007). The unnecessary nature of normal vital data in the ECS process leads to a filtering function that there is a potential to decrease the cost by using a knowledge-based model to filter the abnormal vital data and applying an algorithm-based model for decision-making.

2.3.3 Decision Support Performance/Timeliness to EC functions and PHOs

The core contribution of this PICT Quality Attribute model is to clarify that the performance and timeliness are two quality attributes to improve the PHOs through EC functions. As WHO (2019) defined, the EC-CDSS is an integrated digital platform to facilitate timely recognition, treatment management, and, when needed, continued treatment of the acutely ill. All decision-making on EC functions during ECS process are quality and time sensitive. For example, a poor-performance dispatch related EC-CDSS that makes decisions on target hospital selection could lead the patient into very serious conditions or death in extreme cases because the hospital might not have enough resources to reach the patient, even if the patient could be in a hospital in a very short time (Omoogun et al., 2017). A Holter tool without real-time data transmission functions could not active the ECS service on time, thereby decreasing the life-saving rate of the patient even if it can identify serious rhythm irregularity (Rodriguez et al., 2005; Rasid et al., 2005). Thus, high-quality and timely decisions made by related EC-CDSSs could improve EC Functions, thereby saving patients' lives.

However, the lack of evidence on the direct effects of performance and timeliness on PHOs takes the causal order into account. Although accurate and timely decision-making has proven to improve the PHOs, it is the implementation of EC functions (i.e., transporting patients and providing interventions) to save patient life (Anantharaman et al., 2001; Sharma et al., 2017). This PICT Quality Attribute model indicates that EC functions are conceptually closer to PHOs, and it is necessary to design an integrated EC-CDSS to improve all EC functions for ultimately improving PHOs. Thus, it requires EC-CDSS designers to consider how to incorporate current segmented EC-CDSSs into an integrated one to fulfill all quality attributes while satisfying all stakeholders' information needs.

Chapter 3 Research Methodology

3.1 Design Science

Design science is a research paradigm in which a designer answers questions relevant to the human problem via the creation of innovative artifacts, thereby contributing new knowledge to the body of scientific evidence (Hevner & Chatterjee, 2010). As a science of artificial, design science is an appropriate methodology for this dissertation. As discussed earlier, the problem this dissertation aims to address is how to design a data processing architecture of EC-CDSS that satisfies all desired quality attributes while satisfying all stakeholders' information needs. The design science can solve the problem via a newly designed innovative data processing architecture, thereby contributing new knowledge on challenges during architecture implementation and how does an EC-CDSS use the architecture to fulfill all quality attributes while satisfying all stakeholders' information needs.

Design science has three processes: abduction, deduction, and iteration (Takeda et al., 1990). Abduction includes the awareness of problem and suggestion (Kuechler & Vaishnavi, 2008). In this dissertation, the SLR will have an in-depth knowledge about EC-CDSS to clearly define the problems of existing EC-CDSS and propose alternate solution. Deduction is the process of designing, developing, and implementing the suggestion toward an artifact. In this dissertation, the artifact will be a data processing architecture integrating the EC-CDSS to fill the research gap. Lastly, iteration is to provide essential feedback to the construction phase through consistent evaluation, in order to provide new knowledge and improve the quality of artifacts under development (Hevner et al., 2004; Hevner & Chatterjee, 2010). In this dissertation, the design of data processing architecture will include multiple iterations of design cycle. It will be rigorously and thoroughly tested in laboratory and experimental situations.

This dissertation will be guided by the design science research (DSR) process model proposed by Vaishnavi and Kuechle (2015). The design process starts with the awareness of the problem (described in previous chapters), suggestions (Section 3.2) where the tentative design will be abductively drawn from the ECS Framework (WHO, 2018); development of the designed artifact (Section 4); evaluation to demonstrate the feasibility, functionality, and usability of the new artifact (Section 5); and conclusion to communicate the results and research contributions (Section 6).

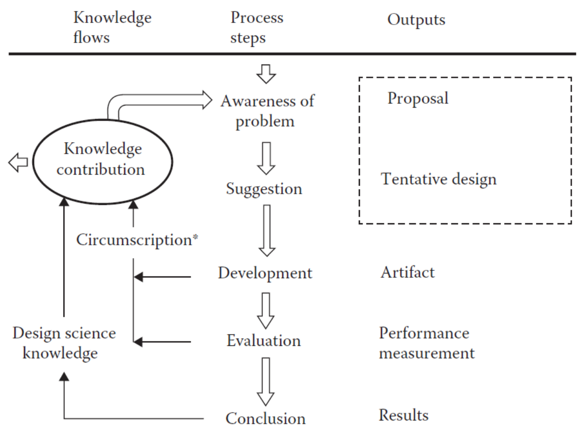


Figure 4. Design Science Research (DSR) Process Model

3.2 Suggestions

The previous chapters have reviewed the state of the problem, which is the lack of a data processing architecture for an integrated EC-CDSS that has all quality attributes while satisfies all stakeholders' information needs with the goal of improving PHOs. With this problem, the designer should have some suggestions for designing an artifact to solve the problem based on fully understand of the key concepts, requirements, and constraints needed to solve the stated problem (Henvor et al., 2004). In this dissertation, three key concepts have been articulated: EC-CDSSs, quality attributes and related metrics, and stakeholders, as summarized in the Chapter 2. The requirements have also been identified as how the data processing architecture would enable all quality attributes while satisfy all stakeholders' information needs. The constraints between EC-CDSSs and stakeholders were described in the kernel theory (Section 1.4). The constraint will be the condition rules for funtionalities that satisfying all stakeholders.

Based on the requirements and constraints, a tenantive design is proposed (see Figure 5).Requirement #1 requires a data pipeline that can transmit the patient's vital data to knowledge- or algorithm-based models. WSD can monitor and collect vital data from patients in real-time. Requirement #2 confirms the real-time technology as the transmit method. Requirement #3 and Requirement #7 determine different knowledge- or algorithm-based models to support four EC functions (i.e., system activation, dispatch, intervention, and triage). Requirement #4 separates the models: the knowledge-based models will be used to filter the abnormal vital data and algorithm-based models will be used for offline data transmission. Requirement #5 leads to a data repository that stores the heterogeneous data through information exchange standard/protocol. The data repository will be the source of the algorithm-based models. Based on SLR and required input data summarized from kernel theory (see Section 3.2), the heterogeneous data sources include patient vital data from WSD, historical records from EHR, and availability and capability informaiton of ambulance and ED in hospitals from the ECS.Lastly, Requirement #6 requires a store-and-forward data pipeline to transmit the normal data from the sources (WSD, EHR, and ECS) to the data repository. Next two sections discussed detailed considerations for the tenatative design.

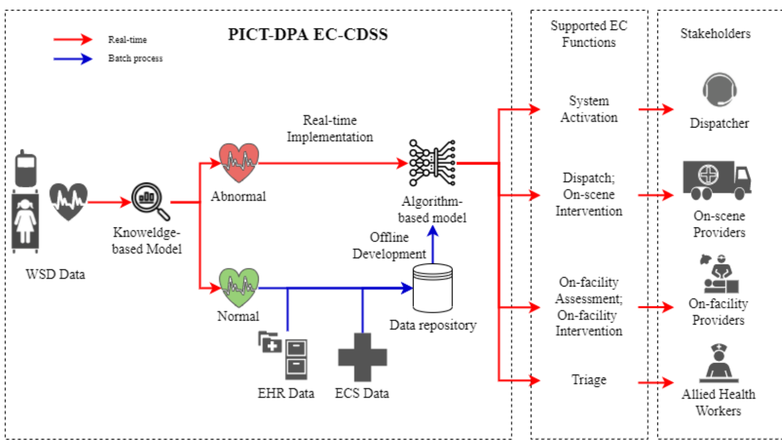


Figure 5. Tenative Design of the new data processing architecture

3.2.1 Quality Attributes

In the SLR, the PICT Quality Attribute model (see Figure 3) shows that the decision support performance can directly improve the performance of EC functions through either knowledge-based models or algorithm-based models (see Section 2.2.1.1). The knowledge-based model can dynamically set up the threshold of abnormal vital data based on existing medical knowledge about the diseases and the patient's historical records and facilitate the identification of acute conditions (Rodriguez et al., 2005). The algorithm-based models use heterogeneous data to train and develop specific predictive or classification models to support clinic decision making with high validity and reliability, which are two metrics of decision support performance. Thus, the first design requirement (Requirement #1) of the proposed data processing architecture should include the ability to extract and transform necessary data that are required for either knowledge- or algorithm-based models. The PICT Quality Attribute model also shows that timeliness can directly improve the performance of EC functions. Real-time technologies for data extraction, transform, and loading (ETL) are best suited to achieve timeliness by decreasing data latency and analysis latency, which are two metrics of timeliness. Thus, the second design requirement (Requirement #2) of the proposed data processing architecture should have real-time ETL capabilities.

From the cost perspective, two methods are relevant based on two related metrics: reducing the cost of infrastructure and reducing the cost of data transmission. Instead of creating an individual EC-CDSS for each EC function, an integrated EC-CDSS that supports all EC functions would be more cost effective using one shared infrastructure. Thus, the third design requirement (Requirement # 3) of the proposed data processing architecture should be able to integrate all required data and support all knowledge-/algorithm-based models. The data transmission cost, on the other hand, can be reduced if only patient abnormal vital data is transmitted in real-time (Chen et al., 2007). Many published studies used knowledge-based models to only alarm stakeholders when patients' vital data is out of the range of predetermined thresholds (Rodriguez et al., 2005; Oresko et al., 2010; Chen et al., 2007; Tartan et al., 2018). Thus, the fourth design requirement (Requirement #4) of the proposed data processing architecture should have a knowledge-based model to filter and only transmit patient abnormal vital data.

Also as shown in the PICT Quality Attribute model, the interoperability quality attribute can improve both performance and timeliness. To ensure the interoperability, the proposed data processing architecture would need to be able to collect data of different formats from different sources and support different information exchange protocols or standards. The fifth design requirement (Requirement #5) would require a centralized data repository that stores data that is extracted from multiple sources and transformed using different information exchange protocols or standards.

There is yet another consideration for the tradeoffs between timeliness and cost. The development and training of algorithm-based models require a massive amount of data. It would be very expensive to training and update these models in real-time. A possible solution is to train these models offline using data stored in the centralized data repository through a traditional batch process. The models are then updated periodically to score abnormal data. This leads to the sixth design requirement (Requirement # 6) of the data processing architecture to have a traditional batch processing data pipeline to process and store data required for training algorithm-based models.

3.2.2 Stakeholders' Information Needs

As shown in Table 1 (see section 1.4), different EC functions have different stakeholders with different data flows in different time intervals. Based on the results of SLR and the ECS framework, the stakeholders' information needs are summarized in Table 8 that shows what input data and EC-CDSS models would be relevant for a specific EC function at a specific time interval for different stakeholders. Note on this table, only EC-CDSS supported EC Functions are presented.

Based on Table 8, the seventh design requirement (Requirement #7) of the proposed data processing architecture should be able to process different types of input data for different types of EC-CDSS models with specific EC-functions and send recommendations to related stakeholders.

Table 8. Stakeholders' Information Needs

Phases	Time intervals	Input Data	EC-CDSS model	EC-CDSS supported EC Functions	Stakeholders
SCENE	Time to Dispatch	Patient's vital data; EHR information;	knowledge- and algorithm-based models	System Activation	Dispatcher
		Patient's vital data; GIS information; EHR information; Ambulance availability; Hospital information;	algorithm-based models	Dispatch	Dispatcher; On-scene Care Providers (rescue team and paramedics)
TRANSPORT	Transport Time	Patient's vital data; EHR information;	algorithm-based models	Intervention	On-scene Care Providers (rescue team and paramedics)
		Patient's vital data; EHR information;	algorithm-based models	Early Triage	On-scene Care Providers (rescue team and paramedics); Allied Health Workers
FACILITY	Length to Stay	Patient's vital data; EHR information;	algorithm-based models	Intervention (Assessment; Resuscitation)	On-facility Care Providers (physicians and nurses)
		Patient's vital data; EHR information;	algorithm-based models	Triage	Allied Health Workers

3.3 Development

The development is an iterative process where the tenatative design is continously improved. The tenantive design presented in Section 3.2 will be improved through multiple design cycles. The final PICT-DPA will be presented in Section 4. To demonstrate the usability of the PICT-DPA, a second artifact, a prototype EC-CDSS will be built using the PICT-DPA as the backend data processing engine. The front end of the prototype system will have different interfaces with different decision scenairos for different stakeholders. The prototpye system will be presented in Chpater 5.

3.4 Evaluation

It is essential to rigorously demonstrate the usability, quality, and efficiency of a design artifact through well-executed evaluation methods. In this dissertation, the PICT-DPA is first evaluated using descriptive scenarios to show how it works. Further, the PICT-DPA is instantiated into a prototype EC-CDSS to demonstrate the feasibility and usability of PICT-DPA. The prototypes system will use simulated data to evaluate whether the PICT-DPA enhances the quality attributes of EC-CDSS. To assess the usefulness of the PICT-DPA, semi-structured interviews will be conducted with different stakeholder groups. The evaluation will be presented in Chapter 5 and Chapter 6.

