PICT-DPA: A Quality-Compliance Data Processing Architecture

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Abstract

The Emergency Care Clinical Decision Support System (EC-CDSS) has proven to improve the quality of the Emergency Care System (ECS), which is crucial for providing timely life-saving care. The literature lacks a data processing architecture for an integrated EC-CDSS that can fulfill all quality attributes while satisfying all stakeholders' information needs. To address this literature gap, this study designs a new data processing architecture, called PICT-DPA. The PICT-DPA was evaluated by its instantiation of a PICT-enabled EDSS and user interviews. Results demonstrate that the PICT-DPA improves quality attributes and meets stakeholders' information needs. The design process of the PICT-DPA shows the importance of understanding the research domain, integrating the theoretical foundations, and iterative design. Furthermore, the PICT-DPA can enhance the capabilities of data processing tasks in any domain with similar quality attribute requirements.

Keywords: Design Science Research, Data Processing Architecture, Real-time Data Process, Emergency Care, Clinical Decision Support System

1. Introduction

Emergency Care System (ECS) is a critical component of health care systems by providing acute resuscitation and life-saving care (Moresky et al., 2019). A responsive ECS consists of multiple distributed emergency care (EC) functions, which are essential responsibilities performed by different types of healthcare providers during emergency situations (WHO, 2018).

The implementation of the EC Clinical Decision Support System (EC-CDSS) has proven to improve the quality of 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). 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. An integrative EC-CDSS is critical to support distributed clinical decisions on different EC functions and achieve the ultimate goal of the emergency care system, which is to improve patient health outcomes (PHOs) (WHO, 2018).

Like other CDSSs, EC-CDSSs can be classified as knowledge-based or algorithm-based (Berner, 2007). Knowledge-based systems 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 requiring a data source, leverage artificial intelligence, machine learning, or other statistical learning methods to produce recommendations.

An integrated EC-CDSS requires processing a massive amount of data from heterogeneous sources while simultaneously minimizing processing time and decision latency, and achieving all quality attributes (Sariyer et al., 2018). An efficient data processing architecture (DPA) is critical in satisfying those needs.

Past research suggests that an integrated EC-CDSS should meet two fundamental requirements: (1) including four essential quality attributes – performance, interoperability, cost, and timeliness (PICT), and (2) providing the necessary information for all stakeholders to make decisions on their related EC functions (Yu, 2023). The stakeholders include dispatchers who activate the ECS and dispatch the on-scene care providers; on-scene care providers who provide life-saving interventions on the scene and during transportation; on-facility care providers who provide treatment interventions; and allied health workers who decide the triage (WHO, 2018). Few studies have investigated databases designed specifically for EC-CDSSs (Omoogun et al., 2017). To the best of our knowledge, none of the existing research and tools are able to meet the two fundamental requirements due to the limitations of traditional data processing techniques used in EC-CDSS. This leads to the research question: How to present, operationalize, and evaluate a data processing

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architecture for an integrative EC-CDSS with desired quality attributes while satisfying all relevant stakeholders' information needs? This study answers the research question through design science research (DSR) via the creation of an innovative artifact called PICT-DPA (i.e., PICT data processing architecture).

2. Theoretical Foundations

2.1. Emergency Care System Framework

The PICT-DPA design uses the 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. The framework defines the ECS as a sequential process with six time intervals in three phases. Table 1 summarizes phases, EC functions, and related stakeholders.

Table 1. ECS phases, EC functions, and related stakeholders based on ECS Framework (WHO, 2018)

Phases	EC Functions	Stakeholders
Scene	System Activation	Dispatcher
	Instructions	Dispatcher; Bystander;
	Dispatch	Dispatcher; On-scene Care Provider
	Access to Patient	On-Scene Provider
Transport	Positioning	Driver; On-Facility Care Provider
	Intervention Monitoring	On-Scene Care Provider
Facility	Handover	On-Scene Provider; On-Facility Provider
	Assessment; Resuscitation; Intervention; Monitoring	On-Facility Provider
	Triage; Registration	Allied Health Workers
	Screening; Disposition	Clerical Staff

The first phase is SCENE with two related time intervals: Time to Dispatch and Time to Scene/Provider. Once a patient has an acute condition, the bystander initiates an emergency call, relaying patient information and acute condition to the dispatcher who activates the ECS process. Simultaneously, the dispatcher provides instructions for managing the acute condition while dispatching an ambulance with on-scene care providers. The Time to Dispatch interval encompasses three EC functions: system activation, instructions, and dispatch. Acute condition data is transmitted from the bystander to the dispatcher and subsequently to the on-scene care providers. The Time to Scene/Provider represents the duration required for the on-scene provider to access the patient.

