An Electronic Health Records Interoperability Model Among Hebron Hospitals In Palestine

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ABSTRACT

Many healthcare systems are increasingly using Electronic Health Records (EHRs) to facilitate care while maintaining streamlining processes for both physicians and patients. Nevertheless, to share patients' information, a connection is required among clinics and hospitals; these institutions may use different healthcare information systems which makes electronic sharing of health information more difficult. Significant advancement and efficient models were proposed and implemented in many developed countries in Europe and the States. These models were based on international standards designed specifically for data exchange among health care institutions with probably different information systems. However, such models are not being adopted in Palestine. Therefore, this work aims to first investigate the current state of EMR adoption in Palestine, as well as the readiness of various hospitals to implement EHR interoperability, and then to develop a suitable EHR interoperability model that will enable the seamless exchange of EHRs between different healthcare institutions in Palestine.

The mixed-method approach was used to achieve the research goals. The qualitative findings based on interviews with IT specialists at Hebron District hospitals revealed that current EMR systems are of low level of capacity and clinical terminologies, and they do not use interoperability standards. The quantitative research based on a questionnaire that was collected from healthcare professionals working in Hebron District hospitals revealed that there is a lack of data exchange infrastructure, and reported that high cost is an obstacle for implementing interoperability at their institutions. Additionally, the analysis showed that physicians from all disciplines are optimistic about the prospects of electronically exchanging various health data since they see the benefits to society as a whole. Both quantitative and qualitative findings emphasized that there is no electronic exchange of EHRs among Hebron hospitals.

Based upon these findings, the author proposed a model named islEHR based on AI approaches and the HL7 FHIR interoperability standard for enabling data sharing in a standard format that humans and computers can use. The evaluation results indicated that islEHR can be used with a high level of accuracy and efficiency meaning that islEHR is a viable approach for sharing EHRs among Hospitals in Hebron and can be generalized for data sharing among hospitals in Palestine as well.

Key Words: eHealth, Electronic Medical Record, Electronic Health Record, Interoperability, Fast Healthcare Interoperability Resources.

الملخص

تَستخدم العديد من أنظمة الرعاية الصحيّة السّجلّات الصّحيّة الإلكترونيّة (EHRs) بشكل متزايد؛ لتسهيل الرعاية الصحية مع الحفاظ على تبسيط العمليات لكل من الأطباء والمرضى، وما يزال الاتصال بين العيادات والمستشفيات لازمًا لمشاركة معلومات المرضى، وقد تستخدم هذه المؤسسات أنظمة معلومات رعاية صحية مختلفة مما يجعل المشاركة الإلكترونية للمعلومات الصحية أكثر صعوبة. لقد تم اقتراح وتنفيذ العديد من النماذج الفعّالة في الكثير من البلدان المتقدمة في أوروبا وكذلك في الولايات المتحدة الأمريكية، استندت هذه النماذج إلى المعايير الدولية المصمّمة خصّيصًا لتبادل البيانات بين مؤسسات الرعاية الصحية ذات أنظمة المعلومات المختلفة، ولكن مثل هذه النماذج لم يتم تبنيها في فلسطين؛ لذلك فإن هذا العمل يهدف إلى التحقيق في الوضع الحالي لاعتماد السجلات الطبية الإلكترونية في فلسطين، فضلاً عن التأكد من مدى استعداد مختلف المستشفيات لتنفيذ إمكانية الربط البينيّ للسجلات الصحية الإلكترونية، ومن ثم تطوير نموذج مناسب للربط البيني للسجلات الصحية الإلكترونية، يُمَكّن من التبادل السلس للسجلات الصحية الإلكترونية بين مختلف مؤسسات الرعاية الصحية في فلسطين.

استخدمت الباحثة منهجًا مختلطًا لتحقيق تلك الأهداف البحثية، وقد كشفت النتائج النوعية المستندة إلى مقابلات مع متخصصي تكنولوجيا المعلومات في مستشفيات منطقة الخليل أن أنظمة السجلات الطبية الإلكترونية الحالية ذات مستوى منخفض من الإمكانيات، وكذلك استخدام المعايير الطبية العالمية للمصطلحات الطبية والربط البيني. كما أظهر البحث الكمي القائم على تحليل استبيان تم جمعه من المختصين في الرعاية الصحية العاملين في مستشفيات محافظة الخليل أن هناك نقصًا في البنية التحتية لتبادل البيانات، وأفاد بأن التكلفة المرتفعة تشكل عقبة أمام قابلية تنفيذ الربط البيني في تلك المؤسسات، كما أفاد بأن الأطباء من جميع التخصصات متفائلون بشأن آفاق التبادل الإلكتروني للبيانات الصحية المختلفة؛ لأنهم يرون أن ثمة فوائد سوف تعود على المجتمع ككل. كما أكدت النتائج الكمية والنوعية أنه لا يوجد تبادل إلكتروني للسجلات الإلكترونية بين مستشفيات الخليل.

بناءً على هذه النتائج، اقترحت الباحثة نموذجًا يسمى islEHR استنادًا إلى مناهج الذكاء الاصطناعي ومعيار قابلية التشغيل البيني HL7 FHIR لتمكين مشاركة البيانات بتنسيق قياسي يمكن للبشر وأجهزة الكمبيوتر استخدامها. وقد أشارت نتائج التقييم إلى أنه يمكن استخدام islEHR بمستوى عالٍ من الدقة والكفاءة، مما يعني أن islEHR هو نهج قابل للتطبيق لمشاركة السجلات الصحية الإلكترونية بين المستشفيات في الخليل، ويمكن تعميمه لمشاركة البيانات بين المستشفيات في فلسطين أيضًا.

الكلمات المفتاحية: الصحة الإلكترونية، السجل الطبي الإلكتروني (EMR)، السجل الصحي الإلكتروني (EHR)، إمكانية الربط البيني، موارد الربط البيني للرعاية الصحية السريعة (FHIR).

Dedication To My Loving Parents

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“ First and foremost, I am deeply grateful to GOD who gave me the honor, ability, and strength to complete this work ”

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CHAPTER 1 : INTRODUCTION

eHealth is an emerging field in the sector of medical informatics. According to the world health organization, the term eHealth describes the use of information and communication technologies (ICT) for health (WHO, n.d.). The Electronic Health Record (EHR) represents the core component of eHealth.

With the increase in the generation of medical data, many health information systems appeared. They are designed to manage massive and various medical data effectively and efficiently. Recently, Electronic Health Record (EHR) information systems took a position in most healthcare organizations in Palestine. These systems moved the majority of paper-based records into digital ones providing more abilities to manage these records and hence improved the performance of the health care delivery system in general. Nevertheless, EHR in Palestinian health care delivery institutions faces a big issue with interoperability as existing EMR systems in Palestine store a multitude of medical records independently with different structures and formats. It's worth noting that the two terms (EHR and EMR) refer to the same thing: they both refer to the electronic storage of clinical data, but EMR refers to it at the organizational level, whilst EHR refers to the shareable version outside the organization.

To provide effective health care on time, health information should be effectively and efficiently exchanged among various healthcare organizations. The limited access to patient health data poses a major problem especially in the case of patient referral or telemedicine. As in many situations, an urgent consultation is needed by other healthcare providers.

1.1. Problem Statement

Medical information sharing becomes a worthy action for the patient's treatment, unfortunately, existing EHRs have different structures and semantics. Structural differences may refer to the nonconformity of database, data format, or data syntax. Whilst, semantic differences may refer to the use of vocabulary, varied data representations, or languages. There are many solutions proposed for achieving EHRs interoperability worldwide, however, there is poor implementation and adoption of interoperability solutions in the community of Palestine. Our main motivation for this thesis is to research an appropriate approach for achieving semantic interoperability among various healthcare organizations in Palestine.

1.2. Research Questions

The main research question is, **" What would be the most appropriate eHealth interoperability model for Palestine? "** To be more specific, this thesis aims to investigate the ability to improve electronic health record data integration between various Palestinian healthcare organizations. The main research question will be answered by responding to the following sub-questions:

- What is the role of EMR systems in the Palestinian community?
- What is the condition of data interchange among different hospitals in Palestine?
- To what extent is eHealth interoperability applicable in the Palestinian community?

1.3. Research Objectives

The main objective of this research is to find a solution for interoperability between heterogeneous EHRs systems in Palestine. The main research objective could be divided into a set of sub-objectives mentioned below:

- To review the state of the art about existent standards and adoption drivers.
- To review the state of the art about existent interoperability models.
- To find out what EMR systems are in place and their capabilities.
- To find out what interoperability models and standards are already developed in Palestine.
- To find out what are the driving forces for applying interoperability in Palestine.
- To find out what are the barriers to applying interoperability in Palestine.

- To research a potential solution for interoperability in Palestine.
- To develop and test a prototype of the founded solution.

1.4. Relevance And Importance Of The Research

This thesis focuses on investigating the situation of semantic interoperability among heterogeneous EHR information systems in Palestine. Thus, providing an insight view into what is the most appropriate approach to exchange medical data for real-time usage. We suppose that achieving semantic interoperability in the Palestinian community will enhance the quality of healthcare, save time, and reduce costs. Through facilitating the obtaining of the right data at the right time, empowering caregivers with a better understanding of transferred data, and reducing medical errors related to the lack of information. Which all will lead to a great patient experience of care and better population health (Iroju et al., 2013; Luna et al., 2019).

1.5. Summary

The research problem was introduced in this chapter as well as research questions and objectives were discussed. The rest of the thesis is organized as follows. Chapter 2 presents the literature review. In Chapter 3 research methodology is illustrated. Results are discussed in Chapter 4. Chapter 5 introduces the proposed model where the prototype construction is explained. In the end, conclusions are provided in Chapter 7.

CHAPTER 2 : THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1. Introduction

The theoretical basis for electronic health records, interoperability, and semantic interoperability among electronic health record systems is proposed in this chapter. In addition, it lists and organizes the most up-to-date research and applications in this subject. Gaps in current knowledge will also be discussed.

2.2. Theoretical Framework

This section focuses on the most important aspects of EHR interoperability and how to accomplish it.

2.2.1.Electronic Health Record (EHR)

In the scope of eHealth, the EHRs information systems play the main role. EHR is a digital storehouse of medical information in which it can be shared between authorized users of the system to support research, ensure patients' privacy, and continuity of efficient and quality incorporated health care (Adel et al., 2018; Blobel, 2018). EHR holds information from different stakeholders which may be administrative or clinical. Administrative stakeholders such as administration, patient registration, and an insurance company who feed EHRs with information include patient identification, meetings, financials, lawful status, and insurance. Clinical stakeholders such as clinicians, pharmacy, nursing, and physicians who feed EHRs with information include images, scans, and tabular records (Adel et al., 2018). Different types of EHRs can be grouped according to duo points of view, from a logical and organizational perspective an EHR may be centralized, decentralized, or distributed. From a managerial perspective, an EHR may be professionally/organizationally moderated or personally moderated (Blobel, 2018). The use of an EHR offers many benefits, including:1) preventing medication errors, 2) minimizing duplication, 3) smoothing the coordination of long-term patient data, 4) and saving time. Efficient use of EHRs requires the capturing process of data to be done through standardized data definitions and standardized quality measures (Bhalla et al., 2017).

EHR is dependent on the existence of Electronic Medical Record (EMR). Which is an application environment that consists of a clinical data repository, clinical decision support, controlled medical vocabulary, computerized order entry, pharmacy, and clinical documentation applications. This environment feeds the EHR with data. EHR can be founded only if the EMRs of various care delivery organizations have been promoted to create and support sturdy data exchange between different stakeholders within a region (Garets & Davis, 2006).

Healthcare Information and Management Systems Society (HIMSS) Analytics developed an Electronic Medical Record Adoption Model (EMRAM), which is a methodology and algorithm to automatically score hospitals according to their EMR capabilities (HIMSS Analytics, n.d.-a). This model is used all around the world. It consists of eight stages from 0 to 7 used to measure the adoption and utilization of EMR functions. A brief description of the EMRAM stages is listed below:

- Stage 0 — all three ancillaries (laboratory, pharmacy, and radiology/cardiology information systems) are not installed.
- Stage 1 — the three main ancillaries are installed, a full complement of radiology and cardiology Picture Archiving and Communication System (PACS) systems, and digital non-DICOM image management.

- Stage 2 — single Clinical Data Repository (CDR) implemented, internal interoperability enabled, and basic security tools and mechanisms are used such as encryption, antivirus, anti-malware, etc...
- Stage 3 — 50% of nursing and allied health documentation, Electronic Medication Administration Record application (EMAR), and Role-Based Access Control (RBAC) are implemented.
- Stage 4 — 50% of medical orders placed using Computerized Practitioner Order Entry (CPOE) and supported with Clinical Decision Support (CDS) engine, nursing, and allied health documentation reached 90%, clinicians have access to national and regional databases, and precautions for EMR downtime and network intrusion detection are implemented.
- Stage 5 — physician documentation using structured templates implemented, track and report nurse order/task completion possible, and intrusion/device protection implemented.
- Stage 6 — technology-enabled medication and blood products and human milk preparation and tracking in a closed-loop, integration of EMAR with CPOE, pharmacy and laboratory information systems, full CDS used, and Mobile/portable device security applied.
- Stage 7 — complete EMR, data warehousing for data analytics implemented, full interoperability achieved, disaster recovery plan implemented, and physician documentation and CPOE has reached 90%.

Payne et al. (2019) mentioned that Scotland nation is one of the first contributors to technological development in the health field, especially in primary care. It is close now to 100% paperless primary care, practically with networked information systems including digital patient records, electronic prescribing, decision support, clinical communications, and administrative tools. Primary care depends on two government-approved systems, EMIS PCS and Vision, as planned the Microtest

Health system will be used this year. Counter to secondary care which advances slower because of restrictions related to the variation of regional and local systems and data practices.

2.2.2.Interoperability

Interoperability represents a significant point for sharing medical data between different systems and devices. We say the two EHRs are interoperable if they can exchange and use the exchanged data (Adel et al., 2019b; Gansel et al., 2019; Reisman, 2017). ISO/IEC 2382 information technology defined interoperability as " the capability of two or more functional units to process data cooperatively " (ISO, 2015). While the Healthcare Information and Management Systems Society provides a broader definition that describes interoperability as " the ability of different information systems, devices and applications (systems) to access, exchange, integrate and cooperatively use data in a coordinated manner, within and across organizational, regional and national boundaries, to provide timely and seamless portability of information and optimize the health of individuals and populations globally" (HIMSS, n.d.). To clarify the idea of interoperability we can assume a situation in which a patient who visited hospital A needs to have an urgent surgery that can only be done in a hospital B, a patient record can be transmitted from hospital A to hospital B and physicians can quickly provide the needed treatment with no necessity to waste time on doing tests again, even if these two hospitals have different systems, the interoperability made it possible for the two different EHR systems to communicate and exchange data easily and efficiently. The lack of interoperability makes it difficult to treat patients efficiently and hospital B needs to redo many tests and wait for the results.

Researchers discussed different levels of interoperability. According to (Adel et al., 2019b), there are four levels of interoperability from the point of data understanding. These levels are:

- Level 0 — No interoperability: medical information cannot be understood by humans or machines. Also, missing the use of IT in sharing such as mail or fax.
- Level 1 — Syntactic interoperability: medical information syntax is clear and well-defined while its meaning is not. Data is represented using high-level transfer syntaxes such as XML or HTML.
- Level 2 — Technical interoperability: medical information can be transferred between machines.
- Level 3 — Semantic interoperability: medical information is clear and understood for different organizations that do not speak the same language.
- While (Reisman, 2017) said that interoperability can be classified into three categories:
- Level 1 — Foundational: EHR systems exchange data without having the ability to interpret it.
- Level 2 — Structural: EHR systems exchange data and can interpret it at the data field level.
- Level 3 — Semantic: EHR systems exchange information and use it.

2.2.3.Semantic Interoperability

Semantic interoperability is the ability of two or more information technology systems to share medical data and to conveniently use it by capitalizing on its structure and vocabulary (Gansel et al., 2019; Matney, 2016). Semantic interoperability enables the sharing of medical data between heterogeneous EMR systems and provides the ability to effectively use these exchanged data. Of course, protecting its meaning from a misunderstanding by empowering computer systems in understanding meanings. For example, a received patient record contains Grinch Syndrome as a health issue. This term represents a way to symbolize the Postural Orthostatic Tachycardia Syndrome (POTS) which means the patient has a heart that's too small. When a computer information system can't realize this term, a terrible mistake will happen. Semantic interoperability will safeguard the EHRs sharing from a mistake like that. Semantic interoperability is used to fulfill consistent patient care, support decisions, measure outcomes, and research across settings among different healthcare organizations (Matney, 2016). Several issues face semantic interoperability, these can be classified as follows:

- Meaning: may refer to contextual or linguistic reasons.
- Granularity: refer to the completeness of data.
- Temporal: may refer to the change of data meaning over time or terminologies changes due to the advancement of science.
- Structural: may refer to the categorization of information or positioning errors within vocabulary structures (Liyanage et al., 2015).

There are three important elements needed to achieve good EHRs semantic interoperability by setting a common understanding of clinical data vocabulary and concepts. These elements include EHR standards, terminologies, and ontologies (Adel et al., 2019; do Espírito Santo & Medeiros, 2017; Matney, 2016).

Exchange Standards

EHR exchange standards are used to define protocols that enable the digital store and exchange of patients' health data (do Espírito Santo & Medeiros, 2017). Various organizations proposed many standards to achieve semantic interoperability including HL7, DICOM, and ISO/TC 215 standards as the most often used EHR (Adel et al., 2019; do Espírito Santo & Medeiros, 2017).

HL7 is a set of standards for exchanging, integrating, sharing, and retrieving electronic health information to achieve interoperability among healthcare service providers. Four specific standards are 1) Version 2 which is the most used standard in the world for the exchange of orders, results, admission/discharge/transfer (ADT), and public health communication, 2) Version 3 also known as the Reference Information Model (RIM) which is an information model for information representation, 3) Clinical Document Architecture (CDA®) which is a primary HL7 standard for representation of structured clinical documentation on patients, 4) and Fast Healthcare Interoperability Resources (FHIR®) which represent the next-generation standards framework that depends on the best features of the HL7 V2, V3, and CDA® as well leveraging the latest web standards (HL7 International, n.d.-a).