3.5 Contributions

This dissertation makes both knowledge and practical contributions. The first knowledge contribution is the identification of the quality attributes and metrics for EC-CDSSs. The second contribution is the creation of PICT Quality Attribute model that explains how EC-CDSSs may improves PHOs through the relationships between each quality attribute and PHOs. On the other hand, the PICT-DPA and the PICT-EDSS can be used by the practitioners and researchers to guide the design, implementation, and evaluation of integrative EC-CDSSs or other decision support systems with similar quality attributes.

Chapter 4 PICT-DPA

Through multiple design cycles, the proposed data processing architecture, PICT-DPA, was finalized as shown in Figure 6. The architecture comprises three subsystems: the data extraction system, the data integration and transmission system, and the insight delivery system.

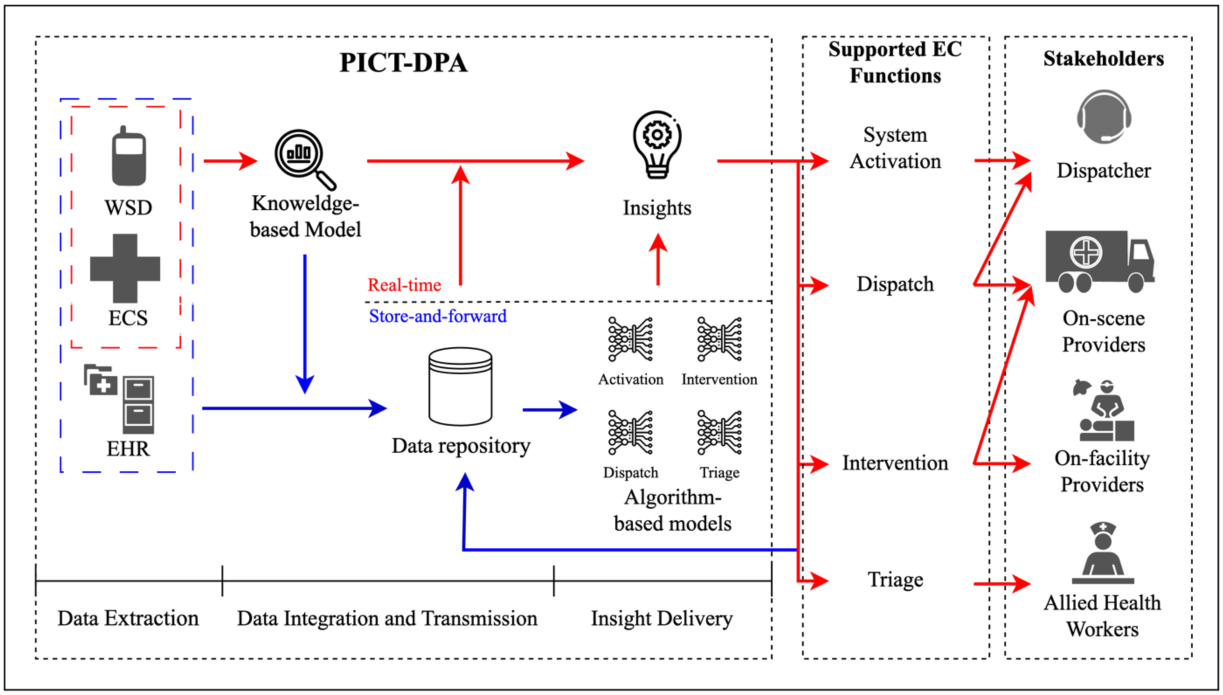


Figure 6. The PICT-DPA

The data extraction system is needed to extract necessary data required for either knowledge- or algorithm-based models (Requirement #1). Based on a systematic literature review, three heterogeneous data sources have been identified: **Wearable Sensing Devices (WSD), Emergency Care Systems (ECS), and Electronic Health Records (EHR).** Additional data sources may be added with future technological advancements.

The data integration and transmission system consists of two layers: a real-time processing layer and a store-and-forward layer. This design is inspired by the Lambda architecture, a leading industry data processing architecture that provides access to batch-processing and streaming-processing methods with a hybrid approach (Marz & Warren, 2015). The real-time processing layer is essential for the time-sensitive

EC-CDSS to deliver necessary information within a limited time window for saving a patient's life (Barcelos et al., 2015). However, real-time data processing is expensive and sacrifices throughput. Thus, this layer should be event-driven and only activated when needed. Information that is not time-sensitive can be transmitted through the store-and-forward layer with a traditional batch data processing pipeline. The store-and-forward layer transforms and integrates heterogeneous data into a data repository, satisfying Requirements #5 and #6. Meanwhile, the real-time processing layer is immediately activated once the knowledge-based model filters abnormal vital data, fulfilling Requirements #2 and #4.

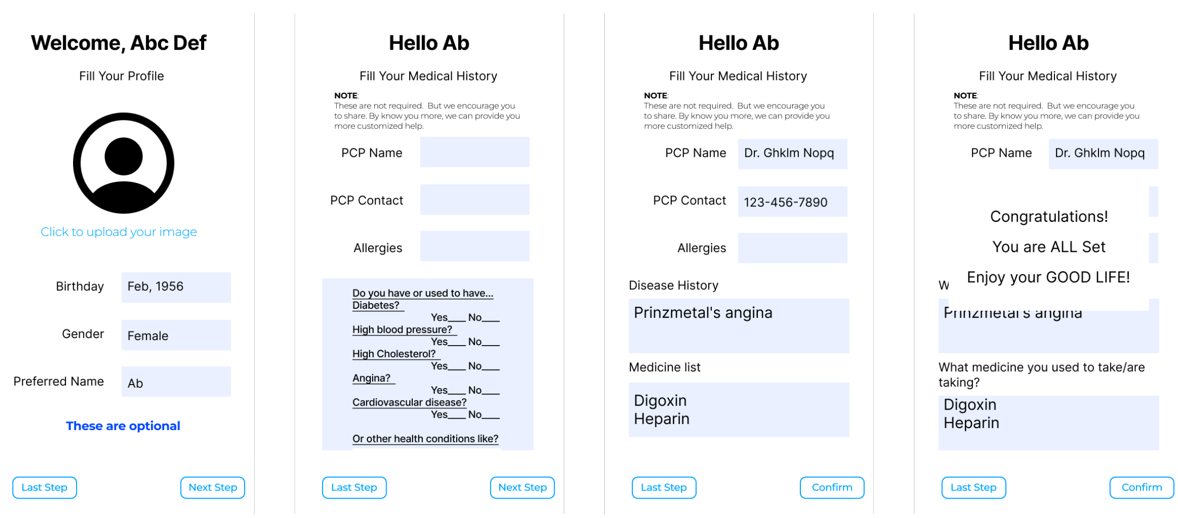
The insight delivery is defined as "*delivering findings that are material, newsworthy, and actionable to stakeholders to remain relevant and add value in a data-rich environment*" (Bryan, 2020). Thus, the insight delivery system processes information from the data extractoin and transmission systems using algorithm-based models and delivers the insights to stakeholders in a clear and meaningful way, satisfying Requirement #7. In store-and-forward layer, the data from the data repository are used to train four algorithm-based models for four different EC functions, while in real-time layer, the data are used to implement those algorithm-based models for decision-makings. The insight delivery subsystem satisfies all stakeholders' information needs in one platform, meeting Requirement #3.

4.1 Data Extraction Subsystem

The data extraction subsystem should be able to extract data from three data sources: Wearable Sensing Devices (WSD), Electronic History Records (EHR), and Emergency Care Systems (ECS). The WSD is a critical source of monitoring patient vital signs. It has wireless bio-sensors capable of measuring vital parameters such as heart rate, blood pressure, insulin levels (Piwek et al., 2016). Additionally, built-in GPS sensors of WSD can also be utilized to track locations of patients (Rodriguez et al., 2005; Tartan et al., 2018). Those data are important in training algorithm-based models to determine the need for medical emergency care, appropriate interventions, and triage.

EHR and ECS data are also crucial for training algorithm-based models. Studies have shown that EHRs have great potential to improve ED efficiency (Wang et al., 2021). The ECS data include incident data collected through the ECS process, such as clinical observations, medications administered, or procedures performed (Poulymenopoulou et al., 2011). Emergency room and ambulance data are also included in the ECS, such as the number of available emergency room beds, the count of ambulances available in ambulance companies, and ambulance type (e.g., Advanced Life Support, Basic Life Support). These data, along with vital data and geolocation data from WSD, can be used to train the dispatch model that identifies the best destination emergency room and provides on-scene care recommendations based on patient's situation.

During the first design cycle, experts highlighted the challenges with EHR data collection, particularly in the US, where EHR sharing among different medical systems is almost impossible. There is a high chance that EHR is not available for a patient newly transimitted to an emergency room. Thus, a mobile application is proposed to allow patients input their own medical history, medications, and allergy information in the second design cycle. The third design cycle then added the privacy policy as the protection of the patient's data and primary care physician (PCP) contact information.



1 2 3 4

Figure 7. Interfaces of Patient's End Mobile Application

Figure 7 shows an example of interfaces for patient to input their medical historical record into the mobile application. First, a patient needs to sign up for the EC-CDSS service (see Figure 7.1). After signing up, the patient will share their primary care physician's (PCP) contact information, provide any potential allergies, and fill a health history questionnaire (see Figure 7.2). The patient's medical history and medicine list will be summarized automatically based on the information from the health history questionnaire (see Figure 7.3). The patients will then receive an 'ALL SET' message when they are ready to use the application (see Figure 7.4). It is important to note that the information sharing is entirely voluntary.

4.2 Data Integration and Transmission Subsystem

The data integration and transmission subsystem includes two layers (store-and-forward layer and real-time processing layer). Such a design ensures timely interventions needed for emergency patients while reducing the data processing costs. Each layer is described in detail below.

4.2.1 Store-and-Forward Layer

The store-and-forward layer first integrates data extracted from the data source system using informatics exchange protocols/standards such as Health Level Seven (HL7) to ensure data consistency (HL7, 2016). Single-payer healthcare systems such as Singapore and Australia have unique identifiers for all patients, thus making the data integration from different source systems straightforward. However, in the US, a patient may have multiple identification numbers across different systems, making data integration much more complex. Health Data Integration (HDI) software may be used to link patient records, accounting for basic data entry errors and misspellings.

The store-and-forward layer is responsible for processing the data at batch intervals and loading the integrated data into a data repository. To optimize the data store, a dimensional data model can be used before forwarding data to algorithm-based models. Each algorithm-based model requires its own dimensional model design. For example, an algorithm-based model for treatment intervention requires patient profile data, vital data, EHR data, and the treatment methods. A dimensional design (see Figure 8) for this model can include a fact table that represents the emergency room operational transactions and different dimensional tables that store related data needed for determining treatment options. This data model makes it easy to query and create needed data input for algorim-based models.

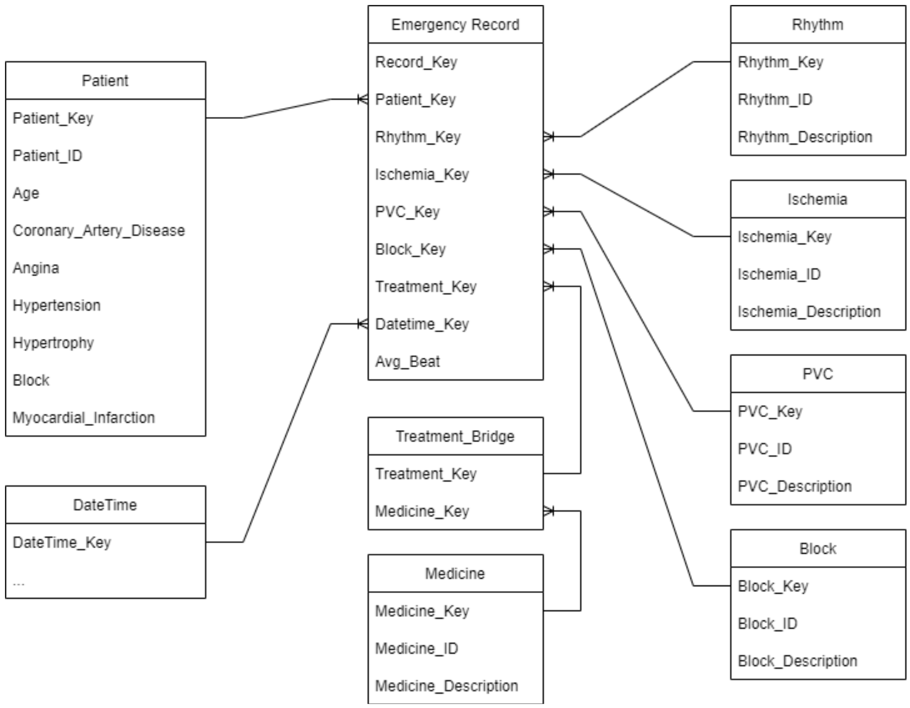


Figure 8. The Example of Dimensional Model for Treatment Interventions

4.2.2 Real-time Processing Layer

The real-time processing layer is an event-driven process, where data extracted from WSD is filtered in real-time through a knowledge-based model. An event is triggered when the knowledge-based model considers a vital indicator to exceed or fall below a predetermined threshold, signaling a possible emergency case.