The second phase is TRANSPORT with one time interval: Transport Time. During this phase, the driver transports the patient to the target hospital, while the on-scene care provider performs interventions and monitors the patient's life situation. Three EC functions are related to the Transport Time: intervention and monitoring provided by the on-scene care providers, and ambulance location information reported by the drivers. The intervention data, patient situation data, and position data are transmitted to on-facility care providers through field-to-facility communication.

The third phase is FACILITY with three time intervals: Time to Provider, Length of Stay, and Time to Operating Theatre. Time to Provider is when the on-scene care provider hands the patient over to the on-facility care provider. Throughout the Length of Stay, the on-facility care provider conducts additional assessment, resuscitation, intervention, and monitoring, followed by collaborating with Allied Health Workers for triage and disposition. Meanwhile, the clerical staff screens and registers the patient. The Time to Operating Theatre encompasses the duration from patient registration and triage to the operating theatre.

2.2. PICT Quality Attributes Model

Prior research (Yu, 2023) proposed a quality attribute model that represents the relationship between EC-CDSS quality attributes, EC Functions, and Patient Health Outcomes (PHOs) (see Figure 1).

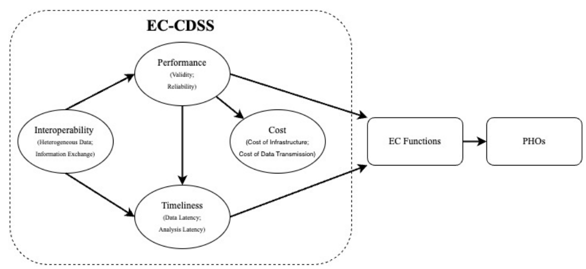

Figure 1. PICT quality attributes model

As shown in Figure 1, **I**nteroperability can improve the decision support **P**erformance by providing sufficient data for training and developing better algorithm-based models (Wang et al., 2021). **I**nteroperability can also increase **T**imeliness by reducing the data latency with a centralized database instead of collecting the historical data from the original source (Crilly et al., 2011). **P**erformance can improve **T**imeliness and reduce **C**ost through reliability (the degree to which a measure is not afflicted by random errors) and validity (the extent to which a score truly denotes a concept) in decision-making recommendations (Alkhawaja et al., 2020). The model highlights that improved **P**erformance and

Timeliness lead to better PHOs through improved EC functions.

2.2. PICT Quality Attributes and Metrics

Based on the PICT quality attribute model, each quality attribute and its related metrics were summarized in Table 2.

Table 2. Quality attributes and metrics

Quality Attributes	Metrics and their definitions
Performance	Validity measures the system's ability to perform expected functions and document expected results.
	Reliability assesses the consistency of guidance or recommendations across repeated trials
Interoperability	Number of heterogeneous data sources measures how many different data sources are used to integrate data for decision support.
	Number of information exchange protocols/standards measures how many protocols or standards are used to integrate the heterogeneous data.
Cost	Cost of infrastructure measures how expensive to build an EC-CDSS based on the required hardware and software.
	The cost of data transmission measures the amount of unnecessary data being transmitted into EC-CDSS.
Timeliness	Data latency is the time between the EC event and when the data is ready for analysis by the EC-CDSS.
	Analysis latency is the time of initiating data analysis and delivering it to the appropriate person.

The decision support **P**erformance measures the ability of CDSS to reduce errors in making decisions or providing recommendations (Ji et al., 2021). It can be measured using two metrics: validity and reliability. **I**nteroperability is the ability to exchange and integrate heterogeneous data (Omoogun et al., 2017). It encompasses two related metrics: the number of heterogeneous data sources and the number of information exchange protocols/standards. **C**ost always goes hand-in-hand with complexity. Some commercial EC-CDSS solutions are often prohibitively expensive. The cost of EC-CDSS can be decreased by reducing the cost of infrastructure and the amount of data for transmission. **T**imeliness refers to the ability to minimize any possible latency during the decision support process, which includes data latency and analysis latency (Hackathorn, 2002).