Digital Imaging and Communications in Medicine (DICOM®) is an international standard for transmitting, storing, retrieving, printing, processing, and presenting medical image information. It defines formats of medical images so they can be exchanged with the data and quality necessary for clinical use (The Medical Imaging Technology Association, n.d.).

ISO/TC 215 health informatics has created a wealth of standards, to facilitate capturing, exchanging, and using health-related data, information, and knowledge (Ed Hammond, 2017; ISO Technical committees, n.d.). One of the well-known standards is the ISO 13606, which is a standard designed by the European Committee for Standardization (CEN) for electronic health records communication between different EHR systems, between EHR systems and a centralized data repository, or between an EHR system and clinical applications or middleware components like decision support. It defines strict and stable information architecture for the communicating part of the whole electronic health record (EHR) of a single patient (ISO 13606 community, n.d.). Another important standard, that facilitates the medicinal products information exchange among multiple stakeholders, the Identification of Medicinal Products (IDMP). It composed of five standards that are:

- ISO 11238: data elements and structures for the unique identification and exchange of regulated information on substances.
- ISO 11239: data elements and structures for the unique identification and exchange of regulated information on pharmaceutical dose forms, units of presentation, routes of administration, and packaging.
- ISO 11240: Data elements and structures for the unique identification and exchange of units of measurement.
- ISO 11616: Data elements and structures for unique identification and exchange of regulated pharmaceutical product information.
- ISO 11615: Data elements and structures for the unique identification and exchange of regulated medicinal product information (Ed Hammond, 2017; European Medicines Agency, 2016).

Terminologies And Classifications

Medical terminology is a set of concepts with a related collection of words that give a controlled vocabulary and structured medical expressions to help in clinical care, choices, search results, and quality change. It makes efficient giving of more exact and shareable expressions in the case of using free text (Adel et al., 2019). Terminologies could be clinical reference terminologies or interface terminologies. The clinical reference terminology is a set of concepts, human language terms, and relationships with some sort of semantic hierarchy that provides a common reference point for the comparison and aggregation of medical data. While the reference terminology (colloquial terminology, application terminology, or entry terminology) is a systematic collection of healthcare-related terms used to support clinicians' in entering information related to a patient using computer systems. A similar concept is a medical classification that provides the data structure necessary to support healthcare clinical and administrative operations as terminologies do but with less degree of specificity (González Bernaldo de Quirós et al., 2018). ICD, LOINC, and SNOMED CT are the most often used medical terminologies and classifications (González Bernaldo de Quirós et al., 2018; Matney, 2016).

International Classification of Diseases (ICD) is a classification standard that defines all existing diseases, disorders, injuries, and other related health conditions and lists them in a comprehensive, hierarchical style. It represents a base of health trends identification, universal statistics, diseases, and health conditions reports. ICD-11 is the newest version of this standard (World Health Organization, n.d.).

Logical Observation Identifiers Names and Codes (LOINC) is a collective language composed of a group of identifiers, names, and codes used to identify health measurements (laboratory tests, clinical measures, and anthropometric measures), observations, and documents. It enables the aggregation and exchange of clinical results by providing a lingua franca for data (LOINC, n.d.).

Systematized Nomenclature of Medicine Clinical Terms (SNOMED CT) is a clinical terminology that provides a standardized way to represent medical phrases to enable the recording of medical data with foster accuracy and consistency (SNOMED International, n.d.)

Ontologies

Ontology is a description of a set of concepts related to a specific domain and relationship links among these concepts. Ontologies' main components are made up of a collection of concepts, their attributes and interrelationships, and assertions (class-level assertions or instance-level assertions) (Liyanage et al., 2015). It can be created using any computer description language such as Resource Description Framework

(RDF) or Web Ontology Language (OWL) (Bauer et al., 2019). In the field of medicine, ontologies represent a good option because of their various advantages include providing a clear definition and perception of the domain and its relations, processing, and reasoning of human information content, enabling machine interpretability, and smoothing medical information exchange between different standards or systems (Adel et al., 2019).

2.2.4. Standardization For eHealth Interoperability

OpenEHR technology is designed to support semantic interoperability and address the main challenges that affect the progress of IT in the health sector. These challenges include the complexity and rate of change of information and processes, the growth of specialization and team-based care, the routine move of patients across the enterprise and jurisdictional boundaries, and the rapid advance of technology versus the longevity of care processes. These challenges were addressed by providing a comprehensive architecture for specifying, designing, and building electronic health solutions. The first component is a multi-level modeling framework that separates data representation from domain content. The second component is an open platform architecture that represents patient-centric health data. A domain modeling formalism is the third component that supports composition, specialization, localization, and flexible binding to terminology. The fourth component is a collection of archetypes that build a library of data points. Archetypes are original models for clinical information capturing, which were developed in any language by domain experts. The fifth component focuses on templates that provide the ability to recombine data points into data sets. And the last component is the implementation of tools that convert domain models into technical forms. This semantic framework of openEHR is shown in Figure 1 (OpenEHR, n.d.).

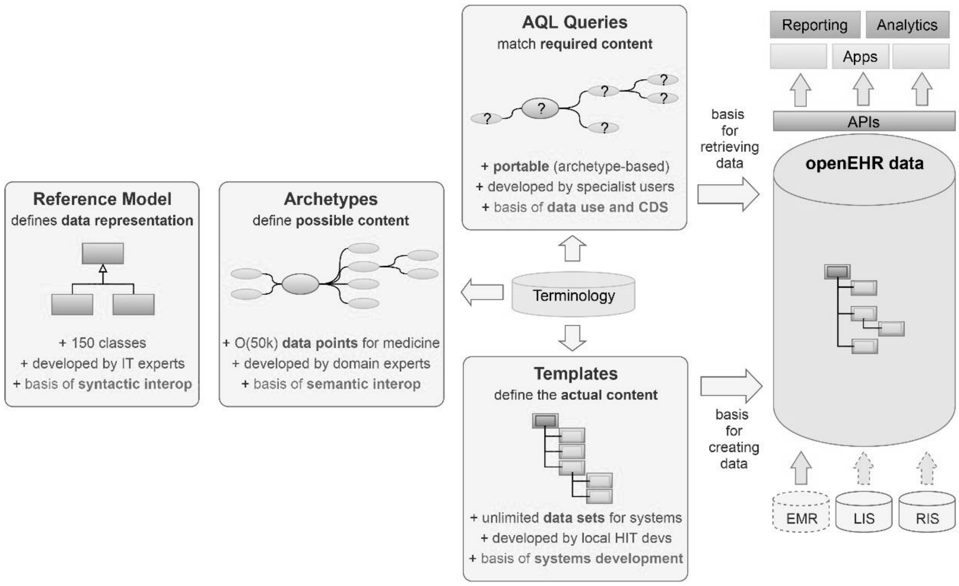

Fig.1. The semantic framework of openEHR - Source: (OpenEHR, n.d.)

2.2.5.eHealth Interoperability Case

As mentioned earlier, Scotland presented early progress with health information technology. With this concern, they implemented a national exchange system called SCI-Gateway to effectively interchange health information and record connections across different parts of the services such as emergency, pharmacies, and outpatients based on the patient identifier that is known as the Community Health Index (CHI). The key component of exchanging patient information is the Emergency Care Summary record (ECS) which contains information about demographics, prescribed medications, allergies, and Adverse Drug Reactions (ADRs). Let us assume that Ms. Jones' want to refer a patient from primary to secondary care, she securely accesses the SCI-Gateway system and completes a structured template by selecting the service requested, adding details of her clinical presentation, updating the pre-populated medical history, and attaching electronic copies of any relevant documents. This template will be sent via SCI-Gateway to the receiving physician or triage unit (Payne et al., 2019). Triage is the process of sorting patients for treatment with the determination of the most important cases that requires attention among large numbers

(F.H. Aljazairi, 2019). In which, the results of previous laboratory tests or scans can be accessed. The key objective of the latest eHealth strategy was released in 2018, to implement a cloud-based National Digital Platform (NDS) with the central Clinical Data Repository (CDR) to provide a single record of patient health and care data. To support interoperability, the NDS will use the OpenEHR architecture and provide APIs to enable access to various services. Also, adoption of HL7 FHIR messaging standards by different health systems suppliers to interoperate with this platform (Payne et al., 2019). This architecture is shown in Figure 2.

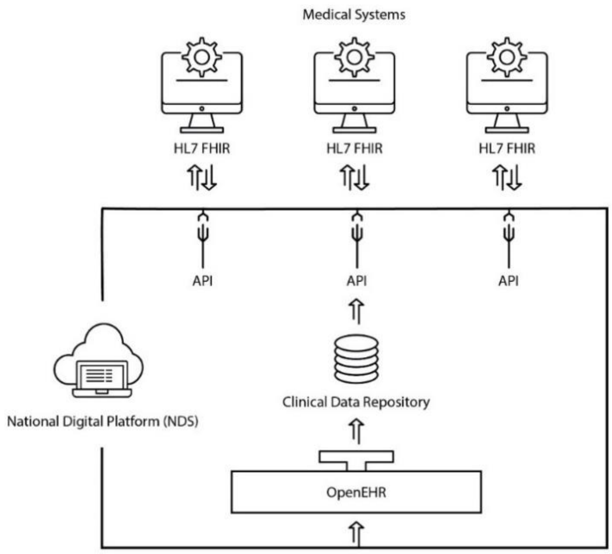

Fig.2. The architecture of Scotland strategy to support interoperability

2.3. Literature Review

In this part, recent EHR interoperability solutions proposed in the last five years were presented and compared. There are also gaps in the existing information stated.

2.3.1.EHR Semantic Interoperability Architectures

Many solutions have been proposed to solve the problem of EHRs semantic interoperability. Later, some of these solutions will be presented.

Legaz-García et al. (2016) solution, called the Archetype Management System (ArchMS) is a semantic framework relying on OWL ontology for the management and reuse of clinical archetypes and EHRs data. Inputs of this system include ADL archetypes and XML EHR data extracts compliant with the OpenEHR and ISO 13606 specifications. ArchMS architecture consists of three main layers, 1) acquisition, 2) repositories, 3) and exploitation. The layer acquisition validates archetypes and converts them to OWL as data extracts are also converted to OWL. The layer repositories store primary data about both archetypes and extracts. The layer exploitation takes advantage of archetypes and EHRs data through archetype annotation, archetype search and similarity, data visualization, semantic profiling, and data classification.

Puttini et al. (2017) present a semantic framework for EHRs called two-level modeling. It consists of two main models, 1) information model 2) and knowledge model which is supported with standardized terminologies. The information model or reference model is substantially based on a set of generic classes to represent EHR-related concepts. It is composed of a set of primitive types and a set of classes that define the organization of information in EHRs, classes that describe context information, and classes that describe the demographic data of patients. The OpenEHR information is a model based on the Clinical Information Ontology (CIR) where the information is placed following its category, administrative or clinical. The knowledge model assigns structures to the proper concepts, their particular data types, aggregations, and terminologies. The OpenEHR knowledge model is based on the archetypes that formally define how an information model hierarchy should be organized and define how clinical data should consistently be mapped with a conserved original meaning.

Blackman-Lees (2018) solution, called the XDataRDF is a master data translation model predicated on the RDF for semantically sharing patient data. This model includes 1) RDF definitions that are used to manipulate and transform data 2) and matching based on defined rules, matching based on name constructs, and matching based on common value inference. In the proposed architecture, patient data flows from EHRs to the target systems by an integration engine that is connected to the XDataRDF model.

Oliveira et al. (2018) proposed a system for EHRs information storage and exchange based on openEHR. This system is made up of three components include 1) information workflow, 2) data generation, 3) and HL7 binding. The information workflow part concerned creating and editing archetypes to organize domain concepts using the Archetype Definition Language (ADL) and creating templates that are needed for inserting new data. The data generation part uses the operational templates previously created and extracts data to generate a graphical user interface (GUI) in which semantic interoperability is ensured by the bind of SNOMED CT terminology and informational structures represented by archetypes. The HL7 binding part uses HL7 V3 and CDA to generate, store, and exchange information.

Adel et al. (2019a) proposed a framework to achieve semantic interoperability that relied on ontology concepts. The architecture of this framework is based on three main layers: 1) the local ontologies construction layer, 2) the global ontology construction layer, 3) and the user interfaces layer. The local ontologies construction layer stores the EHR heterogeneous care information. Store by transforming different inputs into ontologies using mediators like DB2OWL, ADL2OntoModule, R2O, and many more. The global ontology construction layer maps local ontologies to a global ontology. This process is done with the use of mapping algorithms and human experts based on common terminology vocabularies. After that, the generated crisp ontologies are converted to a unified fuzzy ontology. The user interface layer enables physicians or specialists to perform queries and receive answers.

Hong et al. (2019) proposed a framework for integrating EHRs data based on HL7 FHIR. The core of this framework is an NLP2FHIR pipeline that is composed of 3 modules: 1) core NLP engine, 2) integrating structured data, 3) and content normalization. The module of the NLP engine is responsible for modeling unstructured data using FHIR specifications and a set of clinical NLP tools including cTAKES, MedXN, and MedTime. The module of integrating structured data combines structured data with NLP engine outputs. As the last step, the content normalization module stratifies that EHR data match the FHIR specifications through terminology mapping.

Gomes et al. (2019) proposed a Gateway for Interoperability of Electronic Health Record in Low-cost System (GIRLS). The main idea is based on applying the concept of microservices technology to reach interoperability between systems that employ different data standards, namely FHIR and OpenEHR. The solution architecture is made up of the following four layers: 1) API gateway, 2) configuration service, 3) FHIR broker, 4) and monitoring and logging. The API gateway provides endpoints for the data exchange, while the configuration service manages the microservices simultaneously and ensures the quality of communications and configuration between services. The FHIR broker processes the data from the systems that use different standards and mapped them to FHIR. The Zipkin distributed tracing system is used to monitor and log the data flow of the various services.

Kiourtis et al. (2019) proposed a solution for mapping healthcare data to the HL7 FHIR standard using semantic meaning and ontology alignment techniques. The architecture is composed of the following four layers: 1) ontologies and relationships, 2) knowledge base, 3) structure mapping library, 4) and FHIR structure translator. In the ontology and relationships layer, health care data and FHIR resources are transformed into ontological forms (classes, instances, and relationships). Then, the knowledge base stores the generated ontologies in an RDF triple-store and identifies missing values. While the structure mapping library maps healthcare data to FHIR based on the semantic meaning of different classes, relationships, and instances stored in the knowledge base and ontology alignment technique. Finally, the FHIR structure translator obtains the mapped data and translates them into the right HL7 FHIR form.

A comparison of talked-over solutions for EHRs semantic interoperability issues is summarized in Table 1.

Table.1. A Comparison Of Previous Solutions

Publication	Main Idea	Methods / Standards Used	Limitations
(Legaz-García et al., 2016)	The authors proposed a semantic web based framework for interoperability through the management of archetypes and EHR extracts.	– Ontology – openEHR	– There is a need to perform more evaluation studies and the framework wasn't compared with any other existing solutions.
(Puttini et al., 2017)	The authors proposed a semantic framework for EHR to support interoperability.	– Ontology – openEHR	– It's good to implement that structure into action and evaluate its accuracy and effectiveness. Compare it to other solutions as well.
(Blackman-Lees, 2018)	The author proposed a model for translating patient data as a part of a framework for data exchange.	– RDF Schema	– The accuracy of the information exchanged was not determined.
(Oliveira et al., 2018)	The authors proposed a system based on implementing an OpenEHR based EHR system	– openEHR – HL7 V3 – HL7 CDA	– It is necessary to put that framework into practice and assess its accuracy and

	integrated with HL7 standards to reach interoperability.		performance. Also, compare it to other solutions.
(Adel et al., 2019a)	The authors proposed a unified semantic interoperability framework based on fuzzy ontology.	– Fuzzy Ontology	– The framework is still in development and needs to demonstrate its viability.
(Hong et al., 2019)	The authors proposed a scalable HL7 FHIR based EHR data modeling framework for standardizing and integrating unstructured and structured EHR data.	– Clinical NLP – HL7 FHIR	– Total accuracy needs more improvements and the framework hasn't been compared to any other frameworks.
(Gomes et al., 2019)	The authors proposed a microservices-based gateway for interoperability of electronic health records in low-cost system.	– OpenEHR – HL7 FHIR	– The accuracy of the information exchanged was not determined and the framework hasn't been compared to any other frameworks.
(Kiourtis et al., 2019)	The authors proposed a solution for mapping healthcare data to the HL7 FHIR standard using semantic meaning and ontology alignment techniques.	– Ontology – HL7 FHIR	– Framework accuracy could be improved.

2.3.2. Gaps in Existing Knowledge

This review of the existing literature cast light on the current knowledge regarding EHRs semantic interoperability and how it can be achieved. In what consist of the existing work regarding semantic interoperability, we have noticed the following findings:

- Some of the proposed solutions lack integration with new healthcare-related standards.
- Some of the proposed solutions hadn't been compared with other old systems or even tested in a real-life experiment to prove their feasibility.
- Almost all reviewed articles proposed semantic architectures for European communities like Spain, Brazil, and Portugal. With an absence of semantic architectures proposed for the Palestinian community.

In what concerns these findings plus the need for an eHealth interoperability model for Palestinian healthcare organizations, we will look at the most suitable approach for achieving semantic interoperability in the Palestinian community. Which should support the available legacy systems and the integration with available healthcare standards and any new healthcare standards that may appear. Also, desired a high level of security.

2.4. Summary

Literature has acknowledged that interoperability among different information systems is paramount in the healthcare sector. Many researchers sought to reach solutions for data sharing among various health care providers in different societies, which resulted in many implementations for such interoperable solutions in many countries Worldwide. However, we noticed the absence of EHR interoperability solutions offered in the Palestinian community, and hence, our thesis aims at addressing this by investigating a suitable solution for interoperability in Palestine. The next chapter presents the research methodology that will be adopted to reach the objectives of this research.

CHAPTER 3 : RESEARCH METHODOLOGY

3.1. Introduction

This chapter introduces the research methodology for this study including the research approach, the population of the study, the sample of the population, the sampling technique, and instruments for data collection.

3.2. Research Approach

To satisfy the objectives of the study, a Mixed Methods Research (MMR) was held. It involves collecting and integrating quantitative and qualitative data in one research. This approach allows the prove, disprove, or lend credence to existing theories. Also, the build of a robust understanding of the topic, taking out the meanings people ascribe to their activities, situations, and circumstances (Leavy, 2017). This method was used to investigate the available EMR system utilized by Palestinian hospitals. As well as identifying important roadblocks and motivators for implementing EHR interoperability in our community.