The knowledge-based model establishes thresholds for vital data tailored to the physiological status of each patient. The model can be expressed as rules (see Figure 9). It is important that the indicators in the knowledge-based model are limited to vital data collected from the WSD. For example, the WSD monitors the patient's real-time heart rates. If the heart rates are stable within the preset threshold range (false condition), the data will not be transmitted in real-time. Instead, they will be stored in the WSD's memory. If the knowledge-based model triggers an abnormal event, such as the heart rate exceeding or falling below a threshold, the real-time data processing will be activated to transmit the abnormal vital data for further analysis by the algorithm-based model.

Condition: avg rate < personal min rate and gender = 'female' and age > 65
Action: send data to server in real-time
False condition: min rate < avg rate < max rate
Action: store the data and send to database regularly.

Figure 9. Example of Knowledge-based Model Rules

When an event occurs, in addition to the vital data, ECS data (e.g., emergency room capability, ambulance availability), along with a patient identifier, are also transmitted in real-time. The patient identifier will be used to retrieve the patient's medical historical records from the data repository. The extracted data are subsequently evaluated by algorithm-based models to determine whether the patient needs emergency services and to recommend an optimal dispatch plan if needed.

During the fourth design cycle, experts suggested that using the knowledge-based model to determine whether a patient needs emergency medical assistance may not be accurate. For example, in some cases, patients may experience discomfort even when their vital signs appear normal. To address this issue, an active emergency care service feature may be introduced by adding an "activate" button in the mobile application. The activate button allows patients to initiate real-time vital data transmission without the triggered event.

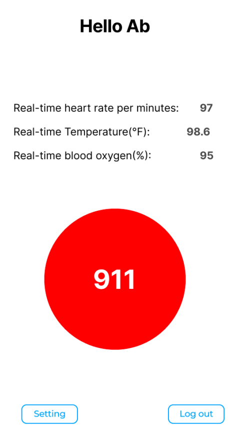


Figure 10. The Activate Button in Patient's Mobile Application

After the "event" is triggered by either the knowledge-based model or the activate button in the mobile application, extracted vital data, location data, and ECS data can be transmitted to the algorithm-based model via API (Tilkov and Vinoski, 2010). Most APIs require an internet connection to function properly. Thus, the wearable sensing device (WSD) uses two methods to achieve the internet connection. First, an internet-enabled chip, such as a Wi-Fi receiver for transmitting data directly in Wi-Fi environments, or a cellular service provider for transmitting data directly when there is a cellular signal, can be added to the WSD (Majumder et al., 2017). However, this approach may increase the cost of the WSD. The second option is to use Bluetooth to transfer data to a nearby mobile phone and then transmit the data using the phone's cellular signal. However, this approach may increase the data transmission time.

4.3 Insights Delivery Subsystem

The insights delivery subsystem includes two main components: four algorithm-based models and model scoring. Each component is described in detail below.

4.3.1 Algorithm-based Models

Four algorithm-based models are trained using data from the store-and-forward layer, with each model supporting a specific EC function, which are system activation, dispatch, treatment, and intervention. The algorithm-based models are trained using artificial intelligence, machine learning, or other statistical learning methods to discover patterns and insights. They are essential for the success of EC-CDSS (Wang et al., 2016; Valenzuela Espinoza et al., 2016; Albahri et al., 2019, Latifi et al., 2007; Tian et al., 2014).

Using the example of treatment interventions from Section 4.2.1, it is possible to train classification models with the aim of predicting the suitability of specific medications for various treatments (see Figure 11.1). The performance of those models is monitored and may be retrained with new data.

During the fourth design cycle, experts suggested that the PICT-DPA should be able to use existing trained models instead of training of new models each time it is installed. This would enable the PICT-DPA to serve across a range of existing EC-CDSSs. Many algorithm-based models with proven performance are available in the lietrature (Wen et al., 2008, Barcelos et al., 2015). Those models may be utilized by the PICT-DPA.

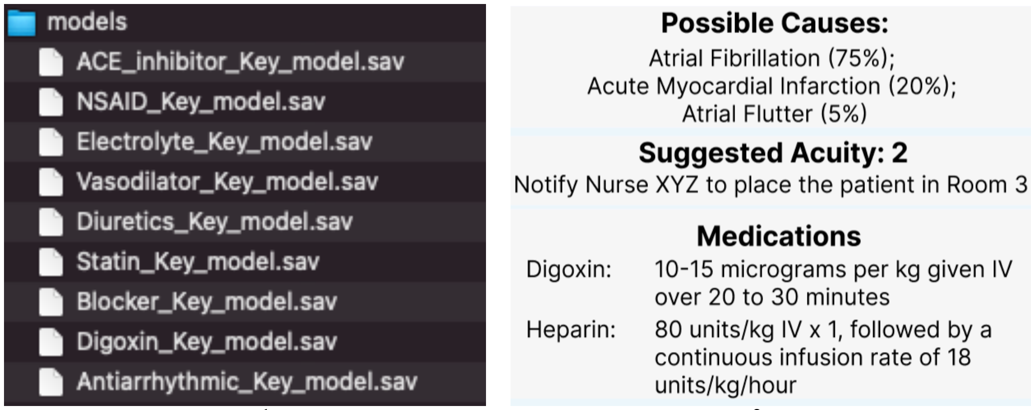


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Figure 11. Example of Algorithm-based Models and Scoring Results

4.3.2 Model scoring

Finally, insight delivery is achieved through model scoring in the real-time layer. Model scoring is the process of applying a trained algorithmic model to new data for insights. The model scoring process involves the application of trained algorithm-based models to the abnormal vital data received from the real-time processing layer. The output of this process provides insights in the form of decision-making recommendations that can be utilized by various stakeholders. Figure 11.2 depicts an example of recommendations related to diagnosis, triage, and interventions.

Through discussions with experts during the fifth design cycle, the recommendation for causes was updated with all possible causes of patient's conditions with their likelihood. This will provide care providers with valuable cues for more comprehensive and accurate assessments because different causes may present similar symptoms due to varying factors such as age and gender.

4.4 An illustration example of PICT-DPA

This section describes the overall data processing of PICT-DPA using an illustrative example, where a patient has registered with a healthcare system that employs a PICT-DPA EC-CDSS. The patient is asked to download a mobile application and voluntarily upload their medical historical records. The records are sent to the data repository along with the ECS data through health informatics exchange protocols/standards. The PICT-DPA also generates a patient-specific identification number that is bound to the patient's WSD. The patient's WSD data is sent to the data repository in batches through the store-and-forward layer with the ECS and EHR data. Those data are used to train four different EC-directed algorithm-based models.

When the knowledge-based algorithm identifies abnormal vital data from the WSD, an emergency event is triggered, where the vital data and ECS data are transmitted through the real-time processing layer. The algorithm-based models would provide real-time scoring using that data and the specific EHR data from repository to provide decision support recommendations for different stakeholders. In this way, the PICT-DPA reduces the costs of real-time data transmission for larger datasets while increasing decision-making speeds through real-time scoring.

4.5 The design cycles of PICT-DPA

The design of the PICT-DPA was an iterative process through repetitive, extensive design and validation discussions with experts and stakeholders (see Figure 12). Each design cycle resulted in updates to the PICT-DPA design. In addition to identified stakeholders, other experts included various types of managers responsible for budgeting or using EC-CDSS systems, such as managers of ambulance companies and directors of emergency care.

The final PICT-DPA involved five design cycles. During the first design cycle, the validity of the knowledge-based model was questioned due to its reliance on the same heartbeat ranges as thresholds for everyone. Experts pointed out that these thresholds would vary depending on gender, age, and underlying diseases. As a result, the knowledge-based model was updated by incorpoerating personal factors.

During the second design cycle, experts pointed out that sharing EHR across multiple systems within the complex healthcare system in the US was almost impossible. Therefore, a mobile application was proposed to allow patients to voluntarily share relevant health information (see Figure 7). This iteration demonstrates the significance of context in the design process (Bashiri et al., 2019).

The third design cycle identified privacy as a major concern. Furthermore, in cases where a patient does not want to provide their medical history, sharing their primary care physician's (PCP) information may be useful. As a result, a policy statement was added to inform patients about data security and privacy protection, and an additional required field was added to capture their PCP's contact information.

The fourth design cycle resulted in two improvements. Firstly, the PICT-DPA may not be used as a new implementation due to the cost of replacing the existing systems. Therefore, the updated PICT-DPA can be embedded into any existing EC-CDSS through open-source APIs. Secondly, in the case of a false negative (i.e., when a patient needs emergency service but the system does not activate), a red button has been added to the mobile application so that the patient can trigger the emergency services by themselves .

In the final design cycle, care providers pointed out that a single recommendation for diagnosis and treatments was not sufficient. Instead, all possible causes and their probabilities are added to the recommendation screen.

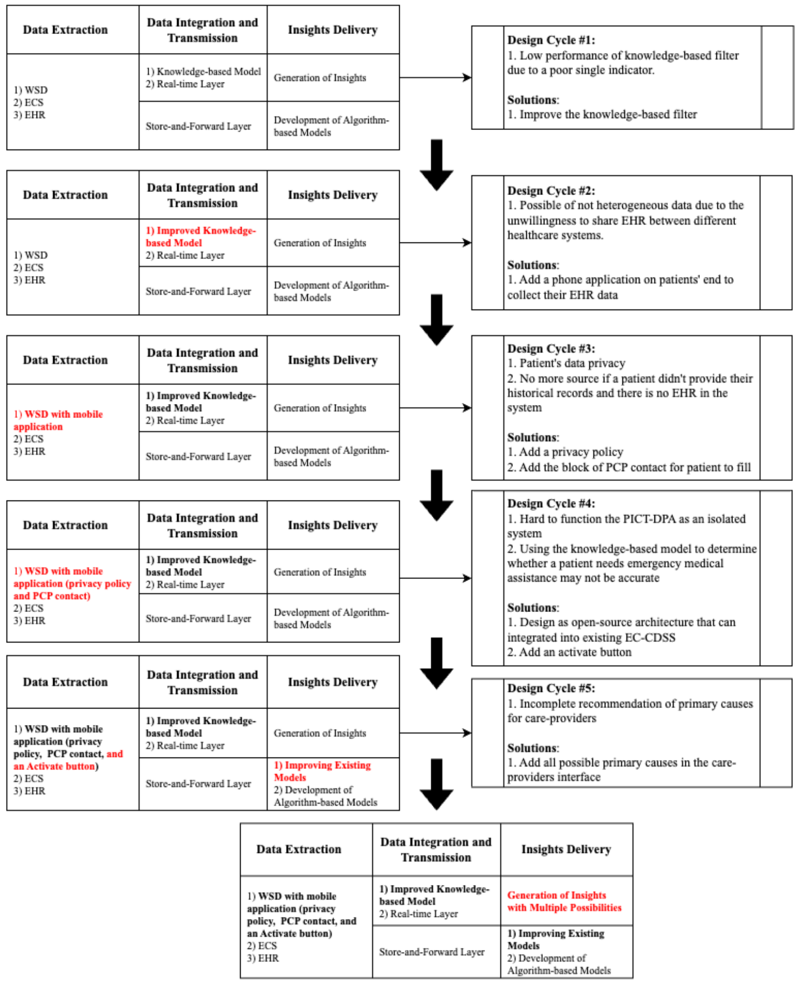

Figure 12. PICT-DPA Design Cycles

Chapter 5 PICT-EDSS: An instaition of PICT-DPA

In Chapter 4, PICT-DPA is evaluated using illustrative examples. As an abstract data processing architecture, the feasibility and usability of PICT-DPA need to be assessed through its instantiation in a system. Thus, this dissertation includes a second artifact, PICT-EDSS (PICT-enabled Emergency Decision Support System). PICT-EDSS is an integrated EC-CDSS prototype that uses PICT-DPA as the data processing architecture. The system includes decision support for different stakeholders as shown in PICT-DPA. Due to the lack of real-world data from the ECS system, the prototype only includes two data sources: WSD and EHR. The system architecture is shown in Figure 13. The data processing of PICT-EDSS implements PICT-DPA with two layers for data integration and transmission. First, the normal vital data extracted from WSD is integrated with EHR data and transmitted to a centralized dimensional data repository in batches through the store-and-forward layer. The integrated data is used to train algorithm-based models. The abnormal data identified by the knowledge-based model will trigger the real-time data transmission and integration to model scoring and insight delivery.