3. PICT-DPA and its instantiation

The design of the new DPA was an iterative process guided by the DSR process model (see Figure 2) proposed by Vaishnavi and Kuechler (2015). The awareness of the problem has been described in the previous sections. In this section, we first show the suggestions about how the tentative design (in the form of design requirements) was abductively drawn from the ECS Framework (WHO, 2018). Then we describe the development of PICT-DPA with related design cycles. The PICT-DPA was evaluated in two ways. First, we successfully instantiated PICT-DPA as a prototype clinic decision support system to show its feasibility. Second, we evaluated the utility of PICT-DPA through a controlled experiment in the prototype system and user interviews.

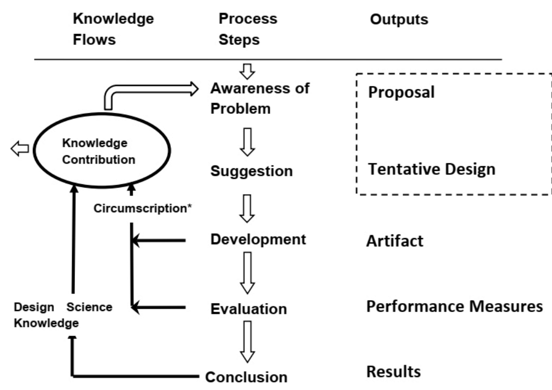

Figure 2. DSR process model

3.1. Design Requirements

The overall requirement of the design is how the data processing architecture (DPA) would enable all quality attributes while satisfying all stakeholders' information needs. To ensure the appropriate decision-making suggestions from the EC-CDSS, the data pipeline must be able to transmit the patient's vital data to knowledge- or algorithm-based models (Requirement #1). The **T**imeliness attribute requires transmitting the data and insights in real-time (Requirement #2). To control the **C**ost of infrastructure, the new DPA should be able to support all EC functions (Requirement #3). To reduce the **C**ost of data transmission, the abnormal vital data should be filtered for real-time transfer and data used for training algorithm-based models may be transmitted in batches offline (Requirement #4). Thus, the new DPA should accommodate both real-time and batch data transmission (Requirement #5). The **I**nteroperability attribute requires information exchange standards or protocols (Requirement #6). Lastly, to satisfy all stakeholder's information needs, the new DPA needs to send decision-making recommendations for different EC functions to relevant stakeholders (Requirement #7).

3.2. PICT-DPA Development

Through five design cycles, the proposed data processing architecture, PICT-DPA, was finalized as shown in Figure 3. The architecture comprises three subsystems: the data extraction subsystem, the data integration and transmission subsystem, and the insight delivery subsystem.