3.3. Population Of The Study

The target population for this research is defined to include physicians and IT directors who work in hospitals located in Hebron, a governorate in Palestine. Which are 9 hospitals. Table 2 below presents a record of the population.

Table.2. Study Population

Hospital Name	Hospital Type	Number Of Physicians	Number Of IT Directors
Al-Amera Alia	Governmental	174	1*
Al-Ahly	Private	105	1
Al-Shaheed Abu Al-Hassan Al-Qasem	Governmental	51	1*

	Palestine Red Crescent Society	Private	44	1
	Al-Meezan	Private	22	1
	St John	Private	6	1
Total	6		402	5

*: The same person

3.4. Sample Of The Population

The population of IT directors is small enough to include all of them in the study. While the number of physicians is large, which cannot all be studied. In this case, a sample of the population is taken. The sample size was determined by the Thompson formula (Thompson, 2012) which is 196 physicians :

$$n = \frac{N \times P\,(1-P)}{\left[(N-1) + \left(\frac{d^2}{z^2}\right)\right] + P\,(1-P)} = \frac{402 \times 0.5\,(1-0.5)}{\left[(402-1) + \left(\frac{0.05^2}{1.96^2}\right)\right] + 0.5\,(1-0.5)}$$

$$= 196$$

Where :

n= the sample size.

N= the total number of population, 402.

d= the percentage error (0.05).

P= proportion of the property offers and natural (0.5).

z= is the upper α⁄2 of normal distribution (1.96 for 95% confidence level).

3.5. Sampling Techniques

In this study, listing all physicians in the population and randomly selecting individuals to participate in this study was impossible. So, nonprobability sampling was adopted as a method for this study. The efficient way to choose the sample that represents the population is a proportional quota sampling because hospitals don't have the same number of physicians. Accordingly, the researcher divided the population into 6 subgroups, each one of them representing one hospital. Then, assign a quota for each subgroup based on the total numbers of each subgroup in the population (Sekaran, 2003). The proportion in which subgroups exist in the population is calculated using the following formula:

$$Subgroup\ Weightage = \frac{Total\ Number\ Of\ Physicians\ In\ The\ Group}{Total\ Number\ Of\ Physicians\ In\ The\ Population} \times 100\%$$

By finding the weightage of each subgroup in the population, these percentages are then used to calculate the size of the quotas. This with the use of the following formula:

$$Quota\ Size\ =\ Subgroup\ Weightage\ \times Sample\ Size$$

Table 3 summarize study quotas.

Table.3. Study Quotas

Subgroup	Subgroup Weightage	Quota Size
Al-Amera Alia	43.28 %	85
Al-Ahly	26.12 %	51
Al-Shaheed Abu Al-Hassan Al-Qasem	12.69 %	25
Palestine Red Crescent Society	10.95 %	21
Al-Meezan	5.47 %	11
St John	1.49 %	3

3.6. Instruments For Data Collection

The researcher designed a questionnaire as one of the data collection instruments for this study. Also, personal interviews were used.

3.6.1.Interview

An interview is a powerful qualitative method for eliciting data that allows researchers to examine people's views in the utmost depth (Alshenqeeti, 2014). The researcher conducted a set of semi-structured interviews with IT professionals who are responsible for using EMR systems in hospitals of the population. This is for studying the capability of the available EMR systems in Hebron.

Interview Guide

A semi-structured interview guide presented in Appendix A was developed before interviewing. An interview guide is a method that lists the questions that the researcher will ask. It assists in making the interviewing process more systematic and comprehensive by specifying the matters to be explored (Brayda & Boyce, 2014). The gained insights from the existing literature besides research questions were used as an inspiration for the interview guide questions. Related topics were collected and to each of them, several closed-ended and open-ended questions were developed.

Data Gathering

In this study, a total of 5 interviews were undertaken with IT directors responsible for EMR systems used by all hospitals of the population. About governmental hospitals, which counted 2 in this study, one IT director is responsible for the EMR, as it is the same system. All interviews were planned to be in-person interviews but one of them was tele-interview due to some reasons caused by the COVID-19 pandemic. These interviews were previously arranged with interviewees. Interviews ranged from half an hour and an hour and a half in duration. All interviews have been conducted in Arabic. The interviewees were asked to permit to record the interview, some of them agreed, and some did not. However, detailed notes were taken during these meetings.

Data Analysis Technique

Manual data interpretation was conducted as the number of carried-on interviews was small. Also, the spoken language cannot be handled using a computer application. The content analysis deductive approach was used for data analysis. Content analysis is a strategy for written or oral data analysis of qualitative descriptive studies (Cho & Lee, 2014). The deductive approach uses an organizing framework of establishing themes based on preconceived categories borrowed from existing literature on the topic of investigation or prior relevant theories with the assistance of research goals and interview questions (Azungah, 2018; Cho & Lee, 2014). To make a comprehensive sense of the data, a start list of a priori categories was generated. Then, the researcher worked through data and analyzed coded data according to previously defined categories.

3.6.2. Questionnaire

A questionnaire is a technique for data collection, composed of a series of questions that are given to participants to answer (Patra, 2019). In this study, a questionnaire is designed in a way that all types of close-ended questions are used, including 1) two-way questions that allow the respondents to select one from a pair of options such as Yes or No, 2) Multiple-choice questions that allow the respondents to select one from several options, and 3) Scaled questions that allow the respondents to select one from a range of options. The questionnaire was divided into five main sections. Section 1 contained questions on demographic information of the participants, including gender, age, medical specialty, place of getting the medical specialty, place of work, years of experience, and years of using an EHR system. Questions in section

2 focused on checking the condition of interoperability among the community. It is composed of a mix of two-way and multiple-choice questions. In section 3 participants asked for their opinions on EHR interoperability barriers. While section 4 looks for their opinions on EHR interoperability benefits. For section 5, it specified interoperability requirements from the physician's point of view. In sections 3, 4, and 5 respondents were required to indicate their answer based on a 5-point Likert scale. The 5-point Likert scale range values need to be interpreted as numeric values as they showed in table 4.

Table.4. The 5-point Likert scale

1	**2**	**3**	**4**	**5**
Strongly Disagree	Disagree	Agree To Some Extent	Agree	Strongly Agree

The study questionnaire is presented in Appendix B.

Questionnaire Validity

In the validation process of the tool, copies of the questionnaire and a summary of study objectives and questions were given to experts from different fields including medicine, statistics, and psychology to evaluate the content validity of the questionnaire. These experts went through the questionnaire statements carefully to check the appropriateness of the instrument the purpose for which it was designed. They suggested some modifications to some items of the questionnaire. All useful observations were made.

Pilot Test

Before the launch of the final questionnaire, a pretesting survey took place to ensure the clarity of the questionnaire statements to respondents and to detect any weaknesses in the questionnaire. According to Lancaster et al. (2004), a sample of 30 participants or greater is good enough for a pilot test. So 30 physicians who work in hospitals located in Hebron governorate with an EHR were chosen using a proportional quota sample. 13 of them were from Al-Amera Alia hospital, 8 from Al-Ahly hospital, 4 from Al-Shaheed Abu Al-Hassan Al-Qasem hospital, 3 from the Palestine Red Crescent Society hospital, 1 from Al-Meezan hospital, and 1 from St John hospital. After data collection, Cronbach's Alpha was calculated to measure the reliability using SPSS statistical software. Results were 0.65, 0.84, and 0.81 for interoperability obstacles, interoperability driving forces, and interoperability requirements respectively. The total value of Cronbach's Alpha coefficient was 0.81 which indicates that the instruments have high reliability (Hair et al., 2014). So, these pilot questionnaires were included and considered in the final research results.

Questionnaire Reliability

The reliability of the instrument is judged by estimating whether the items reflect similar results if it is used at different times with similar conditions. This is expressed using the statistical test Cronbach's Alpha. The total value of alpha was 80%. Cronbach's Alpha measures for all questionnaire parts are shown in Table 5. According to Hair et al. (2014), the results prove the reliability of the instrument.

Table.5. Results Of Cronbach's Alpha For Instrument Reliability

Questionnaire Part	Number Of Items	Cronbach's Alpha
Interoperability Obstacles	6	0.60
Interoperability Driving Forces	9	0.77
Interoperability Requirements	10	0.86
Total Degree For The Instrument	25	0.80

Data Gathering

Physicians who work in population hospitals were personally given the questionnaire. Until quotas were met, these surveys were proportionally dispersed according to the size of established quotas.

To avoid getting biased samples. The researcher visited hospitals at different times in a day and different days in a week and asked all physicians on the job to fill the questionnaire.

Data Analysis Technique

The IBM SPSS statistical software version 20 was used to analyze the data collected. Two statistical techniques of data analysis used in this study include descriptive and inferential statistics. Descriptive statistics is a branch of statistics that involves methods for transforming raw data into organized and summarized forms such as tables, graphs, and numerical summaries. Which increases understanding of the data and provides an effective way to present it. While inferential statistics is the branch of statistics that involves generalizing from a sample to the population from which it was selected. This technique involves determining the probability of getting an incorrect conclusion and assessing the reliability of the generalizations (Peck et al., 2008). To examine research questions, the researcher used some statistical tools as follows:

- Frequencies and percentages to describe the sample's characteristics.
- Mean and standard deviation to describe the sample's responses, where the mean is a measure of the central value for a set of numbers and the Standard deviation is a measure of the spread of a set of values (Everitt & Skrondal, 2010).
- Mann-Whitney U test was used to examine the differences of variables that consist of two groups with one group at least was not significantly different from normal (Neideen & Brasel, 2007). As the p-value is less than 0.05 the null hypothesis is rejected because there is a difference between groups.

- One Way Analysis of Variance test (ANOVA) was used to examine the differences of variables that consist of more than two groups if the distributions of the variables in at least one group were not significantly different from normal or have a homogenous variance. Otherwise, a non-parametric Kruskal Wallis test was used (Neideen & Brasel, 2007). As the p-value is less than 0.05 the null hypothesis is rejected because there is a difference between groups.

The researcher determines the weighted average of each point of the 5-point Likert scale. By calculating the range by subtracting the value of the first scale from the last scale ($5 - 1 = 4$). Then, the result is divided by five as it is the highest value of the scale ($4 \div 5 = 0.8$). Afterward, the minimum value of the scale which is 1 was added to identify the weighted average of the first scale. The weighted average for all scales is shown in Table 6.

Table.6. Weighted Average key

Scale	Weighted Average
Strongly Disagree	1 – 1.80
Disagree	1.81 – 2.60
Agree To Some Extent	2.61 – 3.40
Agree	3.41 – 4.20
Strongly Agree	4.21 – 5

3.7. Summary

This chapter explored the research design including the overall scheme of the research approach, where the mixed methods approach was adopted in order to study the research problem from several aspects. Also, the study population and sample selection process were discussed in detail. Data recording methods, as well as their design and use, were also explained. Furthermore, the content analysis procedures for both quantitative and qualitative parts of the research were also presented. The data analysis and findings of collected data will be presented in Chapter 4.

CHAPTER 4 : RESULTS AND DISCUSSION

4.1. Introduction

To complete this study properly, it is necessary to analyze the data collected to achieve research objectives and answer research questions. This chapter comprises the presentation, analysis, and discussion of research findings. The analysis of data was carried out in two parts. The first part, which is based on the results of the interview, is a qualitative interpretation. While the second part is based on the results of the questionnaire, deals with a quantitative analysis of data.

4.2. Qualitative Data Analysis

A total of 5 individual interviews were used to interpret the results. The purpose was to answer the first and third research questions. The researcher applied the deductive approach to analyze the collected data.

4.2.1.EMR Systems

This section reviews the results gained from interviews that figure out what EMR systems are in use in Hebron, which is recorded in Table 7.

Table.7. Existing EMR Systems

Hospital	EMR System	Duration Of Use / Years
Al-Amera Alia	Avicenna	8
Al-Ahly	Care	20
Al-Shaheed Abu Al-Hassan Al-Qasem	Avicenna	2
Palestine Red Crescent Society	Al Sahl	6
Al-Meezan	HMS	5
St John	APEX	5

The above table shows that the eldest EMR system is Care, used by Al-Ahly hospital. Whereas Al-Amera Alia and Al-Shaheed Abu Al-Hassan Al-Qasem governmental hospitals use the same EMR system called Avicenna, whereas the launch date differs, Al-Amera Alia first used Avicenna in 2012 while Al-Shaheed Abu Al-Hassan Al-Qasem started using it in 2018. The Palestine Red Crescent Society has been using Al Sahl system for 6 years until now. 5 years ago, Al-Meezan and St John started using EMR systems called HMS and APEX respectively.

4.2.2. EMR Adoption

This section aims to assess the capabilities of the available EMRs by basing interviews analysis on the EMRAM model that measures the overall adoption level of EMR functions. The analysis is organized in Table 8 Where A represents Al-Amera Alia hospital, B represents Al-Ahly hospital, C represents Al-Shaheed Abu Al-Hassan Al-Qasem hospital, D represents the Palestine Red Crescent Society hospital, E represents Al-Meezan hospital, and F represents St John hospital.

Table.8. EMR Adoption

Stage	Aspects	A	B	C	D	E	F
7	▪ The hospital no longer uses paper charts to deliver and manage patient care and has a mixture of discrete data, document images, and medical images within its EMR environment.	×	×	×	×	×	×
	▪ Data warehousing is being used to analyze patterns of clinical data to improve quality of care, patient safety, and care delivery efficiency.	×	×	×	×	×	×
	▪ Clinical information can be readily shared via standardized electronic transactions (i.e., CCD) with all entities that are authorized to treat the patient, or a health information exchange (i.e., other non-associated hospitals, outpatient clinics, sub-acute environments, employers, payers, and patients in a data-sharing environment).	×	×	×	×	×	×
	▪ The hospital demonstrates summary data continuity for all hospital services (e.g., inpatient, outpatient, ED, and with any owned or managed outpatient clinics).	✓	×	✓	×	×	✓

	▪ Physician documentation and CPOE have reached 90% (excluding the ED), and the closed-loop processes have reached 95% (excluding the ED).	✓	×	✓	×	×	✓
6	▪ Technology is used to achieve a closed-loop process for administering medications, blood products, and for blood specimen collection and tracking. These closed-loop processes are fully implemented in 50 percent of the hospital. Capability must be in use in the ED, but ED is excluded from the 50% rule.	✓	✓	✓	✓	×	×
	▪ The eMAR and technology in use are implemented and integrated with CPOE, pharmacy, and laboratory systems to maximize safe point-of-care processes and results.	✓	✓	✓	✓	×	×
	▪ A more advanced level of CDS provides for the “five rights” of medication administration and other 'rights' for blood products, and blood specimen processing.	×	×	×	×	×	×
	▪ At least one example of a more advanced level of CDS provides guidance triggered by physician documentation related to protocols and outcomes in the form of variance and compliance alerts (e.g., VTE risk assessment triggers the appropriate VTE protocol recommendation).	×	×	×	×	×	×
	▪ Mobile/portable device security policies and practices are applied to user-owned devices. The hospital conducts annual security risk assessments, and a report is provided to a governing authority for action.	×	×	×	×	×	×
5	▪ Full physician documentation (e.g., progress notes, consult notes, discharge summaries, problem/diagnosis list, etc.) with structured templates and discrete data is implemented for at least 50 percent of the hospital. Capability must be in use in the ED, but ED is excluded from the 50% rule.	✓	✓	✓	✓	✓	✓
	▪ Hospital can track and report on the timeliness of nurse order/task completion.	✓	✓	✓	✓	✓	×
	▪ The intrusion prevention system is in use to not only detect possible intrusions but also prevent intrusions. Hospital-owned portable devices are recognized and properly authorized to operate on the network and can be wiped remotely if lost or stolen.	×	×	×	×	×	×
4	▪ 50 percent of all medical orders are placed using Computerized Practitioner Order Entry (CPOE) by any clinician licensed to create orders. CPOE is supported by a clinical decision support (CDS) rules engine for rudimentary conflict checking, and	✓	✓	✓	✓	✓	×

	orders are added to the nursing and CDR environment.						
	▪ CPOE is in use in the Emergency Department, but not counted in the 50% rule.	✓	✓	✓	✓	✓	✗
	▪ Nursing/allied health professional documentation has reached 90% (excluding the ED).	✓	✗	✓	✗	✗	✓
	▪ Where publicly available, clinicians have access to a national or regional patient database to support decision-making (e.g., medications, images, immunizations, lab results, etc.).	✗	✗	✗	✗	✗	✗
	▪ During EMR downtimes, clinicians have access to patient allergies, problem/diagnosis lists, medications, and lab results.	✗	✗	✗	✗	✗	✗
	▪ Network intrusion detection system in place to detect possible network intrusions.	✗	✗	✗	✗	✗	✗
	▪ Nurses are supported by the second level of CDS capabilities related to evidence-based medicine protocols (e.g., risk assessment scores trigger recommended nursing tasks).	✗	✗	✗	✗	✗	✗
3	▪ 50 percent of nursing/allied health professional documentation (e.g., vital signs, flowsheets, nursing notes, nursing tasks, care plans) is implemented and integrated with the CDR (hospital defines formula). Capability must be in use in the ED, but ED is excluded from the 50% rule.	✓	✓	✓	✓	✓	✓
	▪ The Electronic Medication Administration Record application (eMAR) is implemented.	✓	✓	✓	✓	✗	✗
	▪ Role-based access control (RBAC) is implemented.	✓	✓	✓	✓	✓	✓
2	▪ Major ancillary clinical systems are enabled with internal interoperability feeding data to a single clinical data repository (CDR) or fully integrated data stores that provide seamless clinician access from a single user interface for reviewing all orders, results, and radiology and cardiology images.	✓	✓	✓	✓	✓	✓
	▪ The CDR/data stores contain a controlled medical vocabulary and order verification is supported by a clinical decision support (CDS) rules engine for rudimentary conflict checking.	✓	✓	✓	✓	✗	✓
	▪ Information from document imaging systems may be linked to the CDR at this stage.	✓	✓	✓	✓	✓	✓
	▪ Basic security policies and capabilities addressing physical access, acceptable use, mobile security, encryption, antivirus/anti-malware, and data destruction.	✓	✓	✓	✓	✓	✓

1	▪ All three major ancillary clinical systems are installed (i.e., pharmacy, laboratory, and radiology).	✓	✓	✓	✓	✓	✓
	▪ A full complement of radiology and cardiology PACS systems provides medical images to physicians via an intranet and displaces all film-based images. Patient-centric storage of non-DICOM images is also available.	✓	✓	✓	✓	✓	✓
0	▪ The organization has not installed all three key ancillary department systems (laboratory, pharmacy, and radiology).	×	×	×	×	×	×

✓: reached, ×: not reached

The above table shows that 4 hospitals (A, B, C, and D) have achieved stage 3 of the EMRAM, while the remaining two private hospitals, F and E, have reached stages 2 and 1, respectively. As the EMR systems' level was decided by meeting all of the conditions set to each stage.