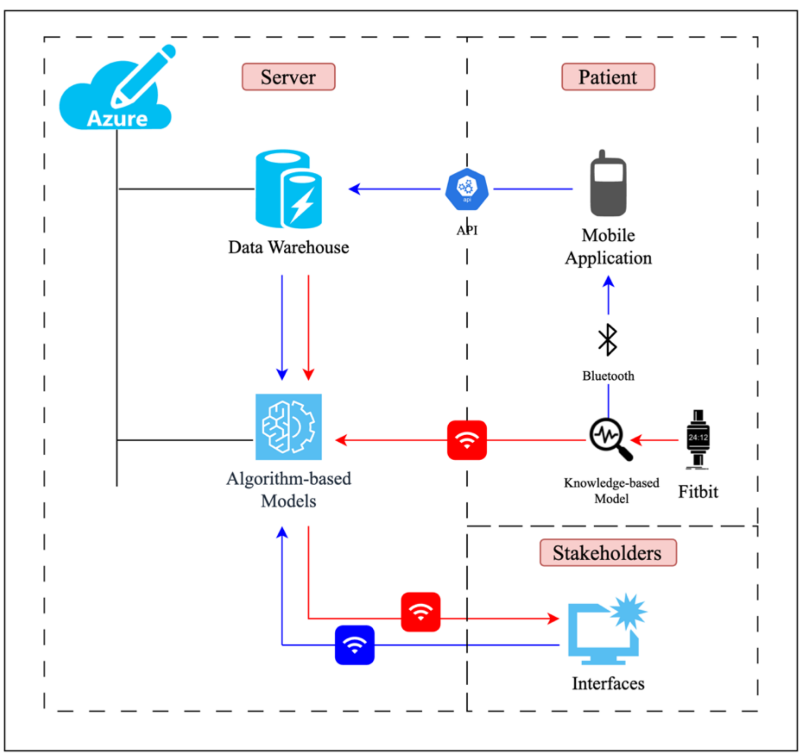

Figure 13. The Architecture of PICTEDS

The prototype system focuses on acute atrial fibrillation, atrial flutter, and premature ventricular contraction, the top three cardiovascular disease (CVD) as examples for the emergency care service due to reasons. Firstly, they carry high relative risks of CVD, which is currently the leading cause of acute death that is mostly treated by emergency care services. Secondly, the vital data required for identifying those CVD symptoms has been reliably tracked by WSDs. In building the prototype system, Fitbit smartwatches are used as WSDs because of their ability to provide accurate heart rate and ECG reports. Lastly, there exist several trained machine learning models with demonstrated high accuracy in identifying those CVD events. More specifically, the prototype system incorporates algorithm-based models for system activation that are built upon an existing machine learning model created by Rodriguez et al. (2005) to identify acute atrial fibrillation, atrial flutter, and premature ventricular contraction.

5.1 Back-end Technology

The PICT-EDSS was implemented on a test server environment in Azure SQL Server to store integrated data and algorithm-based machine learning models. The data repository uses a star schema for efficient and effective integration and analysis of large amounts of data. The star schema includes a fact table for emergency room operational transactions, where each record contains the patient's basic profile and historical record keys to connect with related dimension tables. Additionally, the fact table also stores the real-time vital data transported from the WSD.

5.2 Data Extraction System

As there is limited real-world data for EHR and ECS, Monte Carlo simulation was used to generate sufficient data for the prototype system. In building PICT-EDSS, a total of 1,212 patient records were used, including 412 real-world records obtained from four data sources, and 800 simulated records generated using Monte Carlo simulation. The four data sources are the Sudden Cardiac Death Holter Database (Greenwald, 1986), Lobachevsky University Electrocardiography (Kalyakulina et al., 2020), MIT-BIH Arrhythmia Database (Moody et al., 2001), and Long-Term ST Database (Jager et al., 2003).

Each data source provides a different number of ECG records from emergency patients and non-emergency individuals. These records also contain information on whether the patient received emergency treatment, their EHR data, and intervention data for acute atrial fibrillation treatment. As the data comes from four different databases, the data format is not consistent. After being reviewed by multiple experts, the data was combined into one final dataset with a unified format for simulation purposes. The metadata of the final dataset for simulation is shown in Table 9.

Table 9. Data Dictionary of Sample Dataset for Simulation

Features	FeatureType	DataType	Distinct	Simulation	Simulated Range	Validation
Dispatch	Target	Binary	2	N/A		
Need Dispatch	Target	Binary	2	N/A		
Gender	Profile	Binary	2	Crude Monte Carlo	M/F	Distribution
Age	Profile	int64	72	Crude Monte Carlo	average or median	Variance
Coronary_Artery_Disease	EHR	Binary	2	Crude Monte Carlo	Yes/No	Distribution
Angina	EHR	Binary	2	Crude Monte Carlo	Yes/No	Distribution
Hypertension	EHR	Binary	2	Crude Monte Carlo	Yes/No	Distribution
Hypertrophy	EHR	Binary	2	Crude Monte Carlo	Yes/No	Distribution
Block	EHR	Binary	2	Crude Monte Carlo	Yes/No	Distribution
Myocardial_Infarction	EHR	Binary	2	Crude Monte Carlo	Yes/No	Distribution
Rhythm	Vital Data	Binary	8	Biased Sampling	Based on age, sex	Distribution
Ischemia	Vital Data	Binary	2	Biased Sampling	Based on age, sex	Distribution
PVC	Vital Data	Binary	2	Biased Sampling	Based on age, sex	Distribution
Block_Now	Vital Data	Binary	2	Biased Sampling	Based on age, sex	Distribution
Avg_Beat	Vital Data	float64	381	Importance Sampling	Based on profile and other vital data	Variance
Digoxin	Intervention	Binary	2	Biased Sampling	Based on profile and vital data	Distribution
Antiarrhythmic	Intervention	Binary	2	Biased Sampling	Based on profile and vital data	Distribution
Vasodilator	Intervention	Binary	2	Biased Sampling	Based on profile and vital data	Distribution
NSAID	Intervention	Binary	2	Biased Sampling	Based on profile and vital data	Distribution
Blocker	Intervention	Binary	2	Biased Sampling	Based on profile and vital data	Distribution
Statin	Intervention	Binary	2	Biased Sampling	Based on profile and vital data	Distribution
ACE_inhibitor	Intervention	Binary	2	Biased Sampling	Based on profile and vital data	Distribution
Electrolyte	Intervention	Binary	2	Biased Sampling	Based on profile and vital data	Distribution

As described earlier, Fitbit smartwatches are used to monitor and capture vital data. Fitbit uses Bluetooth as its transmission mode, sending collected data to the mobile application in a nearby smartphone. The mobile application also includes a knowledge-based filter model that determines the normalcy of the vital data.

5.3 Data Integration and Transmission Subsystem

The simulated heterogeneous data from Section 5.2 is integrated and transmitted into the data repository through the store-and-forward layer. The store-and-forward layer is implemented following the traditional ETL process. If a new patient does not have any related EHR data, the patient would sign up for the PICT-EDSS service using its client mobile application and then fill in relevant EHR information. Simultaneously, a unique identifier for the patient is generated.

As described earlier, patient vital data extracted from the Fitbit is sent to the knowledge-based filter model in the mobile application. The filter model is configured with a pre-set heart rate threshold range. When the patient's heart rate is within the normal range, the vital data is stored in the mobile application and transmitted via the batch processing through the store-and-forward layer. If the patient’s heart rate is out of the threshold range, it will be flagged as abnormal through the real-time layer. The patient’s EHR data will be extracted at the same time from the data repository and integrated with the abnormal vital data using a pre-generated identifier. The integrated data will then be transmitted in real-time to the pre-trained algorithm-based models.

5.4 Insights Delivery Subsystem

The PICT-EDSS insights delivery subsystem includes two algorithm-based EC-CDSS models: the system activation model and the treatment model. The ECS system activation model is trained using the WSD vital data (e.g., average heartbeat, rhythm type, Ischemia, Premature Ventricular Contraction and Cardiovascular Blockage), demographic data (e.g., gender and age), and medical historical data as input, with dispatch sent as the target. These data are proven to effectively determine whether a patient is suffering from acute cardiovascular disease and requires emergency care services (Rodriguez et al., 2005; Oresko et al., 2010; Rasid et al., 2005; Chen et al., 2007; Barcelos et al., 2015). Additionally, a new variable named ‘Need Dispatch’ is created with the help of experts to evaluate the accuracy of the ‘Dispatch’ column. The treatment decision model is trained using the EHR and vital data.

To deliver insights to different stakeholders, the PICT-EDSS displays the model scoring results through a web-based application with user-friendly interfaces. All stakeholders will first register with different roles. The roles include administrators (who have the authority to edit the data and manage other stakeholder roles), dispatchers, on-scene/on-facility care providers, and allied health workers. Once registered, the user can then log into the system to see decision support results provided by the system with respect to their roles. Figure 14 shows the login page.

Figure 14. PCIT-EDSS login page

The PICT-EDSS provides insight deliveries for two types of stakeholders currently, namely dispatchers and care providers. Decision support functions for other stakeholders will be added later. Next, the decision support functions for each stakeholder type will be explained.

5.4.1. Dispatchers

After logging into the system, the dispatcher is presented with a dashboard featuring a map-based interface. The dashboard provides real-time ECS data, including the availability of emergency rooms (e.g., the number of available beds, doctors, and nurses) (see Figure 15.1) and ambulances (e.g., the number of available ambulances and their types) (see Figure 15.2).

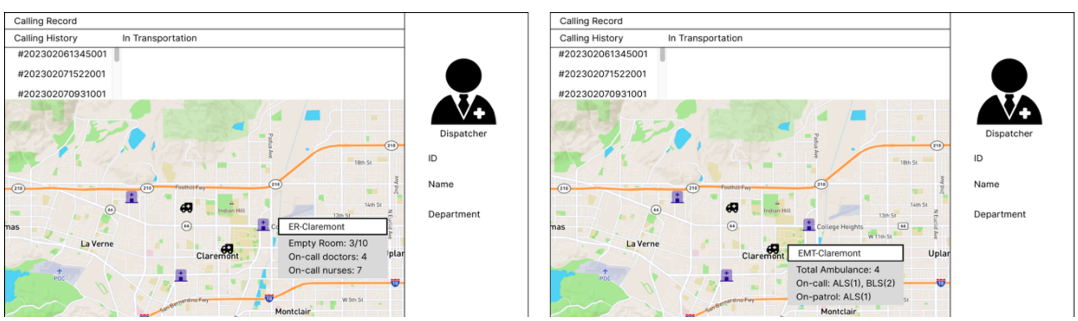

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Figure 15. The dispatcher dashboard

Whenever abnormal vital signs are detected in a patient, their vital signs and geolocation data will be displayed on the dispatcher's real-time dashboard map (see Figure 16.1). The activation algorithm-based model immediately scores the data to determine whether emergency services need to be activated. If the scoring results do not show a need for system activation, the dispatcher may call the patient to confirm their status and determine if other services are required. Once the patient confirms the alert, the dispatcher can remove it and arrange for non-emergency transportation to the patient's preferred hospital if necessary (see Figure 16.1).

Figure 16. Screens that deliver different insights to the dispatcher

If the scoring results show that emergency services are needed, the dispatcher must contact the patient to activate the service, and the patient must confirm (see Figure 16.2). An exception is when the patient is unconscious. The dispatch algorithm-based model analyzes the data and recommends the best transportation plan, such as dispatching the nearest available ambulance (ALS or BLS) to the nearest emergency room/hospital via the fastest route (see Figure 16.3). During patient transport, the dispatcher can click on the patient's avatar on the map to view the patient's real-time vital signs and transportation status. At this point, the patient's data is not limited to the vital signs provided by the WSD but also includes more accurate vital signs provided by the ambulance, which can be used to better assess the patient's condition. The transportation status indicates how long it will take for the ambulance to pick up the patient and how long it will take to arrive at the designated hospital after picking up the patient (see Figure 16.4).

Throughout the activation and transport process, the privacy and security of patient data is strictly protected based on the rules of the Health Insurance Portability and Accountability Act (HIPAA) (US Department of Labor, 2009). For example, sensitive information, such as the patient's name and address, is not displayed. The dispatcher can only access the patient's temporary location when abnormal vital signs are detected by the WSD, along with basic information such as age and gender.

5.4.1. Care providers

Once patient transportation begins, care providers in the emergency room, are alerted with information about the incoming patient. Before the patient arrives at the medical facility, care providers can access the patient's basic information and estimated time of arrival via the dashboard (see Figure 17.1). By clicking the 'view detail' option, they can further access three different types of information: Electronic Health Records (EHR), real-time condition updates, and recommendations.