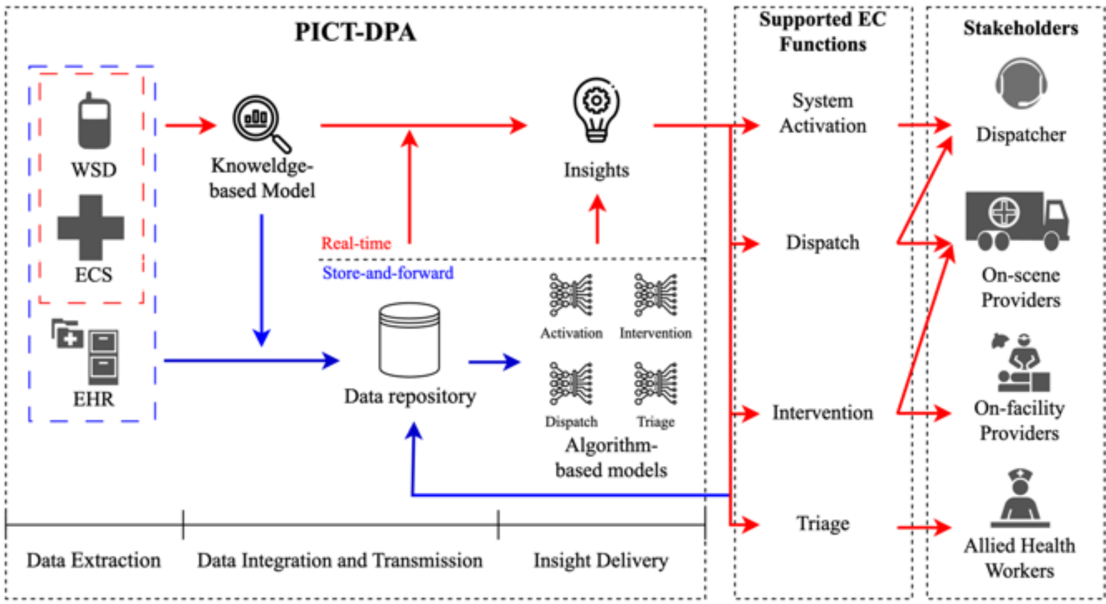

Figure 3. The PICT Data Processing Architecture

The data extraction subsystem is to extract the necessary data for knowledge-/algorithm-based models from three heterogeneous data sources: Wearable Sensing Devices (WSD), Emergency Care Systems (ECS), and Electronic Health Records (EHR). WSD is a crucial data source for capturing patient vital signs, such as heart rate, blood pressure, and insulin levels, using wireless biosensors (Piwek et al., 2016). Additionally, its built-in GPS sensors enable the tracking of patient locations (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. The ECS data includes incident data collected through the ECS process, such as clinical observations, medications administered, or procedures performed (Poulymenopoulou et al., 2011). ECS data also incorporates emergency room and ambulance data, 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). Additionally, EHR data are used to improve ED efficiency (Wang et al., 2021).

The data integration and transmission subsystem consist of two layers: a real-time processing layer and a store-and-forward layer. This design is inspired by the Lambda architecture, a prominent industry data processing architecture that combines batch-processing and streaming-processing methods (Marz et al., 2015). Real-time processing is essential for time-sensitive EC-CDSS (Barcelos et al., 2015). However, it is expensive and sacrifices throughput. Thus, this layer should be event-driven and only activated when needed. Normal information can be transmitted through the store-and-forward layer with traditional batch data processing. 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 maintain data consistency, followed by loading the integrated data into a data repository. To optimize the data store, a dimensional data model can be used.

The last subsystem is the insight delivery subsystem, which refers to the provision of material, newsworthy, and actionable findings to stakeholders, ensuring relevance and value in a data-rich environment. This subsystem should satisfy all relevant stakeholders' information needs in one single platform.

The development of the PICT-DPA included extensive design and validation discussions with four experts, each representing a different type of stakeholder shown in Figure 3. There are a total of five design cycles, each resulting in the improvements of artifacts as summarized in Figure 4.

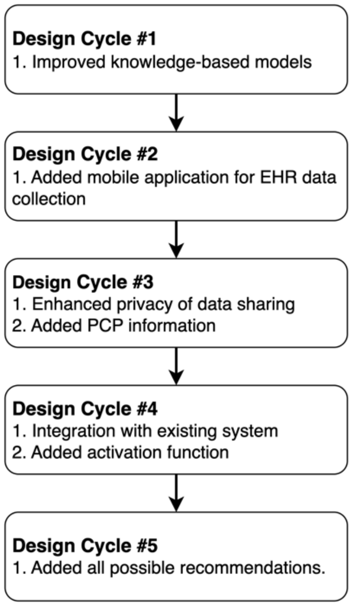

Figure 4. The PICT-DPA design cycles

During the first design cycle, experts questioned the same heartbeat ranges as thresholds for everyone in the knowledge-based model. Based on their recommendations, the model performance was improved by incorporating personal variations such as gender, age, and underlying health conditions.

During the second design cycle, a concern was raised about the difficulties in sharing EHR among different medical systems, especially in the US. Thus, to keep the interoperability, a mobile application was developed to allow patients to voluntarily share relevant personal health information such as medical history and any potential allergies.

The third design cycle involved the privacy concerns of patients in sharing their EHR data. Thus, a privacy policy was added within the mobile application, assuring confidentiality and non-disclosure of data. Another challenge was raised when some patients were not aware of their own medical history. Thus, the mobile application added a field to capture the patient's Primary Care Physician's (PCP) contact information, which serves to supplant the traditional data source of EHR.