Regarding the other incomplete stages, it was noticeable that Al-Amera Alia and Al-Shaheed Abu Al-Hassan Al-Qasem hospitals come in the first place in EMR usage, it is worth mentioning here that both hospitals are public ones and they use the same EMR system. The main issue noticed in their system is that there is an absence of using CDS for supporting physicians and nurses in their work. Also, applying more strict security procedures does not take enough attention from these hospitals which may lead to some security and privacy issues. Both hospitals have a good turnout towards patients' information sharing, but they are focused on information sharing among only governmental hospitals and clinics, of course, they need to start thinking about data exchange with other healthcare institutions especially private sector institutions that use different EMR systems. Another issue that should be employed for public hospitals is implementing a data warehousing system to analyze patterns of clinical data to support research, which is very important for improving the quality of care. Plus enabling access to the most important information of patients’ information like allergies, problem list, etc., during EMR downtimes.

Subsequently, the Palestine Red Crescent Society Hospital and Al-Ahly Hospital are ranked second because they have the same flaws as public hospitals. Moreover, they need a greater imposition of clinical documentation. To what concern data exchange, both hospitals have no work in this regard, which needs high attentiveness.

In the remaining two spots, we have St John and Al-Meezan hospitals, both of which have major flaws that prevent them from moving forward with EMR deployment, notably Al-Meezan, which required more effort. It's worth noting that St John Hospital has achieved health data interchange at the hospital branch level in many governorates.

4.2.3.Existing Interoperability Models

This section finds out if there are any EHR interoperability solutions among Hebron hospitals. Where the results of the interviews showed that there are no applied interoperability models for data interchange among hospitals located in Hebron. All governmental hospitals use the same EMR system in which the data is collected, combined, and stored in a single database. Physicians who work in these hospitals have access to patients' EHRs created from different governmental health care organizations. Otherwise, physicians from the private sector can't access these EHRs of governmental hospitals or EHRs created by other private hospitals. Also, they can't electronically exchange EHRs.

4.2.4.Standards Compliance

This section outlines EHR and interoperability standards employed by Hebron hospitals, which are summarized in Table 9.

Table.9. Standards Compliance

Standard	Types	A	B	C	D	E	F
ISO/TC 215	▪ ISO 13606	×	×	×	×	×	×
	▪ ISO 11238	×	×	×	×	×	×
	▪ ISO 11239	×	×	×	×	×	×
	▪ ISO 11240	×	×	×	×	×	×
	▪ ISO 11616	×	×	×	×	×	×
	▪ ISO 11615	×	×	×	×	×	×
ICD	▪ ICD-10 or 11	✓	✓	✓	✓	×	✓
SNOMED CT	--	×	×	×	×	×	×
LOINC	--	×	×	×	×	×	×
DICOM	--	×	×	×	×	×	×
HL7	▪ Clinical Document Architecture (CDA)	×	×	×	×	×	×
	▪ Fast Health Interop Resources (FHIR)	×	×	×	×	×	×
	▪ HL7 Version 2 or Version 3	×	×	×	×	×	×

✓: used, ×: not used

As shown in the table above, all hospitals save Al-Meezan use the ICD-10 standard for medical classification of diseases in their EMR systems. While other health informatics standards including HL7, DICOM, LOINC, SNOMED CT, and ISO/TC 215 aren't used in all hospitals. These standards are very important to achieve semantic interoperability as they define protocols for digitally storing and exchanging patients' health-related data, information, and knowledge.

4.3. Quantitative Data Analysis

A total of 196 questionnaires were used to interpret the results. Statistical analysis was used to test the collected data and examine the relationships among study variables. The results were used to answer study the second and third questions.

4.3.1.Respondents' Demographic Profile

This section sought to identify the demographic characteristics of the respondents. Which are outlined in Table 10.

Table.10. Respondents' Demographic Profile

Gender	Frequency	Percentage
Male	166	84.7 %
Female	30	15.3 %
Age		
< 30	71	36.2 %
30-39	92	46.9 %
40-49	26	13.3 %
>=50	7	3.6%
Medical Speciality		
Internal medicine	36	18.4 %
Surgery and its subspecialties	51	26.0 %
Obstetrics and Gynecology	19	9.7 %
Emergency medicine	6	3.1 %
Pediatrics	36	18.4%
Ophthalmology	7	3.6 %
Radiology	6	3.1 %
General medicine	33	16.8 %
Other	2	1.00%
Place Of Getting The Medical Specialty		
Palestine	132	67.3 %
One of the Arab world countries	48	24.5 %
One of the European Union countries	6	3.1 %
One of East Asia countries	1	0.5 %
One of the Soviet Union countries	6	3.1 %
Turkey	3	1.5 %

Place Of Work		
Al-Amera Alia	85	43.4 %
Al-Ahly	51	26.0 %
Al-Shaheed Abu Al-Hassan Al-Qasem	25	12.8 %
Palestine Red Crescent Society	21	10.7 %
Al-Meezan	11	5.6 %
St John	3	1.5 %
Years Of Experience		
1-4	85	43.4 %
5-8	59	30.1 %
9-12	29	14.8 %
>12	23	11.7 %
Years of using EHR systems		
<1	30	15.3 %
1-4	102	52.0 %
5-8	46	23.5 %
>8	18	9.2 %

4.3.2. Data Exchange Conditions

This section aims to check How data currently interchanged among different hospitals. The data collected through the questionnaire was subjected to frequencies. In other words, physicians' responses were added together to find the highest frequency of occurrence. Then, the results were presented in percentage forms. Analysis results are given in Table 11.

Table.11. Interoperability And Data Exchange Conditions

Answer	Frequency	Percentage
Ability to electronically exchange patients' information together with other hospitals using the same EHR system		
Yes	120	61.2 %
No	76	38.8 %
Ability to electronically exchange patients' information together with other hospitals use different EHR systems		
Yes	7	3.6 %

No	189	96.4 %
Outside patient information is typically sent and received from other hospitals with different EHR systems in Hebron using		
Paper	164	83.7 %
Fax	18	9.2 %
Email	11	5.6 %
Computer System	3	1.5 %
Outside patient information is mostly used in the case of		
Day to day life	43	21.9 %
Referral	142	72.4 %
Consult	11	5.6 %
The usual time frame for receiving information from other hospitals in Hebron that use a different EHR system		
Within 30 minutes	32	16.3 %
Within 24 hours	136	69.4 %
From 2 to 3 days	20	10.2 %
More than 3 days	8	4.1 %

According to the data in the table above, 61.2% of physicians claimed they can electronically obtain patient information from hospitals other than the ones where they work that utilize the same EHR system. While 38.8% of them stated that they are unable to do so. These findings are consistent with the findings of the interviews, which revealed that public hospitals and St John hospital can electronically exchange data between their branches, accounting for 57.7% of all respondents. Another point to consider is that 3.6% of physicians indicated they can electronically obtain patient information from hospitals other than the one where they work that utilize a different EHR system. 96.4% of respondents answered they couldn't. This supports the findings of the interview, which revealed that there is no electronic interchange of EHRs between hospitals.

In terms of the methods used to send and receive patient information among different hospitals in Hebron, the results show that the most common means of data exchange between different hospitals in Hebron is paper, as confirmed by 83.7 % of physicians, and that computer systems are not being used even really.

Respondents were also asked about instances in which patients' health-related data from other hospitals were primarily utilized. According to the findings, 72.4% of respondents agreed on the referral case. While 21.9% of respondents indicated it is mostly used in everyday life. Only 5.6% of respondents indicated it is mostly used when a consultation is required for a unique situation.

The results show that receiving patient information from other hospitals in Hebron usually takes 24 hours, as stated by 69.4% of the respondents. While 16.3% of them stated it takes them about 30 minutes. Some acknowledged that it could take two to three days and that it could take longer in some cases.

4.3.3. Interoperability Barriers

This section aims to explore what barriers have more impact on interoperability. Also, to fulfill this objective a related hypothesis was tested, which is "Hospitals' internal barriers are less influential than external barriers associated with interoperability". For analyzing the collected data to answer these questions, the researcher used mean and standard deviation measures. As well as display the total degree based on the 5-point Likert scale defined in Section 3.6.2. Analysis results are presented in Table 12.

Table.12. Barriers To Apply eHealth Interoperability

Item	Mean	Standard Deviation	Total Degree
There is no electronic system for connecting different EHRs	4.56	0.772	Strongly Agree
There is no infrastructure for information exchange	4.09	0.943	Agree

Increase in information system costs	3.69	1.163	Agree
This may cause some leaks of patients' private information	3.27	1.161	Agree To Some Extent
External Barriers	3.90	0.58	Agree
Hospitals prefer to depend on their internal sources of information	3.70	1.065	Agree
The hospital has strict policies regarding information sharing	3.34	1.090	Agree To Some Extent
Internal Barriers	3.51	0.91	Agree

The results in the above table indicate that the degree of external interoperability barriers is slightly higher than the degree of internal interoperability barriers, even though both of them have a high degree of agreement. Furthermore, the most influential interoperability barricade is that there is no electronic system for connecting different EHRs with a mean of 4.56 which is a very high degree with a standard deviation of 0.772 denotes that responses slightly deviate from the mean. Followed by no infrastructure for information exchange has a mean of 4.09 which high degree with a standard deviation of 0.943 denotes that responses slightly deviate from the mean. They also see that the increase in information system costs and hospital's preference to depend on their internal sources of information as strong barriers for electronic data exchange as they obtained the following means, in order, 3.69 and 3.70 which is a high degree. And standard deviations were 1.163 and 1.065 respectively, which denote that responses, on average, were a little over one point away from the mean. The two last statements of barriers about that the hospital has strict policies regarding information sharing and interoperability may cause some leaks of patients' private information were obtained a means equal to 3.34 and 3.27 orderly, which is slightly high. And standard deviations were 1.090 and 1.161 respectively, which denote that responses, on average, were a little over one point away from the mean.

Besides the above-discussed results, this section also tested another hypothesis which is "Public hospitals have fewer barriers than private hospitals". The Mann–Whitney U-test technique was used to study the differences in the barriers to applying eHealth interoperability in the Palestinian community in accordance with hospital type. As study hospitals were classified into two types, governmental or private. The results clarifies that there are no statistically significant differences [sig =0.54, 0.82, 0.63, 0.75, 0.80, and 0.26 respectively>0.05]. Figure 3 shows the relation between the barriers to applying eHealth interoperability according to hospital type. The total degree of all barriers at both private and governmental hospitals is high. The biggest barrier from the physician's perspective at both private and governmental hospitals is there is no electronic system for connecting different EHRs with means equal to 4.57 and 4.55 respectively. While the least affected one is this may cause some leaks of patients' private information at both private and governmental hospitals with means equal to 3.30 and 3.25 respectively.

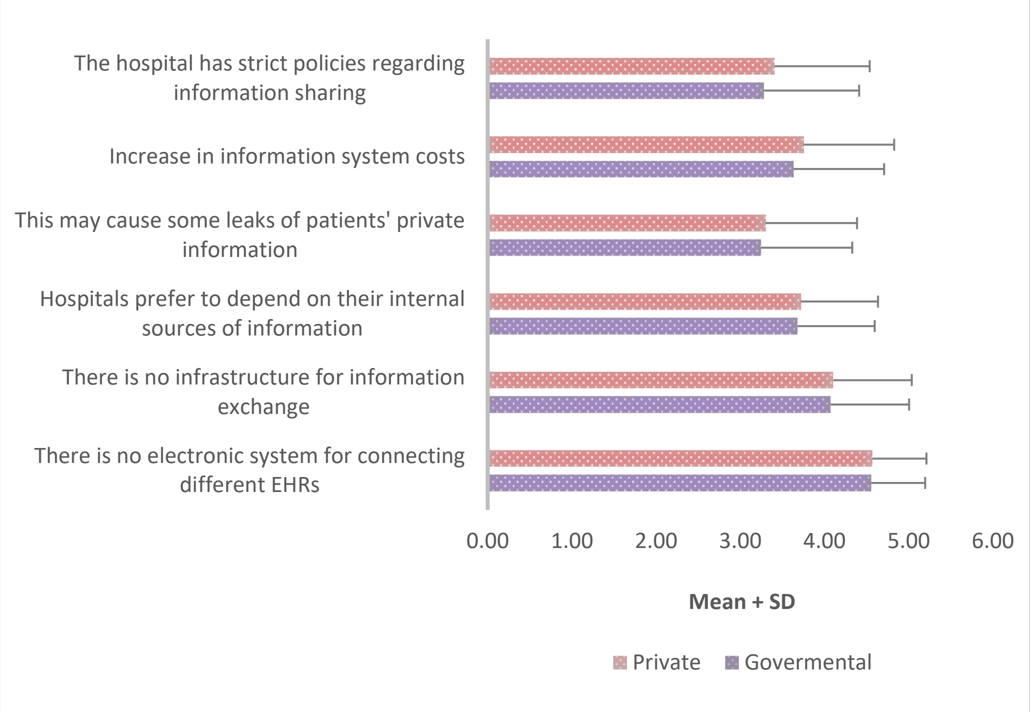

Fig.3. Summary Of The Relationship Between Interoperability Barriers And Hospital Type

4.3.4.Interoperability Need

This section aims to check whether physicians are highly motivated to have interoperable systems among hospitals as a part of driving forces for achieving EHRs interoperability in Palestine. For analyzing the collected data to answer these questions, the researcher used mean and standard deviation measures. As well as display the total degree based on the 5-point Likert scale defined in Section 3.6.2. Analysis results are presented in Table 13.

Table.13. The Degree Of Agreement On The Need For Interoperability Solution

Mean	Standard Deviation	Total Degree
4.62	0.626	Strongly Agree

The above table shows that physicians strongly agree with the need for an eHealth interoperability solution where the mean of responses reached 4.62. The value of 0.626 standard deviation denotes that responses slightly deviate from the mean.

4.3.5. Interoperability Benefits

This section aims to check whether physicians are highly aware of interoperability benefits as a part of driving forces for achieving EHRs interoperability in Palestine. For analyzing the collected data to answer these questions, the researcher used mean and standard deviation measures. As well as display the total degree based on the 5-point Likert scale defined in Section 3.6.2. Analysis results are presented in Table 14.

Table.14. Benefits Of Applying An eHealth Interoperability Solution

Item	Mean	Standard Deviation	Total Degree
Having an accurate diagnosis	4.69	0.516	Strongly Agree
Reducing duplication of lab and imaging tests	4.55	0.753	Strongly Agree
Preventing drug-drug interactions	4.58	0.664	Strongly Agree
Time-saving in patients sessions and treatment decision making	4.59	0.570	Strongly Agree
Improving decision making	4.56	0.609	Strongly Agree
Avoiding filling multiple forms	4.34	0.772	Strongly Agree
Reducing health care costs on patients	4.46	0.747	Strongly Agree
Increasing the reputation of hospitals and clinics	3.73	1.064	Agree
Total Degree	4.43	0.451	Strongly Agree

The above table shows that the total degree of agreement on interoperability benefits is strongly agreed with a mean of 4.43, which indicates that physicians have a high level of awareness of interoperability benefits. Respondent physicians strongly agree that reaching eHealth interoperability will positively affect the health care sector in having an accurate diagnosis, saving time in patients sessions and treatment decision making, preventing drug-drug interactions, improving decision making, reducing duplication of lab and imaging tests, reducing health care costs on patients, and escaping from filling multiple forms. As their means were 4.69, 4.59, 458, 4.56, 4.55, 4.46, and 4.34 in order. While the standard deviation of responses on these statements was 0.516, 0.570, 0.664, 0.609, 0.753, 0.747, and 0.772 respectively, which indicates that responses slightly deviate from the mean. However, they agree that interoperability will Increase the reputation of hospitals and clinics with a mean of 3.73. The value of 1.064 standard deviation means that responses, on average, were a little over one point away from the mean.

Besides the above-discussed results, this section also tested a related hypothesis which is "Physicians' awareness about interoperability does not differ from private and public hospitals". The Mann-Whitney U-test technique was used to study the differences in physicians' awareness regarding the benefits that will be gained from applying eHealth interoperability in the Palestinian community by hospital type. As hospitals can be classified into two types, governmental or private. The results clarify that there are no statistically significant differences [sig=0.60, 0.89, 0.69, 0.13, 0.32, 0.99, 0.27, and 0.29>0.05 respectively]. Figure 4 shows the relation between the physicians' awareness of interoperability benefits according to hospital type. The total degree of physician agreement on interoperability benefits from both private and governmental hospitals is high. The biggest benefit from the physician's perspective at both private and governmental hospitals is having accurate diagnoses with means equal to 4.66 and 4.71 respectively. While least benefit is increasing the reputation of hospitals and clinics with means equal to 3.80 and 3.67 respectively.