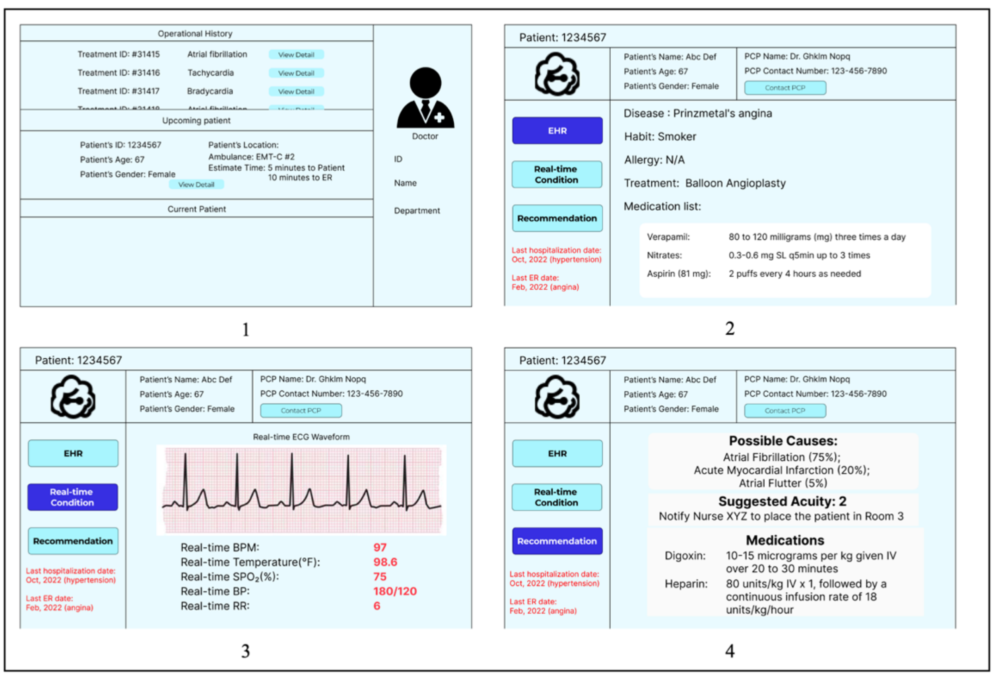


Figure 17. Insights Delivery of Care-providers

Clicking the 'EHR' button leads to the patient's complete medical history, including their medical conditions, habits, allergies, and current medication lists (see Figure 17.2). The 'Real-time situation' section presents real-time vital signs collected from both the WSD and ambulance equipment (see Figure

17.3). The 'Recommendation' section displays the scoring results from the intervention algorithm-based models. These decisions include possible causes of the patient’s main complaints, recommended medication dosages, and triage recommendations for all medical personnel, including doctors, nurses, and allied health workers (see Figure 17.4). All possible causes of the patient’s main complaints are listed along with their likelihood percentages based on expert recommendations.

5.5 Functional Evaluation of PICT-EDSS

The feasibility and usability of the PICT-EDSS were evaluated through a series of experiments. Several trials on different WSDs were performed to assess data transmission using PICT-DPA. The knowledge-based filter model was disabled at first to evaluate the store-and-forward transmission of vital data from WSD to the data repository through APIs. The PICT-EDSS successfully extracted all vital data from the WSD and transmitted it to the data repository, thus meeting Requirements #1, #3, #5, and #6. The knowledge-based filter model was then activated to evaluate real-time data transmission. Volunteers wearing Fitbit Smartwatch did quick cardio exercises (such as sprinting or high knees) to increase their heartbeats above the threshold set in the knowledge-based filter model. The PICT-EDSS successfully captured all abnormal data, thus meeting Requirements #2 and #4. Lastly, the PICT-EDSS successfully delivered scoring results of algorithm-based models, thus meeting Requirement #7.

The systematic literature review identified the number of heterogeneous data sources and the number of information exchange protocols/standards as the metrics of interoperability. The PICT-EDSS has two data heterogeneous sources (WSD and EHR) and one information exchange protocol, making it highly interoperable.

Additionally, the accuracy of decisions on 'Dispatch' was evaluated to determine whether the PICT-EDSS provides valid insights. The baseline result (see Table 10) was based on the 412 real-world records from systems that did not use PICT-DPA. Eight hundred simulated records were used to test the PICT-EDSS, and the results are presented in Table 11. All decisions in the 800 simulated records were confirmed by medical experts. When making the dispatch decision, the PICT-EDSS had a higher precision of 99.2%, a higher recall of 100%, and a higher overall accuracy of 99.5% compared to systems without PICT-DPA, which had a precision of 87.1%, a recall of 76.4%, and an overall accuracy of 77.6%.

Table 10. Confusion Matrix of No PICT-DPA Data Set

Systems without PICT-DPA	Need to Dispatch	No Need to Dispatch	
Dispatch	256	79	335
Not Dispatch	15	69	84
	271	148	419
		Precision	87.1%
		Recall	76.4%
		Overall Accuracy	77.6%

Table 11. Confusion Matrix of PICT-DPA Data Set

PICT-EDSS	Need to Dispatch	No Need to Dispatch	
Dispatch	519	0	519
Not Dispatch	4	277	281
	523	277	800
		Precision	99.2%
		Recall	100%
		Overall Accuracy	99.5%

The PICT-EDSS was also evaluated for reliability, which measures the extent to which a system provides consistent guidance or recommendations on repeated trials (Scott et al., 2019). Reliability was assessed using chance-corrected agreement κ statistics (Everitt et al., 1983). The PICT-EDSS achieved a higher κ value of 98.2% compared to systems without PICT-DPA, which had a κ value of only 42.59%.

Lastly, the timeliness of PICT-EDSS, a desired quality attribute, was evaluated using data and analysis latency (see Section 2.2.1.4). Data latency includes real-time data extraction from WSD, integration, and transmission to the data repository, and delivery of insights from the server to the system's front end. Analysis latency includes the time taken to implement knowledge-/algorithm-based models. Based on literature (Wu et al., 2017), data extraction from WSD and transmission to the algorithm-based model takes an average of 5 seconds, and insight delivery takes an average of 1.5 seconds for EC-CDSS. For the PICT-EDSS, average data latency was 0.5 seconds, and average analysis latency was 0.956 seconds (see Figure 18). These results confirm that PICT-EDSS significantly improves timeliness, achieving one of the design goals of PICT-DPA.

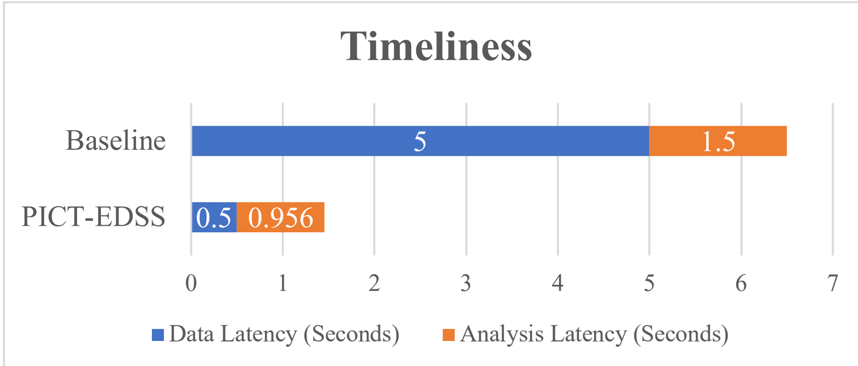


Figure 18. Timeliness of baseline and PICT-EDSS

To this end, the evaluation of PICT-EDSS prototype has demonstrated that PICT-DPA is feasible in the real-world implementation, and adopting the PICT-DPA will improves the interoperability, performance, and timeliness of the EC-CDSS system. Other quality attributes that the PICT-DPA aims to achieve require additional evaluations, which are elaborated in the next section.

Chapter 6 PICT-DPA Evaluation and Discussion

This chapter aims to evaluate the impact of PICT-DPA on the cost of EC-CDSS, which is not evaluated in Chapter 5. Additionally, whether the end users would be willing to adopt the PICT-DPA and its impact on Patient's Health Outcomes (PHO) need to be evaluated. Therefore, it is necessary to observe how users interact with the PICT-EDSS and collect their feedback through semi-structured interviews.

The participant recruitment started after the approval from the Institutional Review Board (IRB) of Claremont Graduate University. A participant must be one of the EC-CDSS stakeholders, either having actively engaged in decision support processing in emergency care context or being responsible for budgeting or using EC-CDSS systems. A total of 12 participants agreed to participate in this interview, and 10 participants were interviewed after watching the demo of PICT-EDSS. The participants include one emergency room manager and one ambulance company managers, six care providers (doctors and nurses), and two dispatchers. Their demographic information is listed in Table 12.

Table 12. Participants Profile

Participant ID	Role	Organization represented	Gender	Years of Experience
Participant 1	Manager	Emergency Room	Male	33
Participant 2	Manager	Ambulance Company	Male	12
Participant 3	Care Providers (Doctors)	Emergency Room	Male	10
Participant 4	Care Providers (Doctors)	Emergency Room	Female	4
Participant 5	Care Providers (Doctors)	Emergency Room	Female	33
Participant 6	Care Providers (Nurses)	Emergency Room	Female	16
Participant 7	Care Providers (Nurses)	Emergency Room	Female	6
Participant 8	Care Providers (Nurses)	Emergency Room	Male	3
Participant 9	Dispatchers	Ambulance Company	Male	8
Participant 10	Dispatchers	Ambulance Company	Male	2

Each interview was approximately one hour, including a twenty-minute demonstration of PICT-EDSS. During the interview process, all participants were asked a series of standardized questions to evaluate the PICT-DPA and PICT-EDSS in three sections. The first section focused on the comparison between quality attributes of existing EC-CDSS and the PICT-EDSS. The second section asked their willingness to adopt the PICT-DPA within in their system. The last section investigated their perceptions on how the PICT-DPA may improve PHOs. The standardized questions are listed in Appendix 6. The detailed results and relevant discussions are presented below.

6.1 Quality Attributes

6.1.1 Interoperability

Interoperability is a key feature of EC-CDSS, as it allows for the exchange and integration of heterogeneous data from multiple sources, thereby enhancing decision support capabilities (Handler, 2004; Omoogun et al., 2017). The successful implementation of PICT-EDSS has confirmed that PICT-DPA can provide interoperability for an integrated EC-CDSS. The interview results further confirm that an interoperable EC-CDSS can provide better performance and increase timeliness than the traditional approaches. For example, multiple care providers mentioned that interoperability can improve decision-making performance by providing credible and comprehensive medical data. As the Participant 5 stated, decision-making based on heterogeneous data can:

> *…make the suggestion more believable, especially with those detail vital data, historical records, and comprehensive medical list.*

Almost all participants highlighted the interoperability of the PICT-DPA can save time on capturing and sharing information. For instance, the real-time emergency room capability and ambulance availability data from the ECS can save communication time between dispatcher and the emergency room, as Participant 9 stated:

> *…with this architecture, the dispatchers don't need to confirm the destination of emergency room by calling hospital and ambulance company back and forth.*

The interview findings of interoperability align with previous literature that interoperability can improve EC-CDSS performance by yielding accurate data suitable for further analysis and decrease data integration time (Crilly et al., 2011). Furthermore, the findings validate the quality attribute model (see Figure 3) that highlights the interoperability has a positive impact on performance and timeliness.

6.1.2 Performance

As described earlier, the performance of EC-CDSS can be measured by two quality metrics: validity and reliability. The functional evaluation of PICT-EDSS has shown an improved performance in both metrics, which are further validated by the participants. For example, both dispatchers and doctors confirmed the validity of PICT-DPA. The Participant 10 stated,

> *It is good to know the destination hospitals and their availabilities. Because sometimes, the closest hospitals might be not available because of their emergency bypass states.*

Similarly, the Participant 4 and 5 commented,

> *I like the treatment strategy recommendation. It can give doctors some clues about diseases maybe overlooked.*
>
> *The machine learning, self-learning model, will make the precise of recommendation better and better.*

There are two reasons for the enhanced performance enabled by PICT-DPA. First, the application of both knowledge-based and algorithm-based models are proven to have better accuracy than the traditional processes that reply on the expertise of dispatchers or physicians (Wen et al., 2008; Wang et al., 2016; Latifi et al., 2007). Second, the improved interoperability of PICT-DPA means additional information to be used for decision support. Historically, dispatch decisions in ECS were made solely based on patients' main complaints without access to their medical histories. However, dispatch and transportation decisions require consideration of various factors, including injury severity, injury deterioration, and the emergency response capacity of the destination hospital (Tian et al., 2014). Moreover, physicians could only collect patients' basic vital data upon their arrival at the emergency room, resulting in delays in making treatment decisions. Therefore, there is a need for enhanced information sharing and data collection in the ECS system to facilitate timely and effective patient care, particularly with respect to transportation and treatment decisions.

6.1.3 Cost

Cost is a quality attribute for which a direct evaluation is limited due to lack of real-world data. An interviewee reported that the main barrier to the implementation of EC-CDSS is the limited funding available for emergency departments. The cost-prohibitive nature of EC-CDSS was also reported in the systematic literature review (Wu et al., 2017). Although data on the cost was limited, participants have demonstrated positive reactions and expectations to the PICT-DPA's potential in reducing the overall EC-CDSS costs. For example, the Participant 2 believed that the decreased amount of data required for real-time transmission and analysis could reduce the cost of EC-CDSS. The Participant 3 suggested that the PICT-DPA, if embedded in existing EC-CDSS, could reduce infrastructure costs.