The fourth design cycle resulted in two improvements. Firstly, to address the cost constraints associated with replacing existing systems, experts recommended integrating existing algorithm-based models into PICT-DPA instead of training new models. This would enable the PICT-DPA to serve across a range of existing EC-CDSSs. This can be achieved by incorporating the updated PICT-DPA into any existing EC-CDSS using open-source APIs. Secondly, experts highlighted the limitation of relying solely on the knowledge-based model to determine the need for emergency service. For example, in some cases, patients may experience discomfort even when their vital signs appear normal. Thus, an activation emergency care service feature may be introduced by adding an "activate" button in the mobile application. This button enables patients to initiate real-time vital data transmission without a triggering event.

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.

3.3. PICT-EDSS

As an abstract architecture, the feasibility and usability of PICT-DPA were assessed through its instantiation, the PICT-EDSS (PICT-enabled Emergency Decision Support System). The system was implemented on a cloud server environment to store integrated data and algorithm-based machine learning models, as shown in the system architecture (see Figure 5).

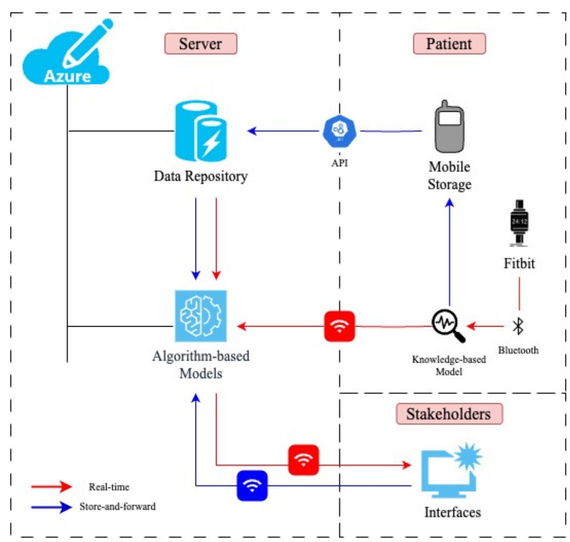

Figure 5. The architecture of PICT-EDSS

For data extraction, Fitbit smartwatches are used as WSD to monitor and capture vital data. The collected data are then sent to a mobile application through Bluetooth. The mobile application includes a knowledge-based filter model that determines the normalcy of vital data.

For the data integration and transmission, patient vital data extracted from WSD is sent to the knowledge-based filter model in the mobile application. The filter model includes a pre-set heart rate threshold range. If the patient's heart rate is within the normal range, the vital data will be stored in the mobile application and transmitted via the store-and-forward layer. If the patient's heart rate is out of the threshold range, it will be flagged as abnormal and transmitted 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. The integrated data will then be transmitted in real time to the pre-trained algorithm-based models.

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 history data, with 'Dispatch Sent' as the target. These data were proven to effectively determine whether a patient was suffering from acute cardiovascular disease and required emergency care services (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 Sent' target. 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. To use the system, the stakeholders are required to register with specific roles, such as administrators, dispatchers, on-scene/on-facility care providers, and allied health workers. Once registered, users can access decision support results tailored to their respective roles. For example, the dispatcher is provided with a real-time dashboard featuring a map-based interface, showing ECS data and abnormal vital signs with geolocation. The activation algorithm scores the data to determine emergency service needs, while the dispatch algorithm suggests transportation plans for the nearest ambulance to the hospital. During patient transport, care providers in the emergency room are notified of the incoming patient. They can access basic information and estimated arrival time via the dashboard. The dashboard also provides detailed information in three sections, including the "EHR" section with medical history, the "Real-Time Situation" section displaying vital signs, and the "Recommendation" section offering intervention algorithm-based suggestions for diagnosis, medication, and triage.

4. Evaluation and Discussion

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 WSDs to the data repository through APIs. The PICT-EDSS successfully extracted all vital data from WSDs 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 elevate their heartbeats above the threshold specified in the knowledge-based filter model. The PICT-EDSS successfully captured all abnormal data in real-time, thus meeting Requirements #2 and #4. Lastly, the PICT-EDSS successfully delivered scoring results of algorithm-based models to different stakeholders, thus meeting Requirement #7 and demonstrating PICT-DPA's ability to satisfy all stakeholder's information needs.