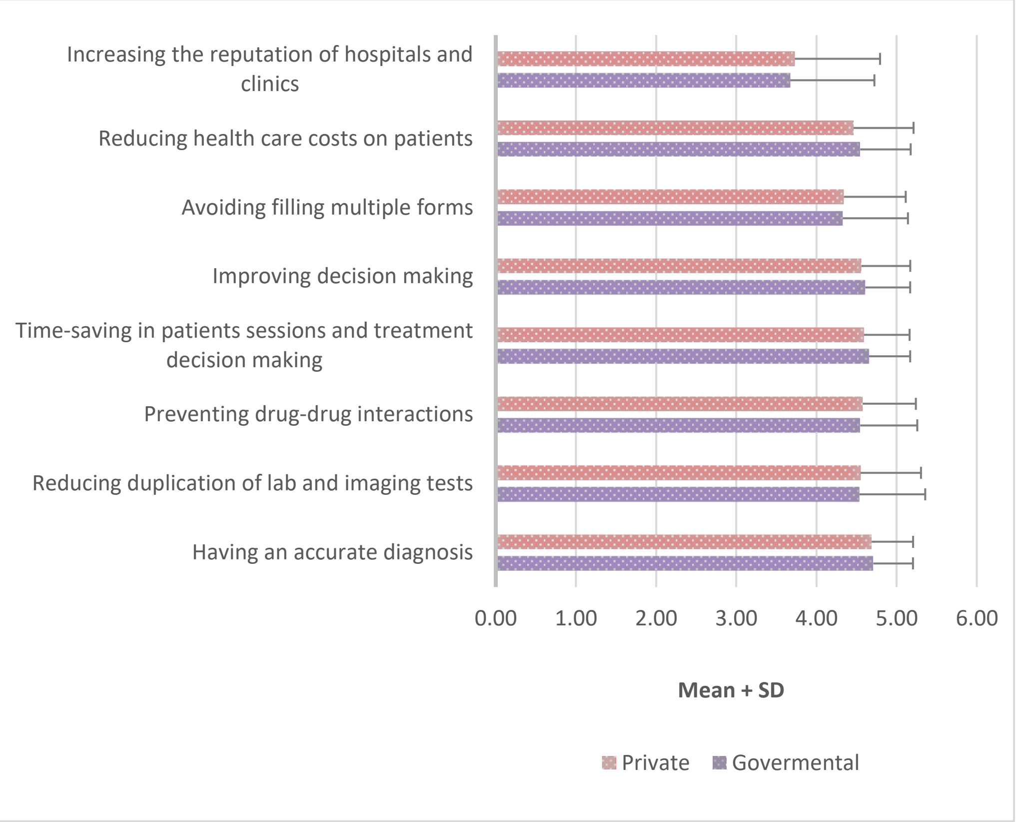

Fig.4. Summary Of The Relationship Between Physicians' Awareness Of Interoperability Benefits And Hospital Type

4.3.6.Information To Interchange

This section is concerned with the importance of interchange all kinds of patient information through an interoperability solution as a part of driving forces for achieving EHRs interoperability in Palestine. For analyzing the collected data to answer these questions, the researcher used mean and standard deviation measures. As well as display the total degree based on the 5-point Likert scale defined in Section 3.6.2. Analysis results are presented in Table 15.

Table.15. Patients' Information To Be Exchanged

Item	Mean	Standard Deviation	Total Degree
Medical history	4.84	0.384	Strongly Agree
Vital signs	4.34	0.882	Strongly Agree
Medication list	4.68	0.583	Strongly Agree
Allergy list	4.72	0.587	Strongly Agree
Problem list	4.66	0.607	Strongly Agree
Laboratory results	4.72	0.504	Strongly Agree
Imaging results	4.76	0.463	Strongly Agree
Discharge instructions	4.34	0.945	Strongly Agree
Implanted medical devices list	4.70	0.628	Strongly Agree
Full record	4.55	0.725	Strongly Agree
Total Degree	4.63	0.435	Strongly Agree

The above table shows that the total degree of physicians' agreement on the need to interchange all kinds of patient information is strongly agreed with a mean of 4.60, which indicates a high need for interchanging patient information. Respondent physicians strongly agree on the need to electronically exchange medical history, imaging results, allergy list, laboratory results, medication list, problem list, implanted medical devices list, full record, discharge instructions, and vital signs. As their means were 4.84, 4.76, 4.72, 4.72, 4.70, 4.68, 4.66, 4.55, 4.34, and 4.34 respectively. The standard deviation values were 0.384, 0.463, 0.587, 0.504, 0.628, 0.5783, 0.607, 0.725, 0.882, and 0.945 respectively, indicates that responses slightly deviate from the mean.

Alongside the above-discussed results, this section also tested a related hypothesis which is "The importance of patient information to be interchanged differ according to the physician's specialty". One-way analysis of variance (ANOVA) and the Kruskal-Wallis tests were used to study the differences in the type of patients' information that physicians see it is important to be electronically exchanged in accordance to physicians' medical specialty. The result of the Kruskal-Wallis test in the case of non-normal distributed data indicates that there are statistically significant differences between physicians' specialty and the medication list as important information to exchange [sig=0.01>0.05]. All participant physicians from different specialties confirm that they need medication lists to be electronically exchanged epically physicians with specialties of ophthalmology and radiology. While there are no statistical differences in physicians' need to discharge instructions due to medical specialization [sig=0.29>0.05]. Otherwise, the result of the One-Way Analysis of Variance indicates that there are no statistical differences of physicians' specialty to all kinds of data including medical history, vital signs, allergy list, problem list, laboratory results, imaging results, implanted medical devices list, and full record due to medical specialization [sig =0.30, 0.40, 0.37, 0.42, 0.12, 0.26, 0.28 and 0.75>0.05 respectively]. From Figure 5 it is noticeable that physicians from different listed specialties strongly agree on the need for the medication list to be electronically exchanged except few physicians with other specialties. Regarding other data types, all physicians strongly agree on the importance of all of them.

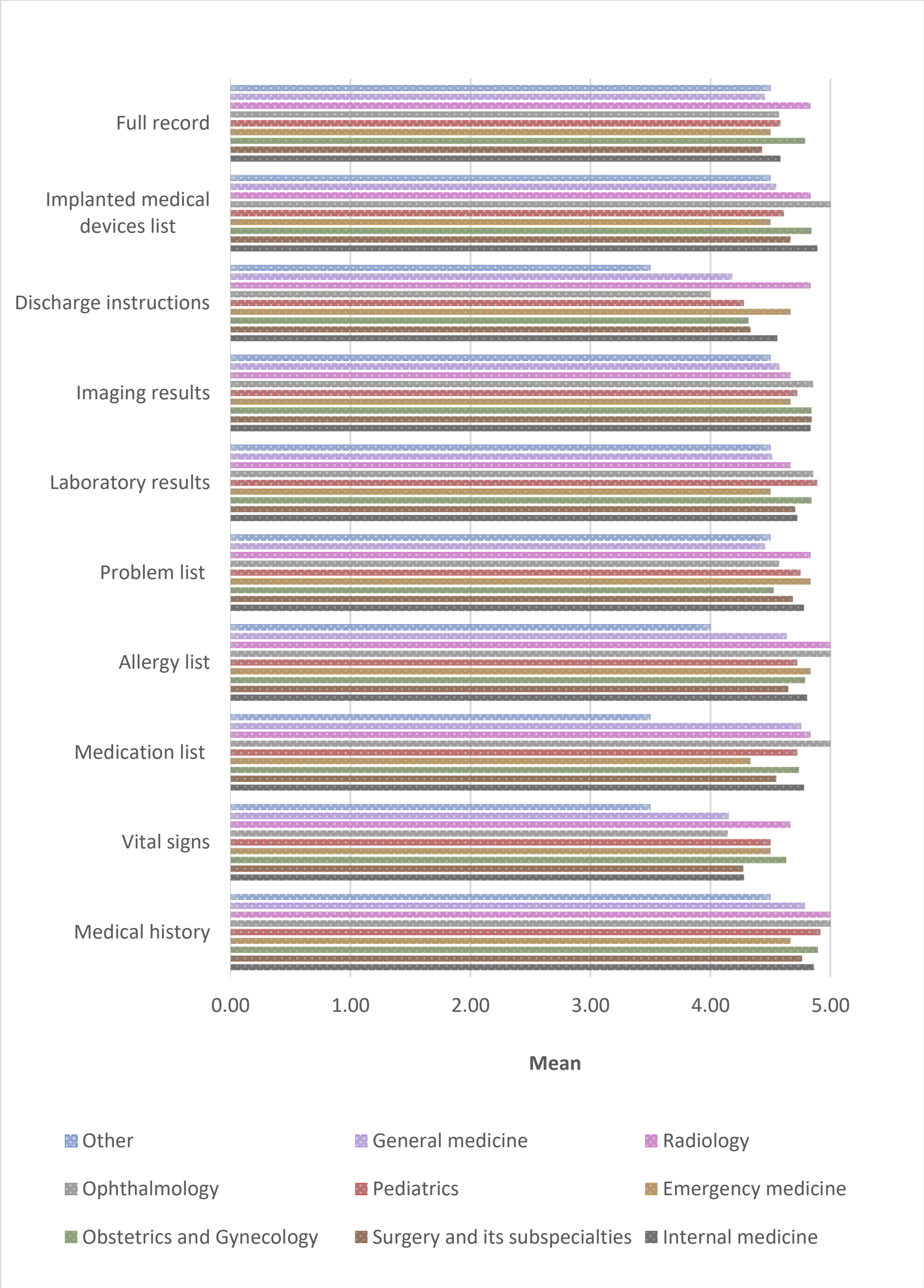

Fig.5. Summary Of The Relationship Between Importance Of Patient Information To Be Interchanged And Physician's Specialty

4.4. Discussion

From previously discussed findings the researcher comes up with answers to research questions, which are discussed in the following sections.

4.4.1. What is the role of EMR systems in the Palestinian community?

The researcher discovered that EMR systems are a bit late in the Palestinian community and are not given enough attention. In general, all available EMRs in both public and private sectors have a low level of capabilities. Following the defined stages of EMRAM, Al-Meezan and St John hospitals were classified as stages 1 and 2 respectively. While the other 4 hospitals, including Al-Amera Alia hospital, Al-Ahly hospital, Al-Shaheed Abu Al-Hassan Al-Qasem hospital, and the Palestine Red Crescent Society hospital reached stage 3. When the data is compared to the EMRAM phases attained around the world, this truth becomes quite evident. The 7th stage has been attained by several hospitals in Canada, the United States, Brazil, Portugal, the United Kingdom, the Netherlands, Russia, Turkey, China, South Korea, Taiwan, Thailand, Australia, and Saudi Arabia. In the Arab world, 7 hospitals in Saudi Arabia reached the 7th stage. While 28 hospitals from Saudi Arabia, the United Arab Emirates, and Lebanon made it to 6th place (HIMSS Analytics, n.d.-b). Also, public hospitals are better than private ones in adopting more advanced EMR features, which makes it easier for these hospitals to keep going and achieve greater success. This might be because public hospitals are getting more financial and technical support from national and global organizations. However, both public and private sectors are required to invest more to enable interoperability among their systems, this might be regulated by the Palestinian ministry of health which can follow up with these institutions to gradually apply EMRAM model phases on a time-based schedule.

4.4.2. What is the condition of data interchange among different hospitals in Palestine?

The researcher discovered that health data is traditionally exchanged between hospitals using papers. There are no electronic systems or services for data exchange. This is probably because eHealth and the use of technology for healthcare is entirely new to Palestinian society. Also, due to the lack of interoperability solutions made for integrating EHRs in Palestine. Training is required to enhance technological skills for healthcare professionals and to broaden their knowledge about the ability to electronically exchange data while maintaining privacy.

4.4.3. To what extent is eHealth interoperability applicable in the Palestinian community?

In what concerns the employing of interoperability standards, the researcher discovered that all hospitals don’t use these standards within their information systems. Some of them implemented the ICD10 standard, but it is rare. Furthermore, this scarcity of using interoperability standards is due to the absence of awareness of the availability of these standards. This poses a challenge to the implementation of interoperability and can be mitigated by conducting training workshops with professionals presenting the feature of the available system.

From the point of view of physicians, it is clear that they are very willing to electronically exchange data, however, the absence of an interoperable solution made this impossible. They believe that their institutions have a weak infrastructure, hence an increase in financial burden is expected if they will implement interoperability.

A powerful motivator toward implementing interoperability in Hebron hospitals is that physicians from all specialties are highly encouraged toward the idea of electronic interchange of patients' health data of various kinds. Besides, they are aware of the benefits that will be gained from having interoperable EMR systems for all parts of society, including organizations, health specialists, and individuals. This emphasizes the necessity of interoperability solutions for the health sector in Palestine and gives a good impression that putting EHRs interoperability in application will face a low level of resistance to change but might require a financial investment.

4.5. Summary

This chapter introduced the examination of data gathered through interviews and questionnaires. In addition, the results were discussed, and research questions were answered. The findings revealed that hospitals in Hebron are using five distinct EMR systems, all of which have limited capabilities. While the need and necessity of a solution for achieving interoperability in the Palestinian community was underscored by all collected insights. The suggested approach is underlined. It must be compatible with the nature of the clinical data created and maintained in Hebron hospitals by EMRs in an unstandardized and unstructured manner. In the next chapter, the researcher will introduce a proposed solution based on these findings.

CHAPTER 5 : PROPOSED MODEL

5.1. Introduction

Based on the literature review and the study of the current situation of EHRs and interoperability in the Palestinian community, we realized that existing systems do not adhere to any of the particular standards for medical data standardization and that there are no rules requiring institutions to do so. Furthermore, because they do not rely so heavily on structured forms to document clinical data, data is represented as free text in an unstructured style. Based on these findings, we propose the Interoperability Smart Lane For Electronic Health Record (islEHR) model as a solution for the data exchange issue among different information systems used by hospitals in Palestine. With this, we sought to alleviate the barriers indicated in Section 4.3.3 by providing a suitable solution for the Palestinian community to allow the sharing of medical data following available capabilities through this proposal definitely with maintaining the confidentiality and privacy of patient data. In addition, The adoption of a secondary system to transfer data proportionally to the available systems will lower the expenses of replacing existing systems with others that allow interoperability. This chapter spots the lights on our proposed model.

5.2. islEHR

The main objective of the islEHR is to facilitate the sharing of EHRs among different hospitals in which data can be processed by healthcare specialists and machines. The model focuses on achieving semantic interoperability using the latest interoperability standards and techniques including artificial intelligence and HL7 FHIR. Various artificial intelligence approaches, such as natural language processing, can be used to extract data from texts, and diverse machine learning methods can be used for the automatic encoding of medical concepts as well as the development of data extraction systems. The HL7 FHIR standard, on the other hand, describes the clinical data formats and elements in a standard format for interchange.

The model focuses on linking hospitals to a data integration service, either as a data provider or a data user, the data then can be shared among hospitals through the data integration service, which is responsible for processing the shared data to extract the patient information and ensure that the final result is standardized and structured in FHIR resources before sending it to its final destination. The architecture of the islEHR model is shown in Figure 6.

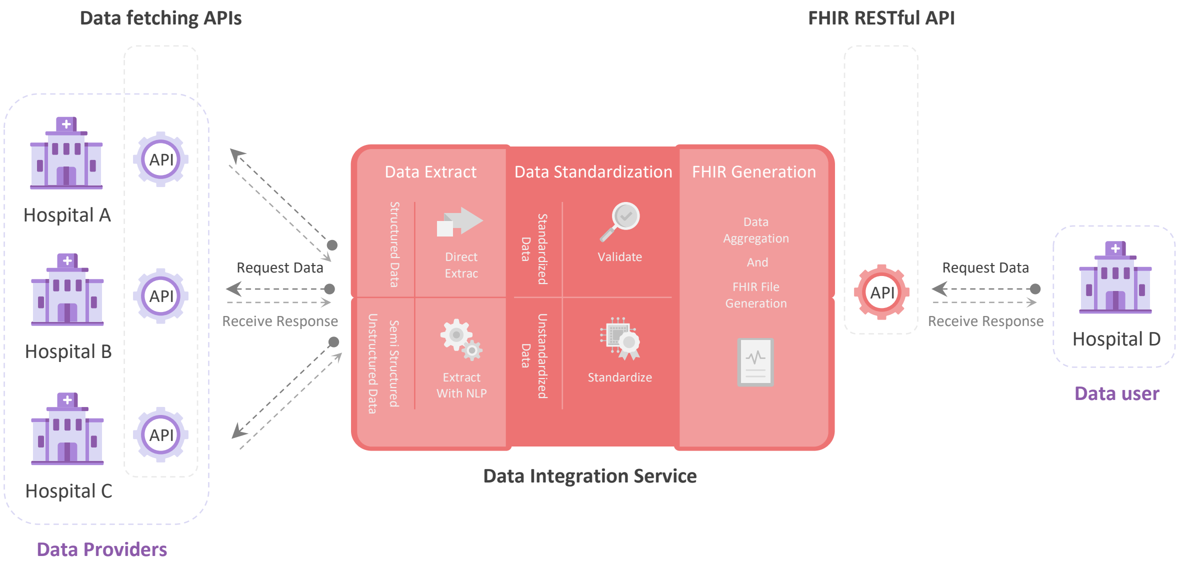

Fig.6. The General Architecture Of The islEHR Model

5.3. islEHR Modules

islEHR architecture is composed of three major modules: 1) data fetching APIs, 2) data integration service, 3) and FHIR RESTful API that complements each other.

5.3.1.Data fetching APIs

Application programming interface (API) is a set of predefined resources (methods, objects, or URIs) that enable access to a software application data or service (Meng et al., 2018). Hospitals seeking to participate in the EHRs interoperability solution should provide an API connected to their EMR system. These APIs will allow the data integration service to get patients' information recorded within the hospital.

5.3.2.Data integration service

The integration service represents the core part of the interoperability model. Which is founded on top of three blocks: 1) data extract, 2) data standardization, 3) and FHIR generation.

Data Extract

In this block, requested data from the hospital's EMR systems go through an NLP-based process to extract patient information either it is in semi-structured or unstructured data formats. Patient information is directly extracted from the structured data while the NLP process is used to extract information from unstructured data. All extracted information is then linked to each other and passed to the standardization block.

Data Standardization

This block is responsible for ensuring that patient information collected from EHRs is following clinical terminologies and classifications and is coded in formats that match FHIR attributes. Where clinical data that is not recorded in a standard format as defined by international clinical terminologies and classifications can be coded using machine learning.

The general form for representing coded elements in FHIR is based on 4 components:

- System: a URI that identifies the code system[1]. Which may be, as categorized by HL7 international organization, 1) external such as ICD10, LOINC, SNOMED CT, et., 2) internal (FHIR) such as medication status codes, task codes, bundle type,

[1] A full list of registered coding systems provided on the official website of HL7: https://www.hl7.org/fhir/terminologies-systems.html

etc., 3) external (FHIR) such as surface codes, action type, admit source, etc., or codes from previous versions of HL7 standard such as HL7 v2 and HL7 v3.

- Version: identification of the version of the coding system.
- Code: concept code as defined by the coding system.
- Display: description for the concept as defined by the coding system.