6.14 Timeliness

Most participants identified timeliness as the key quality contribution of the PICT-DPA, especially for the dispatchers. For example, the PICT-DPA can reduce the latency of data collection and transmission between dispatchers, patients, and hospitals, as the Participant 6 mentioned,

> *... the timeliness will be improved. Especially some communication time between patient and dispatchers, and between dispatchers and ER care providers.*

The Participant 9 also stated,

> *The communication takes most of the time. The guidance does help saving some time on thinking about operation process.*

The ability of PICT-DPA to reduce communication time can be attributed to its quick data extraction from heterogeneous sources and its data integration and processing approach. For example, without PICT-DPA, dispatchers must continuously communicate with the patient and hospital to confirm the destination hospital, which often results in communication-related delays. PICT-DPA reduces the need for such communication because that information is readily available.

Furthermore, PICT-DPA can reduce the analysis latency, such as determining whether to activate the emergency service, the types of ambulance needed, and the destination emergency room, as the Participant 6 summarized,

> *It will help them to make the right decision in the shortest time.*

The results also suggest that the PICT-DPA’s impact on the analysis latency may be limited for regular emergency cases, but more impactful for complex cases, as the Participant 4 stated, *Not sure. Because experienced doctors will make the decision really quick. Maybe it will save time on patients whose condition is really complicated.*

6.2 Intention of Use

All participants confirmed their intention to use the PICT-EDSS because of it can support their needs. For care-providers, the ease-of-use is more important for their intention of use, as the Participants 3 said,

> *Yes, I would like to give it a try. There is a lot of information. The data is enough for ER doctors. And the most important thing is, this information is easy to access.*

The dispatchers appreciate the PICT-EDSS more because its integrated information, such as the Participant 2 mentioned,

> *Yes, I definitely want to use it. We have many EC-CDSSs, each used for a specific EC function, but we do not have an integrated one with enough information for everybody, especially for dispatchers.*

Similarly, the Participant 10 provided the reason for willing to use PICT-EDSS,

> *... there are a lot of features to consider, like the availability of hospitals, the patient's status, if there is a patient preferred hospital because of insurance, and also what kind of ambulance to dispatch, ALS or BLS.*

These feedbacks indicate that in addition to satisfying all quality attributes, the main reason for participants having the intention to use the PICT-EDSS is its ability to meet information needs of all stakeholders. Specifically, the information needs of the dispatchers were not considered in the traditional EC-CDSS design, as the Participant 2 said,

> *…they need more attention because they are an important connection part of the integrated system.*

This confirms with the systematic literature review finding where only 3 EC-CDSSs consider dispatch as the target EC function.

6.3 Patient Health Outcome

As discussed earlier, the ultimate goal of EC-CDSS is to improve patient health outcomes (PHOs). In an emergency event, the main metric of PHOs is the patient's survival rate (Holmén et al., 2020). The improvement of PHOs cannot be evaluated through the prototype system implementation, as it is not used in the real-world setting. In the interviews, some participants were cautious in their assessment of the extent to which the PICT-DPA could enhance PHOs and suggested that real-world implementation was necessary to gather adequate data to evaluate its effectiveness. For example, the Participant 6 explained,

> *I cannot say it will improve the PHO. Because the PHO is impact by multiple features. The effectiveness needs data to assess.*

Nevertheless, multiple participants suggested that the PICT-EDSS could enhance PHOs through expedited information transmission and more effective decision-making processes. For example, the Participants 4 mentioned,

> *Definitely. I believe with the recommendation, the doctor can have more precise treatment on patient, so that at least can keep patient alive.*

This aligns the systematic literature reviews that performance and timeliness of decision-making are key factors influencing patient health outcomes (Poulymenopoulou et al., 2012; Majeed et al., 2013; Wu et al., 2017; Preum et al., 2019). For example, according to Holmén et al. (2020), a 5-minute reduction in patient transportation time has been demonstrated to increase the survival rate by 5%. Thus, it is reasonable to expect that PICT-DPA could have a positive impact on PHOs by reducing the patient transportation time. Yet, future research is needed to evaluate how the performance of EDSS is related to the PHOs.

Chapter 7 Conclusion

This dissertation aims to identify the desired quality attributes and metrics for EC-CDSS that have not been addressed in the literature. Furthermore, this dissertation aims to create a new data processing architecture for designing and implementing integrated EC-CDSSs that have all quality attributes while satisfying the information needs of all stakeholders. To achieve the first research objective, an SLR is performed to identify quality attributes and related metrics for EC-CDSS, stakeholders of EC-CDSSs, and their related information needs. The SLR summarizes four quality attributes (i.e., Performance, Interoperability, Cost, and Timeliness) with related metrics and four types of stakeholders (i.e., dispatchers, on-scene care providers, on-facility care providers, and allied health workers) with their information needs. Additionally, a quality attribute model is developed based on the SLR to explain how the quality attributes and metrics can be used to improve EC functions and patient health outcomes (PHOs), which are the ultimate goal of ECS. To achieve the second objective, a data processing architecture, PICT-DPA, is proposed. To the best of our knowledge, PICT-DPA is the first attempt to integrate a Clinical Decision Support System and the emergency care system while considering all four quality attributes and satisfying the information needs of all stakeholders. Furthermore, the PICT-EDSS, a prototype integrated EC-CDSS, was developed to validate the feasibility and usability of PICT-DPA. The PICT-DPA is also evaluated through end-user interviews, and the findings confirm that the PICT-DPA achieved its design objectives.

This dissertation makes several contributions. First, it contributes to the knowledge of designing Emergency Care Clinical Decision Support Systems (EC-CDSS) with a new PICT Quality Attribute Model. The model uniquely represents the quality attributes and metrics that can be used as foundational principles to guide the design of an effective EC-CDSS with the goal of improving PHOs. Additionally, the model describes the relationship between the quality attributes, which can be used to evaluate the effectiveness of the EC-CDSS after its implementation. Second, the proposed PICT-DPA represents a new data processing architecture for providing real-time information processing while reducing the cost.

While it is built upon the well-known lambda architecture, its use of knowledge-based models for data filtering and algorithm-based models for scoring are innovative. To the best of our knowledge, it is the only event-driven data processing architecture with two-tiered structure (real-time and batch processes). Third, the design process of PICT-DPA shows the importance of understanding the research domain (i.e., the ECS environment), integrating the theoretical foundations (i.e., WHO's ECS Framework), and the iterative design. Thus, it contributes to the IS design science literature by providing an exemplar in developing solution-oriented artifact.

From the practical perspective, the PICT Quality Attribute Model can be used by organizations to evaluate the effectiveness and usefulness of their EC-CDSSs. Meanwhile, the event-driven PICT-DPA can be used to guide the implementation of integrated EC-CDSSs by researchers and practitioners. Furthermore, the PICT-DPA can enhance the capabilities of data processing tasks in any domains with similar quality attributes requirements. More specifically, the knowledge-based model enables the stakeholders to use domain knowledge to set the thresholds of event filter for anomaly detection. The algorithm-based models enable the decision-making system to perform complex artificial intelligence tasks. Thus, the PICT-DPA can be adapted by different industries, such as finance and manufacturing, where real-time decision-making can have significant impacts on outcomes.

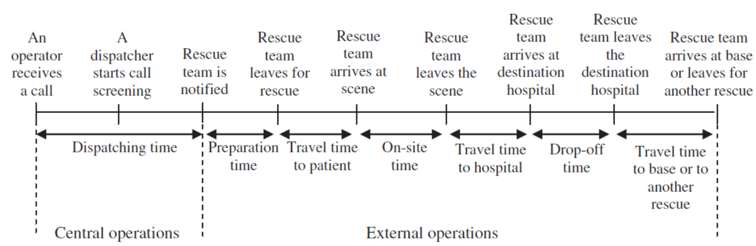
This research also has several limitations. The main limitation is the lack of real-world data used in the evaluation. While the Monte Carlo simulation was used to simulate the operations of EC-CDSS in the emergency care service process, the dispatch model was not evaluated because of the lack of ambulance and emergency room data. Another limitation is related to the explicit considerations for health information security and privacy. The prototype system implemented some security and privacy considerations, such as encrypted data storage and role-based access and control. Additionally, privacy-consent was obtained during the sign-up process of the mobile application. However, further exploration of a comprehensive security and privacy strategy and its impact on the PICT-PCT's design is needed.

Several future research projects are planned after the completion of this dissertation. First, the PICT-EDSS will be improved by focusing on the integration of hospital data and ECS data in a real-world environment. Real-world data can be used to validate the quality attribute model through an empirical assessment. Second, more algorithm-based models need to be explored to enhance the insight delivery subsystem. Currently, most algorithm-based models focus on cardiovascular diseases, while other emergency events, such as trauma and accidents, require further development.

Appendices

Appendix 1 Traditional EMS (Emergency Medical Services)

The traditional EMS is a time sequential healthcare delivery system that provides operations from receiving emergency calls to delivering patient to the target hospital. The traditional EMS operations consists of two specific ones, the central operations, and external operations (Figure, Aboueljinane, Sahin, & Jemai, 2013).



The central operations that aim at providing phone support and to decide the proper response for each call. There is an operator who makes an initial selection and records the information relative to the nature of request, then followed by a dispatcher responsible for performing medical evaluation of calls and determining whether to send a rescue team by evaluates the availability of hospitals and geographical location of fleets (Aboueljinane, Sahin, & Jemai, 2013). Thus, the operators and dispatchers are the key and only human resources to record and share the information about the emergency events. This can lead to complexity of operations management in EMS system. While receiving the calling from patients or bystander, the operator must record the geographic location and physical condition of patients. And while dispatching a rescue team, the dispatcher should know all related information, like geographic locations of, the available capacity and accurate location of rescue teams when a dispatch decision has to be made, the bed availability of destination hospitals to which a patient could be assigned, and the estimated duration time and processing time (Aboueljinane, Sahin, & Jemai, 2013). These make EMS operation difficulty because any missed information, human-made error, or time-consuming assignment can cause to a time-delay or wrong dispatching of emergency healthcare service.

The external operations means prehospital interactions. The patients' survival to hospital discharge from sudden emergency event depends in part on the time and quality of prehospital intervention. The shorter that the time interval is between collapse and the interventions, and the better the quality of the interventions are, the higher the probability of survival (Larsen, Eisenberg, Cummins, & Hallstrom, 1993). Using sudden cardiovascular disease as an example, the prehospital intervention typically occurs in a sequence. The CPR is started by bystanders or EMS personal, which followed by defibrillator shocks administered by emergency medical technicians. At last, the advanced care is administered by paramedics during the way to hospitals (Larsen, Eisenberg, Cummins, & Hallstrom, 1993). This time sequence operations can easily cause EMS processing time-delay. The paramedics can only start the prehospital care till they arrive the scene and evaluate the patients' physical condition. Without any pre-information, the average time of first intervention after arriving the scene is 11.1 minutes. The time can be longer if there is any operational mistake made by paramedics themselves (Spaite, Valenzuela, Meislin, Criss, & Hinsberg, 1993).

Appendix 2 Modern ECS – The integrated EMS

To improve the emergency services, the WHO released a framework called Emergency Care System (Figure) defining an integrated EMS with all human resources, functions, and equipment from different organizations. The core practice of ECS is the data and information practice from core cooperation, which is the predecessor of Integrated Healthcare Delivery System.

A2.1 Integrated Healthcare Delivery System (IDS)

The **Integrated Healthcare Delivery System (IDS)** means an organized, coordinated, and collaborative network that links various health care providers to provide a continuum of care to a particular patient population or community and to be clinically and fiscally accountable for the clinical outcomes and health status of the population it serves (Knickman & Kovner, 2015).

The traditional healthcare delivery system had low cost-efficiency: 30% of budget was used on unnecessary services, inefficient delivery, excessive administration, and prevention failure (Craig et al., 2012). It could not provide the appropriate healthcare services that patients really need, and the patients were translated to emergency department when there was no necessary. There was also care gap in traditional health care delivery system like the lack of post-acute transitional care. In terms of personal healthcare delivery, the traditional system was even less efficiency because of no cross-sectional patient information support.

A2.2 Care Coordination

The one key point of IDS development is the patient engagement, which is generally defined as the process of involving individuals in their healthcare, disease management, or preventing behaviors (Knickman & Kovner, 2015). It can decrease the unnecessary emergency department visits and hospitalization rate, furtherly decrease the cost of healthcare and improve the chronic disease management. Before the term of IDS, the inclusion of patients themselves in their healthcare was called **care coordination**, which meant the deliberate organization of patient care activities between two or more participants (including the patient) involved in a patient's care to facilitate the appropriate delivery of health care services (Knickman & Kovner, 2015).