In terms of quality attributes, the **I**nteroperability was demonstrated by two data heterogeneous sources (WSD and EHR) and one information exchange protocol implemented in the PICT-EDSS.

4.1. Functional Evaluation

The functional evaluation of the PICT-EDSS was conducted through a controlled experiment between two systems: one system with PICT-DPA implementation and one without. All other experimental conditions are identical. Given the scarcity of real-world data, Monte Carlo simulation was employed to generate training data for the prototype system. A total of 1,212 patient records were utilized to train the models in the PICT-EDSS and perform the functional evaluation, including 412 real-world records obtained from four data sources (Kalyakulina et al., 2020; Moody et al., 2001; Jager et al., 2003), and 800 simulated records produced through Monte Carlo simulation. The records from the same dataset were randomly extracted and processed through two systems to observe how they identified and filtered the abnormal data, provided activation recommendations, and how much delay was required for each system to process the data and deliver the insights.

First, the **P**erformance was evaluated using two metrics: validity and reliability. The validity, represented as the accuracy of decisions on 'Dispatch', was evaluated to determine whether the PICT-EDSS provides valid insights. The baseline result (see Table 3) was based on the 412 real-world records from systems that did not use PICT-DPA. The 800 simulated records were used to test the PICT-EDSS, and the results are presented in Table 4. All clinical decision insights 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%.

The PICT-EDSS was also evaluated for its reliability using chance-corrected agreement κ statistics. 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%.

Table 3. Confusion matrix of no PICT-DPA data

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 4. Confusion Matrix of PICT-DPA Data

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%

In addition, the **T**imeliness of PICT-EDSS was evaluated using data and analysis latency. 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 the 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 existing EC-CDSS. For the PICT-EDSS, the average data latency was 0.5 seconds, and the average analysis latency was 0.956 seconds (see Figure 6). These results confirmed that PICT-EDSS significantly improves timeliness, achieving one of the design goals of PICT-DPA.

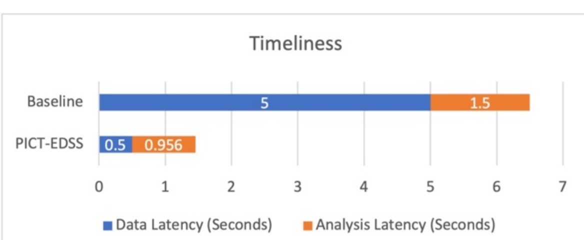

Figure 6. Timeliness of baseline and PICT-EDSS

To this end, the evaluation of the PICT-EDSS prototype has demonstrated that PICT-DPA is feasible in real-world implementation, and adopting the PICT-DPA can improve the **I**nteroperability, **P**erformance, and **T**imeliness of the EC-CDSS system. Other quality attributes that the PICT-DPA aims to achieve require additional evaluations, which are elaborated in the next subsection.

4.2. User Interviews

The quality of PICT-DPA, its impact on PHOs, and the stakeholders' intention to use were evaluated through a series of semi-structured interviews, The participants were EC-CDSS stakeholders, either having actively engaged in decision support processing in an 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 participated in the interview. The participants include one emergency room manager and one ambulance company manager, six care providers (doctors and nurses), and two dispatchers.

The interview results further confirmed that an interoperable EC-CDSS can increase Performance and Timeliness. For example, multiple care providers mentioned that Interoperability can improve decision-making performance with credible and comprehensive medical data. As one participant stated, decision-making based on heterogeneous data

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

It aligns with previous literature that interoperability can improve EC-CDSS performance by yielding accurate data suitable for further analysis and decreasing data integration time (Crilly et al., 2011).

The participants also validated the improved **P**erformance of PICT-DPA as shown in the quote below:

> *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.*

Another participant commented:

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

Most participants identified **T**imeliness as the key quality contribution of the PICT-DPA, especially for the dispatchers. As Participant 6 mentioned,

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

The ability of PICT-DPA to reduce communication time can be attributed to its quick data extraction from heterogeneous sources and its two-layered data integration and processing.

As discussed earlier, the ultimate goal of EC-CDSS is to improve PHOs. Some participants were cautious in their assessment of the extent to which the PICT-DPA could enhance PHOs. As one participant explained,

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

They suggested that real-world implementation was necessary to gather adequate data to evaluate its impact on PHOs.