FHIR Generation

After information standardization in the previous block is done, patient information becomes ready to be parsed in predefined FHIR profiles in this block. A profile is a more specific resource that is customized by setting constraints on the resource according to different needs by healthcare domain, country, institution, or vendor. As FHIR provides superset resources, various profiles can be defined based on these resources. An FHIR resource[2] is a data package with specific modeling of healthcare data used to exchange and store clinical or administrative data.

Profiling constraints may be: 1) rules about which resource elements are or are not utilized and what extra components are included that are not a portion of the base specification, 2) rules about which API features are used and how they will be used, 3) rules about which terminologies are used in particular elements, 4) or and descriptions of how the resource elements and API features corresponding to local requirements and implementations. Figure 8 shows a simple example of FHIR resource profiling.

Then, this block generates a final FHIR file for requested patient-related information by a healthcare organization. The final file can be in JSON, XML, or RDF (Turtle) format.

[2] A full list of FHIR resources is provided on the official website of HL7: http://hl7.org/fhir/resourcelist.html

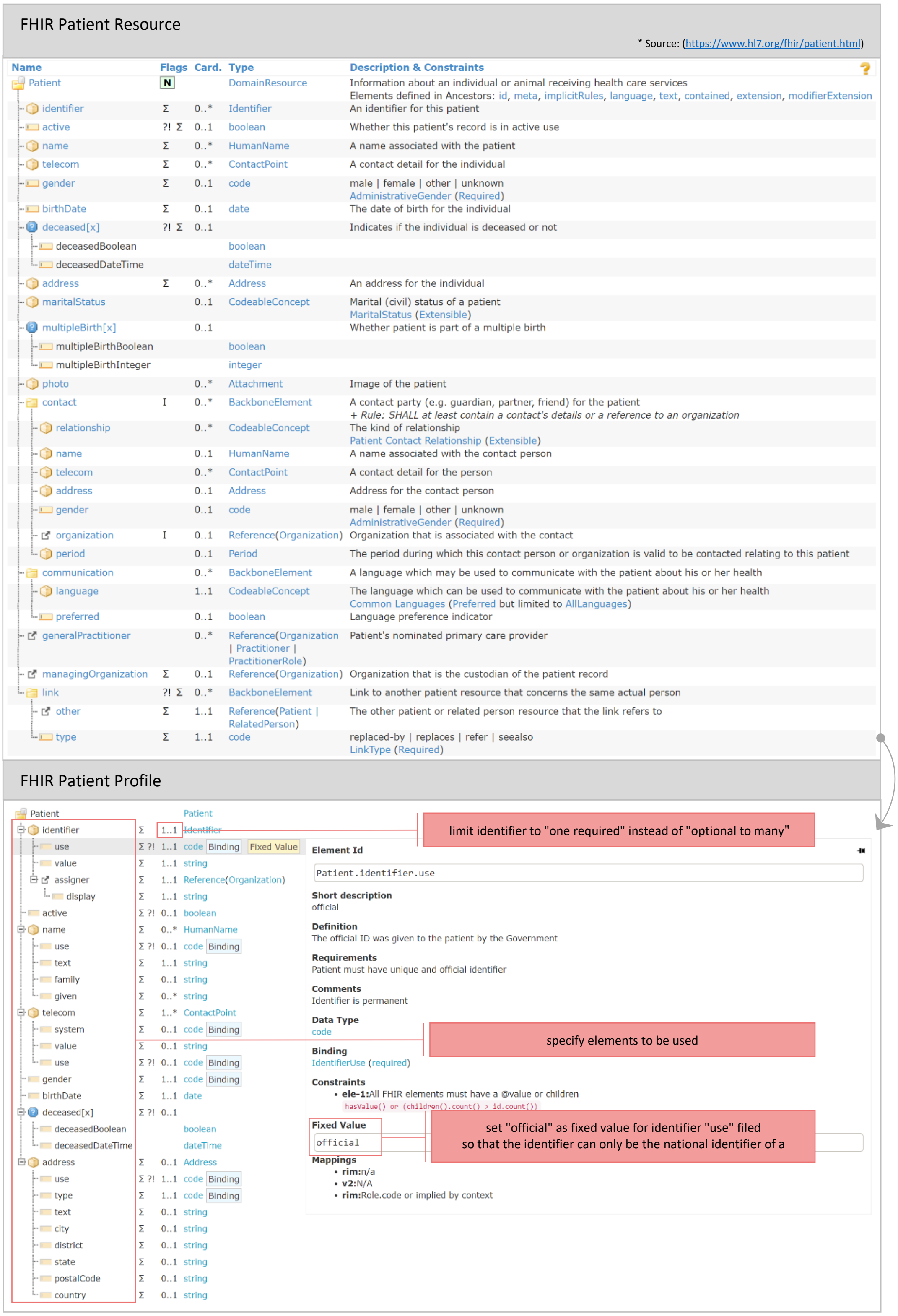

Fig.7. Profiling Example Of Patient Resource

5.3.3.FHIR RESTful API

FHIR defines RESTful API as one of the compatible methods that can be used for data exchange (HL7 International, n.d.-b). The term REST (Representational State Transfer) means a server has a resource that desires to share it with some clients. Where a client can request a representation of the resource's state, which may be stored in a database or flat file or even generated on call. An API must satisfy a set of REST properties to be described as a RESTful API, these properties are: 1) consists of servers and clients, 2) has stateless communication, 3) mark server responses as cacheable or non cacheable, 4) has a uniform interface, 5) and hide system layers behind the server from the client (Lange, 2019). Following the proposed architecture, the FHIR RESTful API should provide a service that allows searching different resources.

5.4. islEHR Workflow

In this section, we introduce how data can be shared through the islEHR. The activity diagram of islEHR is provided in Figure 7, where the workflow of the model is described, the figure shows how a request for patient's information is issued and how the final result is provided through a sequence of steps described below:

- A physician from a hospital sends a request to the integration service through the FHIR RESTful API, asking for specific or general clinical information of a specific person.
- The integration service receives the request sent from a data user.
- The integration service processes the request and sends multiple requests to all connected hospitals as data providers.
- Data providers receive the request from the integration service, query results within their system, and send a response back to the integration service.
- The integration service receives a response from the data providers.

- The integration service checks if there are results. If there are no results, it sends a message to the data user (the physician) telling him that there is no result for his query.
- In case data is found, the data is then moved to the data structure checking process.
- The integration service checks if the data is structured, semi-structured, or unstructured. If the data is structured, it will be passed to a direct extraction process. If not, it will be passed to a natural language processing extraction process.
- After information extraction is completed, the integration service looks at data standardization. If the data is already standardized, it will be passed to a validation process. If not, it will be passed to a standardization process.
- When data standardization is completed, the integration service combines the information and parses them into predefined FHIR profiles.
- The integration service sends the final FHIR file to the data user.
- The data user receives an FHIR file as a result of his request.

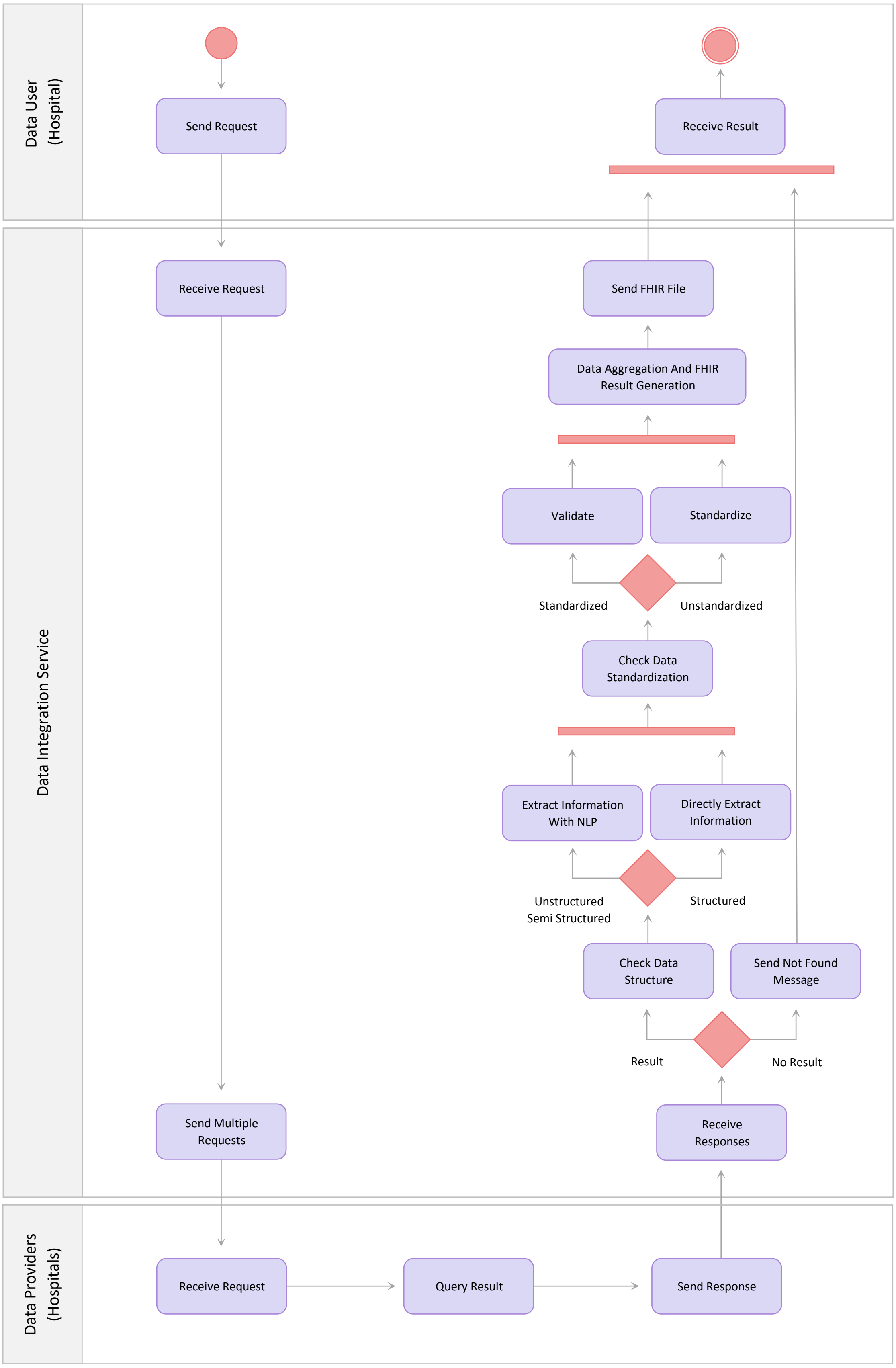

Fig.8. Activity Diagram For A Patient Information Request

5.5. Summary

In this chapter, we proposed a model named islEHR for reaching interoperability among different hospitals, taking into account the status of the clinical data that is produced by the EMR systems used in Palestine and following recent advancements regarding interoperability. The proposed architecture is basically based on the HL7 FHIR standard that is dedicated to clinical data exchange. As well as employs different kinds of AI techniques for data extraction and standardization purposes. islEHR has the benefit of integrating many types of clinical data, as well as supporting both standard and non-standard based EMR systems. In the next chapter, we will introduce a prototype of the proposed solution.

CHAPTER 6 : CONSTRUCTION OF A PROTOTYPE

6.1. Introduction

This chapter explains in detail the implementation of a prototype of our islEHR model proposed in Chapter 5. Testing and evaluation approaches are detailed and a discussion about the results is presented as well.

6.2. Implementation

This section describes all steps carried out for islEHR implementation, including 1) the core part, which is the integration service with its three blocks for data extraction, data standardization, and FHIR file generation, 2) REST API for to enable data users to request data, 3) data fetching APIs, which are replaced in this experiment with a direct connection to a virtual database. The reason for using a virtual database is that we cannot establish a real connection to a local hospital database as well as they do not provide an API for such a service of data sharing. Figure 9 displays the implementation process that is composed of data collection, setup, and running steps. In the following subsections, we will explain each of the above-mentioned steps.

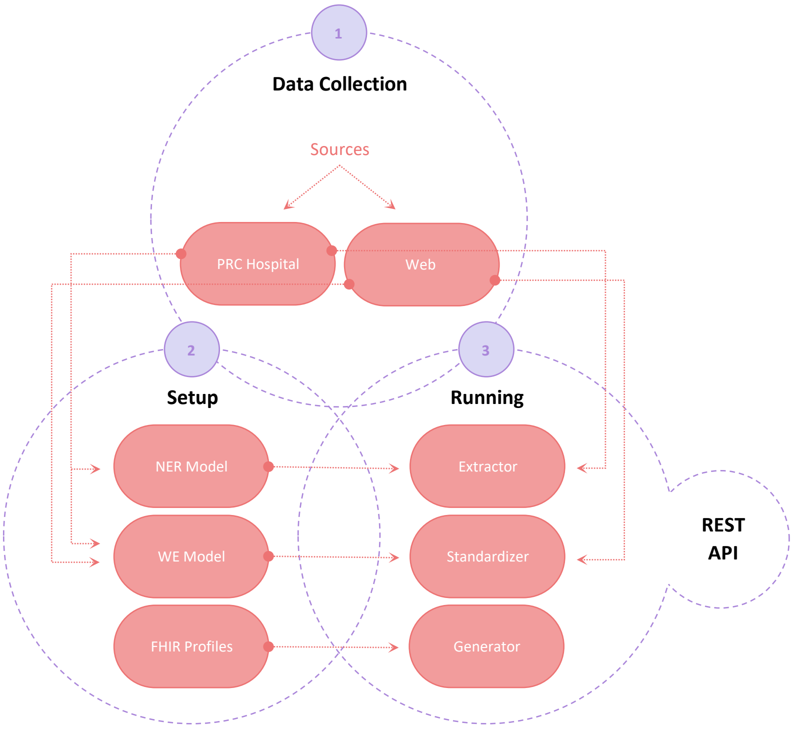

Fig.9. Process Of Prototype Implementation

6.2.1.Data Collection

For the islEHR setup and running, some data are required. These were collected from two primary resources are: 1) the Palestinian Red Crescent Hospital located in Hebron, Palestine, 2) and the web resources. The data collection method seen in figure 9 step 1 will be described in depth in the subsections that follow.

The Palestinian Red Crescent Hospital

A total of 1810 discharge reports were collected from the hospital, the data used was anonymized and a contract to use the data for only scientific purposes was signed. These reports were collected for multiple purposes including building a dataset of medication requests for machine learning, generating a dataset of medical abbreviations within diagnosis text for use in data processing, and providing a database connected to the integration service as a data source.

Consequently, collected data was stored in a virtual database that simulates the storage of discharge reports in the hospital. The database "PRCS-Database" was constructed using the SQLite relational database management system, which consists of two tables (requisite is Reports) as illustrated in Figure 9.

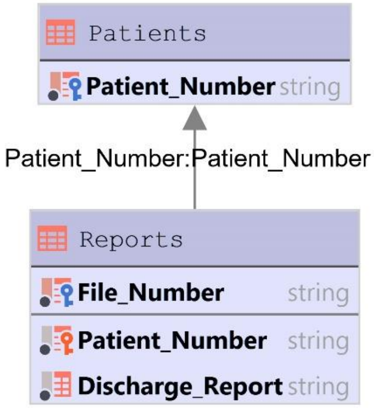

Fig.10. Database Diagram

Subsequently, medication requests were extracted from these reports and stored in a CSV file. Also, medical abbreviations were extracted, and the most frequently used ones were processed by the author with the help of a medical professional to create a tabular of the abbreviations and their origin from words or phrases and then stored CSV format. Figure 11 shows a sample of the used abbreviations.

Abbreviation	Origin
TTN	transient tachypnea of the newborn
CS	cesarean section
DM	diabetes mellitus
PTL	preterm labor
PROM	premature rupture of membranes
IUGR	intrauterine growth restriction
IUFD	intrauterine fetal death
SROM	spontaneous rupture of membranes
RDS	respiratory distress syndrome
CRIF	closed reduction internal fixation
BTL	bilateral tubal ligation
LSCS	lower segment cesarean section
SGA	small for gestational age

Fig.11. Sample Of Abbreviations

Web resources

we have used Web sources to collect the following data:

1. ICD10-CM codes

The latest version of ICD10-CM codes with their descriptions and coding rules, updated in 2021, was downloaded from the Centers for Medicare & Medicaid Services (CMS) website[3] in XML format. This information is important for presenting the result of the diagnosis in a codable format. Also, to validate extracted codes. Figure 12 shows a sample of the collected data.


```xml
</diag>
<diag>
  <name>A04</name>
  <desc>Other bacterial intestinal infections</desc>
  <excludes1>
    <note>bacterial foodborne intoxications, NEC (A05.-)</note>
    <note>tuberculous enteritis (A18.32)</note>
  </excludes1>
  <diag>
    <name>A04.0</name>
    <desc>Enteropathogenic Escherichia coli infection</desc>
  </diag>
  <diag>
    <name>A04.1</name>
    <desc>Enterotoxigenic Escherichia coli infection</desc>
  </diag>
  <diag>
    <name>A04.2</name>
    <desc>Enteroinvasive Escherichia coli infection</desc>
  </diag>
```


Fig.12. Sample ICD10

2. Approximate synonyms of ICD10 diagnosis

A dataset of synonyms was collected from the ICD10Data.com website[4] and stored in CSV format. After that, medical abbreviations extracted before were combined with the synonym's dataset. This dataset is required for building a machine

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[3] https://www.cms.gov/Medicare/Coding/ICD10

[4] https://www.icd10data.com/ICD10CM/Codes

learning model that will be used in the automatic coding process of medical diagnosis. Figure 13 shows a sample of the collected synonyms.

Respiratory distress syndrome of newborn	Respiratory distress syndrome in neonate	
Transient tachypnea of newborn	Transient tachypnea (rapid breathing) of newborn	Wet Lungs in Newborns
Congenital pneumonia due to streptococcus, group B	Congenital group b hemolytic streptococcal pneumonia	Congenital pneumonia due to group b strep
Congenital pneumonia due to Escherichia coli	Congenital escherichia coli pneumonia	Congenital pneumonia due to e coli
Meconium aspiration without respiratory symptoms	Neonatal aspiration of meconium	
Neonatal aspiration co-occurrent with respiratory symptoms	Neonatal aspiration syndromes	Neonatal aspiration with respiratory symptoms
Persistent fetal circulation	Persistent pulmonary hypertension of the newborn	Pulmonary hypertension of infant
Congenital listeriosis	Neonatal listeriosis	
Neonatal candidiasis	Neonatal moniliasis	Neonatal thrush

Fig.13. Sample Synonyms

3. Medication forms codes

A value set of drug forms coded in the HL7 V3 coding system was built of collected data from the HL7 website[5] and stored in CSV format. This information is important for mapping and presenting the final result of the medication form in a codable format. Figure 14 shows a sample of medication forms.