There are multiple practices can improve care coordination, including 1) the periodic home visits; 2) **facilitating and encouraging data sharing through the use of integrated health information system**; 3) providing non-health care services such as transportation to appointment; and 4) employing and incorporating specially trained teams of providers that are aware of each patient's cultural and language backgrounds and can administer guidance and advices as they fit it (Knickman & Kovner, 2015).

The IDS is the system that operates these practices. The IDS not just involved both patient and healthcare providers, but also are focusing on patients' experience, the responsibility of the system and the services and features of the IDS. As what WHO described, the IDS should provide patients the care the in time with a user-friendly way, so then the services turn to the desired results and be worth for the money (Waddington & Egger, 2018). The responsibility of the IDS should be to provide or arrange to provide a coordinated continuum of services to a defined population and be willing to be held clinically and fiscally accountable for the outcome and health statue of the population served (Shortell, Erickson, Anderson, & Gillies, 1996). To do so, one or more hospitals along with physicians, diagnostic centers, and other components of the supply side of supply chain strive to share information, minimize duplication, and make treatment decision based upon the institutional best practice (Margolis, 2011).

The IDS can improve the quality and cost of health care services. In terms of quality, the IDS can improve the clinical effectiveness by lowering the hospital admission rate, shorten the lengths of stay and number of office visits by increasing the use of evidence-based practices. The improvements were associated with health system's clinical service integration and introducing the health information technology that creates operational efficiencies and patient-centered care. On the other side, in terms of cost, one of reason that IDS was built was the huge funding caused by complexity of healthcare industry and its low concentricity. The 80% of previous studies reported that IDS was associated with lower cost of care. For example, substantial cost savings were associated with electronic prescribing implementation due to a tandem generic medication prescription initiative within the IDS involved (Hwang, Chang, LaClair, & Paz, 2013).

A2.3 Emergency Care System (ECS)

As described in formal part, the one key point of IDS development is the patient engagement. The ECS only not includes patient management, but also include the Emergency Department (ED) into the EMS system. The traditional EMS finish their service by delivering the patient into the ED of target hospital, but in ECS, the reception of patients is the last phase, including all ED front-end processing, like initial patient presentation, registration, triage, bad placement, and medical evaluation (Wiler et al., 2010). Timely and precisely delivering the healthcare system outside of the hospital to patients who is suffering on emergency situation is a big challenge because of increasing population and immature emergency services that are access by just making calls to rescue services (Akram et al., 2017).

This requires the **data and information sharing practice, which is one of the key practices to improve the core coordination** between the ED front-end team and EMS rescue team. The decision by the ED team to activate an internal disaster plan is based on the information received from the EMS team about the potential number and acuity of patients that will be transported to the ED. Also, information about the resources (such as beds, physicians, surgery rooms) available at an ED is required by EMS teams to decide how many patients can be transported to that ED. However, the research demonstrated the poor information sharing between these two teams. The lack of complete and accurate information shared between the EMS and ED team potentially result in poor decisions. This can cause poor decision from both ED and EMS side that cause failing to activate the disaster plan at the appropriate time or the incident commander transporting too many patients to a single ED (Reddy et al., 2009).

Appendix 3 Health Information Technology (HIT) in ECS

In some healthcare systems, information technology is slowly but surely starting to have a direct effect on the lives of patients and the practice of medicine, as well as in emergency care system. As shown in Figure 1, there are three phase of emergency care, the scene, transport and facility with multiple functions. All these functions have been slowly implemented by the health information technology (HIT), which are the information technologies that used in healthcare system. It refers to various components, including hardware and software and devices, that function in a larger sociotechnical system, including hardware and software, working together in an organization that involves people, process and workflows (Knickman & Kovner, 2015). The components include **Electronic Health Record (EHR)**, **e-prescribing**, **Computerized Physical Order Entry (CPOE)** (which allows providers to directly place their orders and instructions electronically, whether an order is for medication, a lab test, or an image exam), **Clinical Design Support (CDS)** (which monitors and alerts clinicians and health care staff to a patient's specific conditions, prescriptions, and treatment), and **Patient engagement tools** (which encourages patients to assume greater responsibility for their health has become a bigger priority), and **Health Information Exchange** (which maximizes the use of electronic records between different healthcare related organizations) (Knickman & Kovner, 2015). Almost all the HITs are currently used in different phases of ECS.

A3.1 Patient Engagement Tools (PET)

In Figure 1, there are three phases of emergency care, the scene, transport and facility. During the scene, there are two main functions, one is system activation from bystander or patient, another one is instructions from dispatcher of EMS.

The activation means to active the emergency care system (Aboueljinane, Sahin, & Jemai, 2013). In tradition EMS system, most emergency care system was triggered by a call from a patient or the bystander. But with the assistance of Patient Engagement Tools (PIT), the activation can be started automatically through patient's physical information monitoring. Another function is instructions, which is the guidance of how to deal with disaster from dispatcher of Ems to the patient or bystander. There is no study have done the research on the implement of HIT in this function, but theoretically, the instructions can also be improved by the PIT.

PIT are tools to encourage patients to take part in their own healthcare management is an important feature of integrated healthcare system, which is also the key idea of core coordination (Knickman & Kovner, 2015). PIT makes it easier for patients to participate their own health management by understanding their own health profile. Two main parts that used as PET are patient portals and smartphone applications.

Patient portals are healthcare-related online applications that allow patients to interact and communicate with their healthcare providers. It can extract/load the patient's physical information and medical history from/in EHR based on patient's identification data.

In recent years, with the more attention on innovations in networking and communications, the **mobile information technology implemented in smartphone** has been involved in healthcare services. Back the time, the barrier of care coordination was the traditional medical record system. Patient information was routinely held in static paper storage system and managed with a silo mentality. Thus, the paper medical record was not only a budget waste, but also blocked the communication between patients and healthcare providers, as well as the communication between different healthcare organizations, which furthermore impact the care coordination (Omachonu & Einspruch, 2010).

The mobile and digital technology were made up for this gap. Back to 2001, The Institute of Medicine stated that necessary of redesigning the healthcare delivery system, which should focus on the usability of Information Technology and the cost-efficacy (Institute of Medicine., 2001). The mobile health care technology was then used to involve participation of patients into their own healthcare services. According to the World Health Organization (WHO), **mHealth** is the 'use of mobile and wireless technologies to support the achievement of health objectives' (Estrin & Sim, 2010). mHealth is an application system changing the mode and quality of health care on a global scale based on the wireless and mobile technology (Steinhubl, Muse, & Topol, 2015). The main component of mHealth is the mobile device that can be used to access patients' information for healthcare (Sariyer & Ataman, 2018). For example, the mobile device enables better control of chronic conditions through monitoring, tracking and communication of patients-generated biometric (e.g. blood pressure, glucose levels, heart rate) and activity data (Steinhubl, Muse, & Topol, 2013). The mHealth system that have emerging mobile communications can also allow more rapid diagnosis and treatment of common acute conditions (Kyriacou, etl., 2007; Kyriacou, Pattichis, & Pattichis, 2009).

The benefit of mHealth system is data accessibility by using mobile device to automatically monitor and tracking the users' health information, which furtherly speed up the data collection process. Thus, the two main functions of mHealth is to collection users' health information through mobile device and send the data to smart phone for user report and to medical center for further analysis through network technology (Sariyer & Ataman, 2018).

The combination of mobile technologies and the IDS is called the Mobile Integrated Healthcare Practice (MIHP), which is a strategy framework to redesign current mobile healthcare through inter-professional collaboration and repurposing of existing healthcare infrastructure (Nejtek, Aryal, Talari, Wang, & O'Neill, 2017). MIHP intended to serve a range of patients in the out-of-hospital settings by providing 24/7 needs-based at-home integrated acute care, chronic care and prevention services, which includes: 1) emergency services by communication between patients and physicians and information exchange; 2) define the operations through population-based needs assessment and tools; 3) leverage multiple strategies partnerships operating under physician medical oversight; 4) Improve access to care and health equity through 24-hour care availability; and 5) deliver evidence based practice.

Some research used the mobile phone as the gateway of data transmission. For end user, the mobile phone can be benefit in an emergency alarm system for people who have potential risks while doing sports or elderly people. On the other side, for emergency service, a distant monitoring system can be helpful to deliver first aid in emergency cases (Tartan & Ciflikli, 2018).

Some research had advanced technology as wearable device like Apple Watch targeting falling-down alarming of elder population. The Apple Watch has a function that can measure the end-user's movement change with the three-axis accelerator, which can alert a fall accident. Thus, when there is a fall accident happened, GPS will immediately transform warning messages to the healthcare providers in the care institution. The device will transmit real-time positioning datasets when there are falls for the rapid and proper treatment so as to minimize the elderly injury caused by falls (Tai et al., 2020).

Another example is the mHealth studies based on the Holter monitoring. A Holter monitor is a battery-operated portable device that measures and records your heart's activity (ECG) continuously for 24 to 48 hours or longer depending on the type of monitoring used (Holter, 1961). The Holter monitor was developed at the Holter Research Laboratory in Helena Montana by experimental physicists Norman J. Holter and Bill Glasscock in 1961 (NMAH, 2011). Since then, the ambulatory electrocardiographic (ECG) monitoring has been widely used for many clinical purposes, including correlation of arrhythmias with symptoms, estimation of prognosis, guidance of antiarrhythmic therapy, and detection and therapy of myocardial ischemia (DiMarco, 1990). In recent years, the Holter monitoring has been used more and more in EMS as a patient engagement tool. There were multiple studies used Holter monitoring system to develop a Personal Digital Assistant (PDA) that can collect and classify the real-time ECG data (Rodriguez, Goni, & Illarramendi, 2005). Some of them implied the Holter system with mobile phone or wearable devices, so that the patients can read their own ECG report on their phone (Yuan-Hsiang Lin et al., 2004; Chen, Ho, Lim, & Kyaw, 2007; Oresko et al., 2010; Rasid & Woodward, 2005; Wen, Yeh, Chang, & Lee, 2008). Their target disease is Cardiovascular disease.

Except for Holter monitoring system, there are other mHealth studies. In 2018, (Tartan & Ciflikli) developed an android application for Cardiovascular disease with geolocation information. If anomalies are observed in heart rate variability during the outdoor activities, emergency information can be delivered in the shortest time through mobile application by sending alert message through notification, SMS, email and allows messaging with health expert for consulting. Unlike Holter only collect ECG data, this Android application also collect the heart rate and GPS information, as well as the patients' ID, name, weight and contact information. So that when an alarm situation is detected, the application can inform the health expert. It also providing consultancy module within the application for communication with the health expert to discuss a situation or to get device. In addition, it lists the closet available hospitals for patients. The objective of this research is to prevent the delay that patients with emergency are not able to ask for help. So that the automate alarming function and geolocation information can help EMS to access the patient as soon as possible. It not only fasters the activation phase of ECS, but also provides instructions function.

Among these studies, only two had alerting functions to trigger the ECS activation. For example, in (Yuan-Hsiang Lin et al., 2004), the researchers developed a mobile patient monitoring system, which integrates current personal digital assistant (PDA) technology and wireless local area network (WLAN) technology. The doctors can get the patient's ECG data as soon as the system detected the abnormal information. However, the data transformation can only happen in intra-environment. Another example is Mobicare, which is a mobile phone application is used to evaluate ECG and data is sent to a server only if abnormality is detected. It is alerting server from EMS who receive the data (Chen, Ho, Lim, & Kyaw, 2007). However, such application did not provide continuous transmission for distant monitoring.

A3.2 Health Information Exchange (HIE)

In the transaction phase of ECS, there are multiple functions. For example, the ambulance will provide position of patient to emergency department of target hospital through communication. In addition, the emergency paramedic will provide intervention and monitoring service to patient in the ambulance and send the information to the emergency department in real-time. These functions can be improved by the Health Information Exchange (HIE). In an HIE, the patient's clinical data are shared on a regional network, so that a patient's health information follows the patient from one setting to the next (Knickman & Kovner, 2015).

HIE allows doctors in a network to retrieve information about patients across providers and settings, in real time, creating coordinated or integrated care. The goal of **health information exchange** was to have information available to terms of doctors, nurses, and care coordinators in a way that was private and secure, so that the patient's care can be coordinated among providers. However, information sharing is always a problem in ECS. Interoperability is the key. To build a national wise HIE, a single set of data standard is required. A functional interoperable HIE is essential of a nation's health care system (Knickman & Kovner, 2015).

The technique that mostly used in HIT is **telemedicine**, which was the utilization of telecommunication technology for medical diagnosis, treatment, and patient care. The aim of telemedicine system is to provide export-based healthcare to understaffed remote sites through modern telecommunication and information technology (Abo-Zahhad, Ahmed, & Elnahas, 2014). It could improve a patient's clinical health statues by **HIE**, which allowed doctors in a network to retrieve information about patients across providers and settings, in real time, creating coordinated or integrated care.