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

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

This aligns with the literature that performance and timeliness of decision-making are key factors influencing PHOs (Preum et al., 2019). Future research is needed to evaluate how the performance of PICT-EDSS is related to the PHOs.

All participants confirmed their intention to use the PICT-EDSS because it can support their information needs of related EC functions and its ease of use, as one participant confirmed:

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 appreciated the system more because of its integrated information, as one indicated

…they (dispatchers) need more attention because they are an important connection part of the integrated system.

5. Research Contributions

Our research makes several contributions to both research knowledge and practices.

The most significant knowledge contribution lies within the artifact (i.e., PICT-DPA) itself. It is a new data processing architecture, within which two parallel data pipelines (real-time layer and store-and-forward layer) connect three distinct subsystems (data extraction, data integration and transmission, and insight delivery). While it is built upon the well-known Lambda architecture, to our best knowledge, PICT-DPA is the only event-driven data processing architecture with a two-tiered structure. The structure is possible through the incorporation of knowledge-based models for data filtering and algorithm-based models for scoring. Many have commented that developing artifacts to address a class of problems is one of the goals of design science research (Sein et al., 2011, Iivari et al., 2009). As discussed by Rossi et al. (2012), PICT-DPA represents a generalized knowledge to solve a class of problems (i.e., how to design a decision support system that desires all four quality attributes – performance, interoperability, cost, and timeliness). It contributes to the IS design science literature by providing an exemplar of developing solution-oriented artifacts.

Furthermore, the specific design considerations within the emergency care domain during the design process contribute to the clinical decision support system for emergency care literature and can be used by other ECS researchers when designing IS artifacts in a similar context.

Most importantly, PICT-DPA is a general architecture that can serve as a reference for IS researchers from other domains when designing systems to meet the specific quality attribute requirements and stakeholder information needs. For example, the two-layer three-subsystem architecture enables the transmission of real-time data while controlling the cost. It can be adapted in other domains, such as finance and manufacturing, where real-time decision-making can have significant impacts on outcomes. The researchers in these domains can tailor their own domain-specific functionalities, like knowledge- and algorithm-based models based on the unique domain-specific requirements and stakeholder needs. By replacing domain-specific functionalities of the PICT-DPA for emergency care represented in this study, a domain-specific DPA can be developed.

From the practical perspective, the event-driven PICT-DPA can be used to guide the implementation of integrated EC-CDSSs by researchers and practitioners. It can enhance the capabilities of data processing tasks in any domain with similar quality attribute requirements. More specifically, the knowledge-based model enables the stakeholders to use domain knowledge to set the thresholds of event filters for anomaly detection. The algorithm-based models enable the decision-making system to perform complex artificial intelligence tasks.

6. Conclusion and Limitations

This study proposes a new data processing architecture called PICT-DPA. To the best of our knowledge, PICT-DPA is the first attempt to address the data processing needs of an integrated EC-CDSS while considering all quality attributes and satisfying all relevant stakeholders' information needs. Furthermore, the PICT-EDSS, an instantiation of our proposed data processing architecture, validated 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. The success of instantiation (PICT-EDSS) represents a significant advancement in data processing tasks in the field of EC-CDSS, enabling relevant stakeholders to make more informed and timely decisions.

This research has several limitations. The first is the lack of real-world data used in the evaluation. While the Monte Carlo simulation was used to simulate the EC-CDSS operational data 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 design process. Although experts evaluated iterations of design outputs and provided recommendations, we didn't obtain inputs from them with regard to our design requirements. Furthermore, having just one expert representing one stakeholder type may result in an insufficient representation of expert opinions. Therefore, we plan to recruit additional experts in the enhancement of the data processing architecture. Lastly, our study lacks explicit considerations for health information security and privacy. Although the prototype system included some security and privacy considerations, such as encrypted data storage, role-based access and control, and a privacy-consent form, a comprehensive security and privacy strategy and its impact on the PICT-PCT's design is needed.

Several future research is needed to improve its current design. First, the PICT-EDSS can be improved by focusing on the integration of hospital data and ECS data in a real-world environment. Second, more algorithm-based models should be explored to enhance insight deliveries.

6. References

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