Code	Display
APPFUL	Applicatorful
DROP	Drops
NDROP	Nasal Drops
OPDROP	Ophthalmic Drops
ORDROP	Oral Drops
OTDROP	Otic Drops
PUFF	Puff
SCOOP	Scoops
SPRY	Sprays

Fig.14. Sample Forms

[5] https://www.hl7.org/fhir/v3/orderableDrugForm/vs.html

4. Medication administration methods codes

A value set of administration routes coded in the HL7 V3 coding system was built of collected data from the HL7 website[6] and stored in CSV format. This information is important for mapping and presenting the result of the administration methods in a codable format. Figure 15 shows a sample of Routs.

Code	Display	Definition
_JejunumRoute	JejunumRoute	Jejunum
_LacrimalPunctaRoute	LacrimalPunctaRoute	Lacrimal puncta
_LaryngealRoute	LaryngealRoute	Laryngeal
_LingualRoute	LingualRoute	Lingual
_MucousMembraneRoute	MucousMembraneRoute	Mucous membrane
_NailRoute	NailRoute	Nail
_NasalRoute	NasalRoute	Nasal
_OphthalmicRoute	OphthalmicRoute	Ophthalmic
_OralRoute	OralRoute	Oral

Fig.15. Sample Routs

5. Quantity measures codes

a value set of the quantity measures coded in the Unified Code for Units of Measure (UCUM) coding system was built of collected data from the HL7 website[7] and stored in CSV format. This information is important for mapping and presenting the result of the quantity measures in a codable format. Figure 16 shows sample measures.

[6] https://www.hl7.org/fhir/v3/RouteOfAdministration/cs.html

[7] https://www.hl7.org/fhir/valueset-ucum-units.html

Code	Display
[drp]	drop
cm	centimeter
g/m2	grams Per Square Meter
L/kg	liter per kilogram
cm	centimeter
g/m2	grams Per Square Meter
mg/mL	milligram per milliliter
mL	milliliter
cm3	cubic centimeter

Fig.16. Sample Measures

6.2.2.Setup

Before islEHR startup, some components must be present that are essential to carry out the tasks of the data integration service, these components include the Word Embedding (WE) model, Named Entity Recognition (NER) model, and FHIR profiles. In the following subsections, an explanation of these components will be provided in detail.

WE Model

Word embedding (WE) is a numerical representation of text data, typically in the form of vectors, where related words in semantics or syntaxes are closer to each other than unrelated ones. A WE model can be learned from any corpus of text data in an unsupervised manner without a need for manual labeling or feature extraction (Khattak et al., 2019).

WE is one of the well-known techniques used in the process of measuring the semantic similarity between two short sentences (Babic et al., 2019). Consequently, the researcher considered building a WE model that is trained from the descriptions of the ICD10 codes and their synonyms, as it will be used to derive vectors of two different diagnostic clauses with the intention to calculate the semantic similarity between them.

There are many different methods for WE training such as Word2vec, FastText, and BERT (Khattak et al., 2019). To choose the best method for WE training, the researcher tested the three methods (Word2Vec, Doc2Vec, and FastText), using Gensim, a library for representing unstructured digital texts as semantic vectors using unsupervised machine learning algorithms.

Word2Vec comprises two algorithms for training, Continuous Bag-Of-Words (CBOW) and Skip-gram (SG). With the CBOW model, a word is predicted based on the context, while with the SG model the context is predicted based on a given word (Mikolov et al., 2013). Key parameters for training Word2Vec embeddings are 1) the data corpus, 2) the dimensions of the vectors (vector size), 3) the maximum distance (measured with the number of words) between the current and predicted words within a sentence (window), 4) the minimum frequency of a word to be considered in training (minimum count), 5) the number of iterations over the corpus (epochs), 6) and the training algorithm. More advanced parameters can be found on the Gensim Word2Vec webpage[8].

Doc2Vec is an extension of Word2Vec, but instead of word vector representation, a paragraph vector is represented by adding a paragraph ID to Word2Vec. Noting that the phrase paragraph here includes short sentences to large documents. Similar to Word2Vec there are two models of Doc2Vec, Distributed Memory (DM) model or Distributed Bag Of Words (DBOW). In which the idea of the PV-DM model is inspired by the CBOW model. It predicts the target word based on the context with the addition of a paragraph ID. On the other hand, the PV-DBOW is similar to SG but instead of using a word as an input to predict the context, it uses the paragraph ID (Le & Mikolov, 2014). Basic model training parameters are similar to

[8] https://radimrehurek.com/gensim/models/word2vec.html

Word2Vec, but some extra advanced parameters can be found on the Gensim Doc2Vec webpage[9].

FastText is also an extension of the Word2Vec model, but it treats words as a set of character n-gram. So, a word vector is generated from the sum of these n-grams. FastText provides the same two models for computing word representations as Word2Vec, SG and CBOW. As a feature, FastText can provide a vector representation for any word that is not presented in the training corpus (Bojanowski et al., 2017). Basic model training parameters are like Word2Vec plus determining the minimum or maximum length of character n-grams to be used for training word representations. More advanced parameters can be found on the Gensim FastText webpage[10].

The training data was processed before beginning training to prepare it for machine learning. First, texts were converted to lowercase. Second, stop words, punctuations and special characters were cleaned from the texts. Last, texts were split into tokens (words), as this process is called tokenization. The researcher tested the above mentioned models based on Gensim default settings, where vector size = 100, window = 5, minimum count = 5, epochs = 5. Regarding algorithms, both the CBOW and SG with the Word2Vec and FastText models were tested. Also, both DM and DBOW were used with the Doc2Vec model.

In order to evaluate the generated word embeddings and select the most appropriate one for our work, the researcher has adopted the similarity mechanism. Where the model performance is measured based on the human judgment against the model result (Torregrossa et al., 2020). A dataset of 55 pairs of diagnostic sentences that were human-scored by two annotators was employed for this purpose, as the final

[9] https://radimrehurek.com/gensim/models/doc2vec.html

[10] https://radimrehurek.com/gensim/models/fasttext.html

similarity score was represented by the average of the judgments. Scores were between 0.0 (indicating that words are completely different) and 1.0 (indicating that words totally correspond). Then, following the approach presented by Torregrossa et al., these pairs were digitally-scored based on cosine similarity results between the two vectors that generated with the pre-trained word embeddings. The Spearman correlation between human scores and generated scores from various word embeddings was then calculated. Table 16 reports the results. Spearman correlations indicate that the FastText model performs better than other models. And the SG algorithm is slightly better than the CBOW. Therefore, the researcher used the FastText model with the SG algorithm.

Table.16. Spearman Correlations Between Trained Models And Human Judgments

Word2Vec		**Doc2Vec**		**FastText**	
CBOW	**SG**	**DM**	**DBOW**	**CBOW**	**SG**
0.457	0.496	0.103	0.114	0.605	0.688

FastText models, in general, are stable as they consistently provide similar representations of the given data over multiple runs (Borah et al., 2021). However, the FastText model was tested over 6 parameters with different settings to approve the final design of word embedding training. In this experiment, the researcher inspired the testing settings from the Borah et al. experiment. Results are recorded in Table 17. It showed a slight variation among different training settings, which does not make a difference. Whatever the researcher used the highest ones. So, the final training settings were vector size = 150, window = 2, minimum count = 1, epochs = 20. In terms of algorithms, SG was utilized with some adjustments, which are the minimum length of n-grams = 2 and the maximum length of n-grams = 5. Because we want our model to capture rare medical terms that may not be repeated in the data, we recommended choosing a minimal word of 1, despite the results showing 10 as the optimum number.

Table.17. Spearman Correlations Comparison Among Different Training Settings

		Epochs		
5	**10**	**15**	**20**	**25**
0.685	0.712	0.718	<u>0.726</u>	0.719
		Window Size		
1	**2**	**5**	**10**	**15**
0.659	<u>0.697</u>	0.685	0.682	0.682
		Minimum Count		
1	**2**	**5**	**10**	**15**
0.687	0.670	0.685	<u>0.696</u>	0.678
		Vector Size		
100	**150**	**200**	**300**	**400**
0.685	<u>0.702</u>	0.696	0.687	0.680
		Minimum N-grams		
1	**2**	**3**	**4**	**5**
0.686	<u>0.710</u>	0.685	0.652	0.644
		Maximum N-grams		
1	**2**	**3**	**4**	**5**
0.304	0.305	0.690	0.698	<u>0.701</u>

Table 17 above showed the evaluation results for FastText WE training with multiple measures of training parameters. Considering the number of training epochs, the accuracy increases as the epochs raised from 5 to 20 then, it starts diminishing. In terms of window size and minimum count of words, it was reported that the best accuracy is achieved by a window size of 2 and a minimum count of 10. Vector size between 150 and 200 is the best option for better accuracy and minimum n-grams equal to 2 give the best results as well. Lastly, it is obvious that the accuracy increases as the maximum value of n-grams increases to reach the peak at 5 with 70% accuracy.

NER Model

Named entity refers to a word that is assigned a name or categorized in a particular topic, while NER is about automatically locating named entities in a text. Traditionally NER was used to annotate text based on three main classes 1) person (PER), 2) location (LOC), 3) and organization (ORG). Whereas NER systems are able to be trained and with other class labels relevant to a specific domain. There are two basic architectures for NER systems including rule-based named entity recognition and statistical named entity recognition (Zitouni, 2014).

In this prototype, spaCy was used, a library for natural language processing, to train a customized deep learning model to detect special entities from medication request texts. First of all, training examples were prepared. SpaCy accepts training data as a list of lists. Each list contains the training text and a dictionary. The dictionary includes the start and end indices of the named entity, plus the label of the named entity. So, the researcher manually annotated 131 examples of medication requests extracted from the discharge reports. This process was performed using the Label Studio, a data annotation and exploration tool. First, labels (DRUG, ROUTE, FREQUENCY, DOSAGE, DURATION, FORM, STATUS) were defined. Then, text was annotated based on these labels as seen in Figure 11. At last, examples with annotations were exported in JSON format. Figure 12 shows an example of the final look of training data. It consists of a list of dictionaries. Each dictionary contains the example text, start and end indices, and a list of labels present in the text. This is a bit different from the spaCy specifications, therefore, the training data were reprocessed. An example of the final look of training data is shown in Figure 12.

1

ferromed plus DRUG 1x2x30 FREQUENCY

2

azicare DRUG 500 mg DOSAGE 1x1x5 FREQUENCY

3

paramol extra DRUG 1g DOSAGE 1x3 FREQUENCY prn DURATION

Fig.17. Annotation Example


```
"medication Request": "medication\nوصفه طبيب\n\n\n1\nferromed
plus 1x2x30\n2\nazicare 500 mg 1x1x5\n3\nparamol extra 1g 1x3
prn\n4\n\n\n\ndr",
"label": [
  {
    "start": 72,
    "end": 85,
    "text": "paramol extra",
    "labels": [
      "DRUG"
    ]
  },
  {
    "start": 86,
    "end": 88,
    "text": "1g",
    "labels": [
      "DOSAGE"
    ]
  },
  {
    "start": 89,
    "end": 92,
    "text": "1x3",
    "labels": [
      "FREQUENCY"
    ]
  },
  {
    "start": 93,
    "end": 96,
    "text": "prn",
    "labels": [
      "DURATION"
    ]
  }
]
```


Fig.18. Example of Training Data Exported From Lable Studio

```
["medication\nوصفه  طبيه\n\n\n1\nparamol extra 1g 1x3 prn \n2",
{
    "entities": [
        [
            26,
            39,
            "DRUG"
        ],
        [
            40,
            42,
            "DOSAGE"
        ],
        [
            43,
            46,
            "FREQUENCY"
        ],
        [
            47,
            50,
            "DURATION"
        ]
    ]
}]
```


Fig.19. Example Of Training Data In spaCy Format

Because the NER model is required to extract information only based on our pre-defined categories, the training was done on top of a blank model. In spaCy NER is implemented by a pipeline component named ner. So, a ner pipeline component was created and added to the model pipeline. Then, to train the model based on our labels, the predefined labels were added to the ner. Other pipeline components were disabled because we focus on entity extraction. After that, we start training over 100 iterations to ensure model effectiveness. In each iteration, the examples were shuffled to ensure that the model doesn't make generalizations based on the order of the examples. Finally, pass examples in batches to the NLP update function of spaCy that updates the NER model with these examples.

To figure out the best training settings for our NER model, the accuracy of the trained model has been checked based on hyperparameters, namely, batch size and learning rate. Accordingly, to evaluate model accuracy, 93 different medication requests that were not used in the training process were manually annotated. The same data was passed to our NER system to extract entities. Then, the performance was measured using the Precision, Recall, and F-measures. Where Precision Indicates the percentage of correctly extracted entities. While the Recall indicates the percentage of the entities that should have been found are effectively extracted. F-measure indicates the accuracy with the weighted average of Precision and Recall (Calders & Daelemans, 2004). Regarding hyperparameters, various values were employed, considering experiments done by other authors such as (Dong et al., 2019; Gligic et al., 2020). Table 18 reports the accuracy measures for all entities along with different values of hyperparameters. Results were almost close to each other except the point on the lowest learning rate and maximum batch size that has the minimum accuracy level, especially in low-frequency entities. The best result was on a learning rate = 0.01 and batch size = 50.

Table.18. The Precision, Recall, and F-measure For The NER According To Hyperparameters

Learning Rate 0.01									
	Precision			**Recall**			**F-measures**		
Batch Size	**40**	**50**	**60**	**40**	**50**	**60**	**40**	**50**	**60**
DRUG	0.894	0.908	0.903	0.884	0.916	0.899	0.889	0.912	0.901
ROUTE	0.967	0.967	0.967	0.853	0.853	0.853	0.906	0.906	0.906
FREQUENCY	0.983	0.992	0.988	0.992	0.992	0.992	0.987	0.992	0.989
DOSAGE	1.00	0.988	0.971	0.919	0.977	0.971	0.958	0.983	0.971
DURATION	0.962	1.00	0.893	1.00	1.00	1.00	0.980	1.00	0.943
FORM	0.989	1.00	0.989	0.978	1.00	0.989	0.984	1.00	0.989
STATUS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Total Score	0.971	**0.979**	0.959	0.947	**0.963**	0.958	0.958	**0.970**	0.957
Learning Rate 0.001									
	Precision			**Recall**			**F-measures**		
Batch Size	**40**	**50**	**60**	**40**	**50**	**60**	**40**	**50**	**60**
DRUG	0.904	0.865	0.885	0.904	0.876	0.896	0.904	0.870	0.890
ROUTE	1.00	1.00	1.00	0.853	0.853	0.853	0.921	0.921	0.921
FREQUENCY	0.992	0.987	0.992	0.987	0.983	0.987	0.989	0.985	0.989
DOSAGE	0.982	1.00	0.994	0.971	0.959	0.983	0.977	0.979	0.988
DURATION	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
FORM	0.948	0.938	0.978	0.989	0.989	0.989	0.968	0.963	0.984
STATUS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Total Score	0.975	0.970	0.978	0.958	0.951	0.958	0.966	0.960	0.967
Learning Rate 0.0001									
	Precision			**Recall**			**F-measures**		
Batch Size	**40**	**50**	**60**	**40**	**50**	**60**	**40**	**50**	**60**
DRUG	0.884	0.877	0.866	0.888	0.888	0.859	0.886	0.882	0.863
ROUTE	0.967	1.00	1.00	0.853	0.882	0.882	0.906	0.938	0.938
FREQUENCY	0.996	0.996	0.991	0.996	1.00	0.971	0.996	0.998	0.981
DOSAGE	0.994	0.988	0.966	0.983	0.977	0.983	0.988	0.983	0.974
DURATION	1.00	1.00	0.962	1.00	1.00	1.00	1.00	1.00	0.980
FORM	1.00	0.958	0.958	0.989	0.989	0.989	0.995	0.973	0.973
STATUS	1.00	0.0	0.0	1.00	0.0	0.0	1.00	0.0	0.0
Total Score	0.977	0.831	0.820	0.958	0.819	0.812	0.967	0.825	0.816

Table 19 above shows that with a learning rate of 0.01, NER works better with a batch size of 50 while accuracy diminishes around this value. The 60 batch size provides the best accuracy on a 0.001 learning rate. As opposed, the 40 batch size provides the best accuracy on a lower learning rate of 0.0001.

FHIR Profiles

To get the final output in FHIR format, we have to define our customized FHIR resources (profiles). Based on this, the main resources were initially identified, on which the final results will be based on. The basic resource is a Bundle, which is a container of a set of resources that act as an exchangeable collection, such as a clinical document. Simultaneously with the use of the Bundle, the resource Composition must be used. A Composition defines the basic structure and narrative content of a clinical document. Other resources were used such as Patient, Condition, and MedicationRequest. The Patient resource records demographic and administrative information about a patient (individual or animal). While Condition records detailed information about a patient condition, problem, diagnosis or other events, situation, issue or clinical concept that has risen to a level of concern. MedicationRequest records a medicine order or request, as well as the instructions for administering the medication to a patient (HL7 International, n.d.-b).

After that, to get our profiles, the elements of previously selected resources have been constrained by specifying their main properties that include cardinality, fixed values, data types, is-modifier, and must-support. Cardinality is an important part of the definition of all FHIR attributes, which indicates the number of times the attribute can exist in any instance of the resource type. Only the following cardinalities are defined in this specification: 0..1 (optional to one), 0..* (optional to many), 1..1 (one required), and 1..* (at least one). An element can be disabled by setting its maximum cardinality to 0. Fixed values are used to restrict the content of an element to only one unchangeable value. Some elements in FHIR resources end with an [x], indicating that they have multiple types.

With profiling, these elements can be restricted by choosing only one of the optional data types. Is-modifier is a boolean (true or false) property that indicates whether the element changes the interpretation of the resource that contains it. Must-support is a boolean (true or false) that indicates whether the element must be supported by resources producer or consumer (HL7 International, n.d.-b). Table 19 shows a sample of our profiles.