CVD were still the main disease that telemedicine technology targeting on. In 2001, the HEAL (Hospital and Emergency Ambulance Link) developed a system to improve the medical response by the EAS (Emergency Ambulance Services) and the management of patients by the nation's ED (Anantharaman & Swee Han, 2001). It implied PC front-end application for ambulance mobile computer/notebook, so that emergency medical technicians can send vitals sings and ECG information to a PC workstation in hospital's ED through wireless public mobile data network. As a result, the doctors in the emergency department can get the patient's ECG before patients' arrival and start to prepare other interventions. Furtherly, another study implied a CT scan machine in the ambulance for improve the emergency care service (Sharma, Fleischut, & Barchi, 2017). The information transformation is similar with the above case. Both cases can improve the communication between the EMS ambulance and target ED of hospital. However, the service can only start after ambulance picking up the patients. Also, the information transformation is one direction, from ambulance to emergency department. There is no real come-and-forth communication between two healthcare service providers.

A3.3 Emergency Department Information System (EDIS)

In the last phase of ECS, the emergency department of hospital is the main function providers. They have responsible to provide triage, screening, registration while assessing and monitoring the patient physical situation, as well as providing resuscitation and intervention.

The Emergency Department Information System (EDIS) was designed and developed to fulfill these functions. It is an import and unique movement toward improving quality and outcomes with EHR in emergency department. Variations in EDIS functionality affects physician decision making, clinician workflow, communication, and ultimately the quality of care and patient safety in a particular challenging clinical environment, the high volume and time sensitive emergency department (Farley et al., 2013).

EDIS has multiple potential benefits. First of all, EDIS is intended to decrease practice variability and improve system reliability by ensuring legible communication, facilitated retrieval of past information, and access to CPOE to aid in clinical decision support. In addition, the advanced EDIS can help make medical references easily accessible, assist with important calculations, monitor for potential adverse events. The EDIS can also provide the potential to share medical information across different health system. At last, it may help with early identification of epidemics and assist with population management in an era of increasing shared accountability and quality reporting mandates (Farley et al., 2013).

However, since the EDIS consists of emergency data, which is heavily sensitive to time and quality, any delay in detection of fatal illness or in treatment because of loss of data can lead to medical errors and cause patient safety and quality concern. The importance of well-designed EDIS is increased precisely because of potential for catastrophic outcomes. EDIS-related errors are often attributed to user experience level and training, but they may not prevent human factors errors that result from poor design of such products. But in fact, a growing body of evidence suggested that many errors maybe the result of poor design rather than user errors (Farley et al., 2013). Systems with Patient Engagement Tools (PET), Computerized Provider Order Entry (CPOE) and Clinical Decision Support (CDS) could potentially detect incorrect doses or medication interactions and notify clinicians at the point of care, and they might also reinterpretation of orders and prescriptions due to handwriting (Handel, Wears, Nathanson, & Pines, 2011). This proved that integrating EDIS with different HITs has benefit for emergency care.

Appendix 4 My Understanding of Design Science

A4.1 The Science of Design

Based on Simon's (1996) book, *The Science of Artificial, 3rd Edition*, the design science paradigm has its roots in engineering and the science of the artificial. Design science research is motivated by the desire to improve the environment by the introduction of new and innovative artifacts and the processes for building these artifacts. Simply stated, the design science is to design artifacts to solve the real problems. In this research, the environment that needs to be improved is the ECS system, and to design the artifacts that can improve the ECS system is the objective of this research.

The design science is different with natural science. Natural sciences include traditional research in physical, biological, social, and behavioral domains. Such research is aimed at understanding realities. Natural scientists develop specialized concepts or languages to explain phenomenon. Theories deep principled explanation of phenomenon are the crowning achievement of natural science (March & Smith, 1995). They are searching for truth, and they usually involve two activities discovery and justification. Discovery is the process of generating or proposing scientific claims (e.g., theories, laws). Justification includes activities by which such claims are tested for validity.

However, from the literature review, we have already known the problems of the ECS system. We are not trying to understand reality but to solve the listed research questions through the known causal theories. Therefore, natural science is not the appropriate methodology for this research.

While natural science tries to understand reality, design science attempts to create things that serve human purpose. It is about problem solving. It is technology oriented. Its products are assessed against criteria of value or usability. It is central in fields like architecture, engineering, and urban planning. Rather than producing general theoretical knowledge, design scientists produce and apply knowledge of tasks or situations in order to create effective artifacts (March & Smith, 1995). Design Science consists of two basic activities: build and evaluate. They parallel the discover justification pair from natural science Building is the process of constructing an artifact for a specific purpose; evaluation is the process of determining how well the artifact performs (Hevner, 2007). Like discovery process in natural sciences, the design science build process is not very well understood.

But the components of design science are more complex. Design is a plan for arranging elements in such a way as to best accomplish a particular purpose. Design are the instruction based on knowledge that turn things into value that people use. A number of disciplines have all made design a central element. For example, Engineering design is the systematic intelligent generation and evaluation of specifications for artifacts whose form and function achieve stated objectives and satisfy specified constraints. Furtherly, Software engineering Design is a ‘thing’ as well as a ‘process’ which is conscious, keeps human concerns in the center, is a conversation with materials, is creative, has social consequences and is a social activity. A good design should have three basic characteristics: firmness, no bugs that inhibit its function, commodity, be suitable for the purposes for which it was intended, and delight, the pleasurable experience of using the artifact. Thus, functions, users, constraints, and process are basic components of a design (Akehurst, 2020).

But design science is not just design. The supported methodology for the science is the research. The reason of the research is to address the void in knowledge and those unresolved problems by asking relevant questions and seeking answers to them, and the role of research is to provide a method for obtaining those answers by inquiringly studying the evidence within the parameters of the scientific method. Thus, the research can be defined as an activity that contributes to the understand of a phenomenon. Phenomena is typically a set of behaviors of some entity(ies) that is found interesting by the researcher or by a group a research community. Understanding is knowledge that allows prediction of the behavior of some aspect of the phenomenon. Research is a process through which we attempt to achieve systematically and with the support of data the answer to a question, the resolution of a problem, or a greater understanding of a phenomenon.

To summarized, design science research is a research paradigm in which a designer answers questions relevant to human problem via the creation of innovative artifacts, thereby contributing new knowledge to the body of scientific evidence (Hevner & Chatterjee, 2010). Thus, the designed artifacts should be able to not only answer the un-solved questions, but also create new knowledge with the evidence.

A4.2 Design Science in IS research

The Design Science in IS research is to look for innovation, which can define the new idea, practice, technology and artifact, and through these innovations to improve the efficiency of analytic, design, implementation and management of Information System (Hevner, March, Park, & Ram, 2004). The structural elements of design, mainly artifact and process, are organized or arranged by principles based on human-computer interactions.

A4.2.1 Principles

The principle of DSR in the medical field is very strict because it involves patients' health, life safety, and information security (Hevner & Chatterjee, 2012). The main principles include:

1. Computational Principles: All designs, from function to evaluation, should be based on scientific data. In this research, quantitative indicators are required to decide the efficiency of the new design on the ECS system.
2. Adaptability Principle: it will be impossible to specify or predict a priori all of the behaviors or qualities of the system.
3. Scalability Principle: in order to build ultra-large-scale systems
4. Ethical Principle: implies an ethical responsibility of how the system shapes its environment. In health informatics, data security and privacy are important ones.
5. Economic Principle: Cost always goes hand-in-hand with complexity. The cost-efficiency is also a target of new technical design in ECS system.

A4.2.2 Components

A4.2.2.1 Artifact

The IT artifacts are broadly defined as constructs, models, methods, and instantiations (March & Smith, 1995). The construct is the conceptual vocabulary of a domain. It provides the language in which problems and solutions are defined and communicated. The models are a set of propositions or statements expressing relationships between constructs. They use constructs to represent a real-world situation – the design problem and its solution space (Simon, 1996), aiding problem and solution understanding and frequently representing the connection between problem and solution components, and enabling exploration of the effects of design decisions and changes in the real world. The methods are a set of steps used to perform a task, like how to knowledge. It defines the processes, which can range from formal mathematical algorithms that explicating define the search process to informal, textual descriptions of 'best practices' approaches. The instantiation is the operationalization of constructs, models and methods, which can be implemented in a working system. They demonstrate feasibility, enabling concrete assessment of an artifact's suitability to its intended purpose.

A4.2.2.2 The design processes

The Design Cycle from Takeda El Al. (1990) provided two parts of design process, the abduction and deduction ones. The problem-solving process is abduction, which include the awareness of problem and suggestion (Kuechler & Vaishnavi, 2008). The awareness of problem means all design begins with an awareness of the problem. The design science is called 'improvement research' since it solves problems better. Suggestion means that a problem solution is abductively drawn from existing knowledge and/or theory base for the problem area. The theory is called kernel theory, which are applied, tested, modified, and extended through the experience, creativity, intuition, and problem-solving capabilities of the researcher (Markus, Majchrzak, & Gasser, 2002). Similarity, from the artifact design to implement, the deduction process is guided by high prescriptive design theories (Kuechler & Vaishnavi, 2008). The implementations are then evaluated according to the functional specification implicit or explicit in the suggestion. Thus, the design science is a cycle with iterations of understanding problems and building an artifact (Hevner & Chatterjee, 2010).

Appendix 5 Data Source

- The Sudden Cardiac Death Holter Database has 23 complete Holter recordings of 18 patients with underlying sinus rhythm. All patients had a sustained ventricular tachyarrhythmia, and most had an actual cardiac arrest.
- Lobachevsky University Electrocardiography Database (LUDB) is an ECG signal database with marked boundaries and peaks of P, T waves and QRS complexes. The database consists of 200 10-second 12-lead ECG signal records, representing different morphologies of the ECG signal. The boundaries of P, T waves and QRS complexes were manually annotated by cardiologists with the corresponding diagnosis.
- MIT-BIH Arrhythmia Database includes a set of over 4000 long-term Holter recordings that were obtained between 1975 and 1979. Approximately 60% of these recordings were obtained from inpatients. The database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979.
- The Long-Term ST Database contains 86 ECG recordings of 80 human subjects, chosen to exhibit a variety of events of ST segment changes. The database has supported the development and evaluation of algorithms for differentiating ischemic and non-ischemic ST events.

Appendix 6 Interview Standard Questions

Interviewee Background:

1. Could you describe a regular workday for us?
   Probe: Why did you decide to be an ECS care provider?

A. Current EC-CDSS practice:

2. Do you use any emergency care decision support tools currently in your daily work?
   1. If YES:
      1. Can you describe how you engage with the tool?
      2. Can you describe the cost of the tool?
         a. How much the decision-making tool cost, Including maintenance and operational cost?
         b. Do you think the decision support tool help reduce the Medicare cost, such as preventing unnecessary visit to ER, or reducing the tirage time?
      3. Can you describe the performance of the tool?
         a. Is the recommended treatment strategy provided by the tool accurate?
         b. Do you think your tool provide consistent recommendations for patients with similar conditions?
      4. Can you describe the interoperability of the tool?
         a. Do you know the data resources of the tool? What are they?
         b. If multiple resource: are the information always consistent for the same patient?
         c. Do you use any health data exchange protocol/standard?
      5. Can you describe the timeliness of the tool in the decision making? (i.e., how long it takes to receive the recommended decision from the tool)
      6. Do you think that the tool can improve patient health outcomes? If so, to what degree?
   2. If NO:
      1. Can you describe how you make a decision in your daily work?

B. Impact of PICT-DPA:

3. After showing how the PICT-DPA,
   If the interviewee has current EC-CDSS, ask:
   Comparing to your current tool:
   1. Do you think that the architecture can reduce the maintenance and operational cost of your current tool? Why or why not?
   2. Do you think the architecture by integrating heterogenous data can improve decision-making system to provide better or more valid recommendations? Why or why not?
   3. Do you think that the architecture can improve the current tool's performance in providing more accurate recommended treatment/dispatch strategy? Why or why not?
   4. Do you think that the architecture can improve the current tool's performance on providing consistent recommendation under similar circumstances? Why or why not?
   5. Do you think that the architecture can make it faster for the tool to recommend treatment/dispatch strategies?
   6. Do you think that the architecture can increase the ability of the current tool in improving patient health outcomes?

   If the interviewee has no current EC-CDSS:
   Comparing to the traditional tool:
   7. Do you think that the artifact can reduce the maintenance and operational cost of traditional decision-making process? Why or why not?

8. Do you think integration of heterogenous data can improve decision-making system to provide better or more valid recommendations? Why or why not?
9. Do you think that the artifact can improve the performance of traditional decision-making process in providing more accurate recommended treatment/dispatch strategy? Why or why not?
10. Do you think that the artifact can improve the performance of traditional decision-making process on providing consistent recommendation under similar circumstances? Why or why not?
11. Do you think that the artifact can make it faster for the traditional decision-making process to recommend treatment/dispatch strategies?
12. Do you think that the artifact can increase the ability of the traditional decision-making process in improving patient health outcomes?

4. Are you willing to use a decision-making tool with this architecture? Why?
    1. If YES:
        a. do you agree that a decision support tool with the proposed architecture can provide better Patient Health Outcomes?
    2. If No:
        a. Explore the reasons and ask how it may be improved.

5. Do you have any other recommendations?

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