Table.19. Patient Profile

FHIR Element	C	FV	DT	IM	MS
Patient.identifier	1..1	-	-	true	true
Patient.identifier.use	1..1	official	-	true	true
Patient.identifier.value	1..1	-	-	true	true
Patient.identifier.assigner	1..1	government	-	-	true
Patient.active	1..1	-	-	true	true

Patient.name	1..1	-	-	-	true
Patient.name.use	1..1	official	-	true	true
Patient.name.text	1..1	-	-	-	true
Patient.name.family	0..1	-	-	-	-
Patient.name.given	0..*	-	-	-	-
Patient.telecom	1..1	-	-	-	true
Patient.telecom.system	1..1	phone	-	-	true
Patient.telecom.value	1..1	-	-	-	true
Patient.telecom.use	1..1	-	-	true	true
Patient.gender	1..1	-	-	-	true
Patient.birthDate	1..1	-	-	-	true
deceased[x]	0..1	-	deceasedDateTime	-	-
Patient.address	0..1	-	-	-	-
Patient.address.use	1..1	-	-	true	true
Patient.address.type	1..1	-	-	-	true
Patient.address.city	0..1	-	-	-	-
Patient.address.district	1..1	-	-	-	true
Patient.address.country	1..1	palestine	-	-	true

C: Cardinality, **FV**: Fixed Values, **DT**: Data Type, **IM**: Is Modifier, **MS**: Must Support

6.2.3.Running

In this section, the operation of the islEHR was discussed including the three core components of an extractor, standardizer, and generator data integration service plus the service API.

Extractor

This block is responsible for querying a discharge report based on the parameters sent through the REST API and the extracted information from the fetched result. Accordingly, a discharge report can be retrieved from the prebuild database (PRCS-Database) via an SQL SELECT command supported with query parameters (the number of the patient to whom the report belongs). Following the design of the SELECT command:

```
SELECT Discharge_Report FROM Reports WHERE Patient_Number = ?
```

When the extractor receives the query result, it extracts the information with Regular Expression (RE). This is an NLP technique based on pattern matching for text extraction (Singh, 2018). Information is extracted in the following four categories:

- Report details: include report title, number, timestamp, and author. The format of the timestamp should match the following format, using the DateTime Python package.

```
Date (YYYY-MM-DD) Time (HH:MM:SS) Time Zone (default=Asia/Hebron)
```

- Patient personal details: include patient national number, name, birth date, gender, contact number, and address. Then, if possible, process the patient's name to divide it into two parts, a given name and last name, using a Python module named NameParser. Also, ensure that the format of the birthdate matches the following format, using the DateTime Python package.

YYYY-MM-DD

- Medical diagnosis: include diagnosis type which is sent to the standardizer. Then, it is checked whether the listed diagnostics include ICD codes. If a code is extracted from the text, it is verified that it is an ICD code. And if a code is not found, the diagnosis text is passed to the standardizer.
- Medication request: Medication request: this part is passed through a sub extraction process, where our NER system extracts the predefined entities from the medication request text. Some of the extracted entities, including ROUTE, FORM, and DOSAGE, are passed to the standardizer.

Standardizer

This block aims to parse raw data to the corresponding standard values of clinical coding systems. This process is carried out based on either direct mapping or semantic mapping:

- Direct mapping: used to standardize the medication information, where the measures of drug route, dosage, and form are mapped to their codes codded with HL7 V3 and UCUM codding systems using the previously stored value sets. Also, the diagnosis type is directly coded in the LOINC coding system. Where in this experiment we have only two options, a final diagnosis or postoperative diagnosis.
- Semantic mapping: used to standardize medical diagnosis to ICD10-CM according to the semantic similarity degree between the recorded diagnosis and ICD10 diagnosis and their synonyms.

  To reach the final result we worked through several steps. First, the diagnostic text is processed to be in lowercase and without stop words, punctuations, or special characters. Also, the spelling of words is checked using a library named PySpellChecker and correct mistaken ones. Second, the diagnostic text is tokenized, and a vector representation is generated using the pretrained word embeddings. Third, all ICD codes and synonyms must be cleaned and then a vector representation to each one of them is generated. To avoid repeating this process we performed it once and store the result in a PKL format, which is loaded once when the service is launched. So, vector representations of the ICD codes and synonyms are only called in this step. Fourth, semantic similarity degree is calculated between the vector of the diagnostic text and each ICD10 code along with its synonyms using the cosine similarity measure. The highest score will be confirmed as the most suitable ICD 10 code to the written diagnosis in the discharge report. Also, the highest score must be larger than 0.7 to be recommended as relative.

Generator

This block is responsible for mapping the information extracted from the discharge report to their corresponding elements in the FHIR profiles. This process is done based on a set of predefined mapping rules. For example, dosage information generated from the extractor and standardized with the standardizer is mapped to the following FHIR elements of the medication request resource:

1. MedicationRequest.dosageInstruction.doseAndRate.doseQuantity.value
2. MedicationRequest.dosageInstruction.doseAndRate.doseQuantity.unit
3. MedicationRequest.dosageInstruction.doseAndRate.doseQuantity.system
4. MedicationRequest.dosageInstruction.doseAndRate.doseQuantity.code

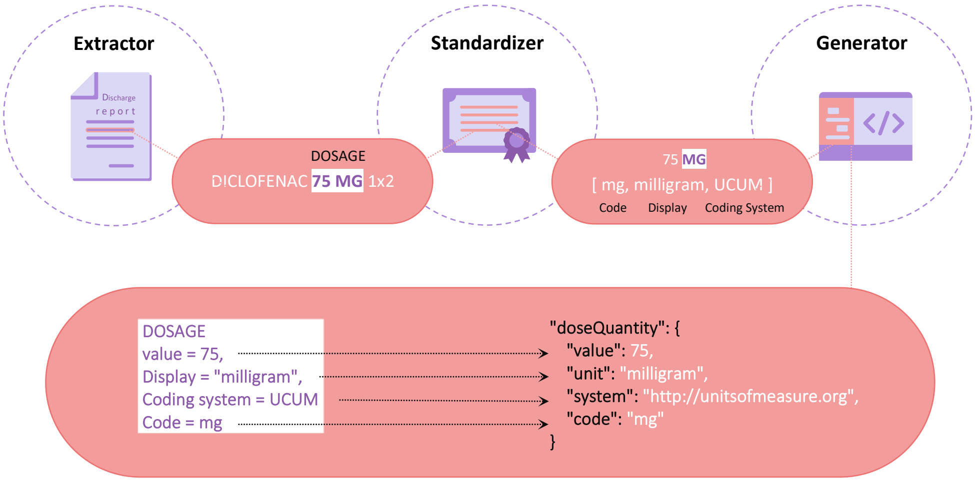

Fig.20. An Example Of FHIR Generation Of Drug Dosage

After mapping report information to its corresponding FHIR resources is completed, all filled FHIR resources are grouped in a Bundle resource and sent to the end-user through the REST API in JSON format. An Example of a complete result of the islEHR is shown in Appendix C.

REST API

In order to create a REST API with Python programming language, Flask was employed. Which is a microframework for web development, including web applications and APIs. It is designed to pull in discharge reports from the integration service and send them to the end-user upon his request. The specifications of the implemented REST API include:

- Service base URL: represent a common prefix of all requests URL that gives access to the resources defined by this interface. In this prototype, the base URL takes the form of:

```
http://localhost:8000/
```

- HTTP verbs: the HTTP verbs used with REST are POST, GET, PUT, and DELETE. In this prototype, only the GET verb was used, which corresponds to retrieving a patient discharge report through the integration service. Following the HTTP GET command designed for this work:

```
GET /DischargeReport?{Query parameters}
```

- Query parameters: to enable the user to filter or find specific resources a list of formal parameters can be supported by a request. In this prototype, we enable the search of a discharge report based on the patient number, which sends within the request. Thus, a request to the REST API final look:

```
http://localhost:8000/DischargeReport?Patient.identifier={patient number}
```

6.3. Evaluation

In this section, we describe the evaluation of results obtained with islEHR over multiple tests. The evaluation was carried out based on two criteria, performance and accuracy.

6.3.1. Performance

The performance islEHR was determined by measuring the time required to receive a result from the data integration service. The duration was examined according to different discharge reports, which differ in the amount of details that are needed to be processed. Noting that this study used a processing environment with 16GB RAM and Intel i7-6700HQ @ 2.60 GHz × 4 CPU Cores – 8 Logical Processors. Which showed that the minimum execution time is 0.04 seconds, and the maximum execution time is 84.49 seconds ≈ 1.40 minutes.

Table.20. Evaluation Results On The islEHR Performance

Total Time Of Execution (Seconds)										
Trial 1	**Trial 2**	**Trial 3**	**Trial 4**	**Trial 5**	**Trial 6**	**Trial 7**	**Trial 8**	**Trial 9**	**Trial 10**	**Average**
9.09	17.38	0.04	19.94	12.23	32.45	84.49	8.59	0.05	8.07	19.233

In comparison to other solutions, Kiourtis et al. (2019) experimented with measuring the total time of execution for their proposed Structure Mapping mechanism of EHR data to HL7 FHIR. Data used in the experiment was for vital signs (heart rate). As well as the processing environment was 16GB RAM, Intel i7-4790 @ 3.60 GHz × 8 CPU Cores. The comparison was based on two different datasets of measurements (small and large). Results showed that the minimum time required to perform transformation is 2 seconds and 12 seconds at maximum. These results are not comparable to our results due to the difference between the proposed works and the evaluation designs. But, we can say that in our system, the simplest case of only extracting information and mapping them to FHIR without standardization, which is the most time-consuming process among others (extract and generation), required a time between 0.04 and 0.05 seconds.

6.3.2. Accuracy

The accuracy of the islEHR prototype was measured by validating the outputs against FHIR specifications and our FHIR profiles and comparing the results to manual results.

In the first part of accuracy testing, an online FHIR validation service named Inferno Validator was used. This validator is one of the suggested validators by the HL7 organization. It validates FHIR resources structure, cardinality, value domains, and coding bindings. All resources were tested in 10 experiments. Results showed that outputs are 100% correct.

In the second part, the accuracy of report core elements extraction, standardization, and normalization in FHIR format were tested. For that purpose, the researcher manually extracted diagnoses and medications data within 30 discharge reports and standardized them if it is applicable. Then, parsed them to their corresponding FHIR elements. The same reports were passed through our data integration service and the results are compared to the manual ones using the measures of precision, recall, and F score. The results are summarized in Table 21.

Table.21. Evaluation Results On The islEHR Accuracy

FHIR Resource	FHIR Element	Precision	Recall	F-Score
Condition	**clinicalStatus.coding.code**	1.0	1.0	1.0
	code.coding.code	0.894	0.894	0.894
MedicationRequest	**status**	0.972	0.986	0.979
	medicationCodeableConcept.text	0.917	0.914	0.913
	dosageInstruction.timing.repeat.frequency	1.0	1.0	1.0

dosageInstruction.timing.repeat.period	1.0	1.0	1.0
dosageInstruction.timing.repeat.periodUnit	1.0	1.0	1.0
dosageInstruction.timing.repeat.boundsDuration.value	1.0	1.0	1.0
dosageInstruction.timing.repeat.boundsDuration.unit	1.0	1.0	1.0
dosageInstruction.route.coding.code	0.958	0.957	0.956
dosageInstruction.asNeededBoolean	1.0	1.0	1.0
dosageInstruction.doseAndRate.doseQuantity.value	0.974	0.971	0.971
dosageInstruction.doseAndRate.doseQuantity.code	0.986	0.971	0.977

The table above showed that generally, our proposed solution has a high degree of accuracy across several elements. Where the highest value of 100% was for condition code and medication frequency, period, period unit, dosage repeat value, dosage repeat unit, and as needed. These high results are attributed to building our custom rules for data extraction and mapping. And the NER model was trained on top of data collected from our hospitals. Also, for these elements, the standardization process was done through direct mapping. While the accuracy for the medication dose quantity code, dose quantity value, status, route code, and text was 98.6%, 97.4%, 97.2%, 95.8%, and 91.7%, respectively. These values were lower than the prior ones because of the NER error rate, which could be due to the lack of examples in the training data (particularly because the NER model was trained on a small dataset) or ambiguity (semantic or structural) in the text to be annotated. This problem may be solved by increasing the size and diversity of the learning sample. Finally, there's condition coding, which has an accuracy rate of 89.4 %. The lack of accuracy of this element is due to semantic standardization. This may result from a lack of diagnostic synonyms. Also, the nature of medical terms may cause some ambiguity, for example, hypertension and hyperparathyroidism are totally different diagnoses, but they may have close vector representations due to the structural similarity. This can be avoided by including these terms in synonyms lists, which will ensure a perfect match score. Another option for lowering the error rate is to classify the patient's condition based on both diagnostic data and observations, and then attach the standardization process to this classification to rule out any diagnoses not included in this category.

In comparison to other solutions, Hong et al. (2019) proposed a pipeline for clinical data normalization named NLP2FHIR. As they employed NLP for data extraction as we did, the accuracy measures between the two works were compared. It is important to mention that they carried out the evaluation on discharge reports, but they concentrate on other different parts. Anyway, a comparison of accuracy results of common FHIR elements between islEHR and NLP2FHIR is shown in Table 22.

Table.22. islEHR Accuracy Against NLP2FHIR

FHIR Element	Solution	Precision	Recall	F-Score
Condition.code.coding.code	**islEHR**	0.894	0.894	0.894
	NLP2FHIR	0.865	0.696	0.771
MedicationRequest.medicationCodeableConcept	**islEHR**	0.917	0.914	0.913
	NLP2FHIR	0.996	0.982	0.988
MedicationRequest.dosageInstruction.timing.repeat.frequency	**islEHR**	1.0	1.0	1.0
	NLP2FHIR	0.795	0.873	0.832
MedicationRequest.dosageInstruction.timing.repeat.period	**islEHR**	1.0	1.0	1.0
	NLP2FHIR	0.959	0.914	0.936
MedicationRequest.dosageInstruction.timing.repeat.boundsDuration	**islEHR**	1.0	1.0	1.0
	NLP2FHIR	0.600	1.0	0.750
MedicationRequest.dosageInstruction.route	**islEHR**	0.958	0.957	0.956
	NLP2FHIR	0.957	0.816	0.878
MedicationRequest.asNeededBoolean	**islEHR**	1.0	1.0	1.0
	NLP2FHIR	1.0	0.571	0.727

The table above showed that the accuracy of the islEHR is better than outperforming the NLP2FHIR across all elements except the medicationCodeableConcept. As its accuracy reached 98.8% and 91.3% in the NLP2FHIR and islEHR, respectively. In the NLP2FHIR the accuracy degree for other elements was ordered as 93.6%, 87.8%, 83.2%, 77.1%, 75.0%, and 72.7% for medication repeat period, medication route, medication repeat frequency, condition code, medication repeat duration, medication as needed, respectively.

In general, the results proved that the islEHR, which was created to improve EHR interoperability compared to various existing solutions, does not cause a decrease in performance. Whereas, the average accuracy of islEHR is 98% while for Structure Mapping and NLP2FHIR it is 93% and 83%, respectively.

6.4. Summary

In this chapter, we explained the construction of a prototype of the islEHR starting from data collection to running. As well as, discussed the results of the islEHR prototype evaluation. According to the results, IslEHR outperforms previous models in terms of variety, accuracy, and performance. This indicates that it is a viable option for achieving EHR interoperability. Our conclusions and future work will be provided in Chapter 7.

CHAPTER 7 : CONCLUSIONS AND FUTURE WORK

7.1. Introduction

This chapter introduces the findings of this thesis on EHRs interoperability. The conclusions were drawn from the thesis research questions and findings. The consequences of these findings, as well as the recommendations that follow, will be discussed. Discussion of future work will be provided as well.

7.2. Summary Of Thesis Contributions

In the realm of medical informatics, eHealth is a growing field. In Palestine, most healthcare organizations have implemented electronic health record (EHR) information systems. Interoperability difficulties with multiple structures and formats affect EHRs in Palestinian health care institutions. Hence, electronic access to patient health data is restricted, which is a serious issue. This research aimed to discover the most appropriate eHealth interoperability model for Palestine. To achieve the objectives of the research, the researcher looked through the existing state of the art regarding the research topic to find out the recent trends related to EHR interoperability. Then, employed a mixed-method approach to investigate the role of EMRs in Palestine and the current situation of eHealth interoperability and readiness for its implementation in the community. After that, and based on findings, the researcher proposed a model for reaching interoperability and developed a prototype for the proposed solution.

Many literary works have emphasized the importance of using medical terminology and interoperability standards such as ICD10, LOINC, SNOMED CT, HL7 V2/V3/FHIR, and many more as a foundation for attaining eHealth interoperability. They were also constantly looking for good EHRs interoperability solutions, therefore they suggested numerous architectures and systems for that goal, which are discussed in detail in Chapter 2. During our research, we discovered that there are no proposed solutions for interoperability in Palestine.

Based on the qualitative analysis of the role of EMRs in Palestine and their conformity with data-sharing, it can be concluded that:

- Existing EMR systems have a low level of capability overall.
- Except for the ICD10, which is incorporated within EMR systems but is rarely used, there are no terminologies or interoperability standards in use.
- And there are no interoperability models for the Palestinian community that has been implemented.

The quantitative analysis of the survey data obtained in this study:

- Emphasized the results gained from the qualitative part and demonstrated that medical data was typically shared between hospitals via paper.
- Found that the main obstacle to achieving interoperability is the lack of such a solution.
- Another limitation is that Palestine is a developing country where there is a lack of data exchange infrastructures, besides implementing interoperable electronic medical record systems will lead to increasing the financial burden on healthcare institutions,
- Discovered that physicians of different disciplines are enthusiastic about the prospect of exchanging various types of patient health data electronically, and
- Physicians are also aware of the benefits that having interoperable EMR systems will bring to all aspects of society, including organizations, health professionals, and individuals.

Finally, in response to the main study question, the author proposed a model (islEHR) that is believed to be a good way to implement eHealth interoperability in Palestine. The model is based on AI techniques and the HL7 FHIR interoperability standard for enabling data sharing in a standard format that is applicable for use by humans and machines. Whereas the heart of the islEHR is the data integration service that is made of three blocks, data extraction, data standardization, and FHIR generation. The researcher has risen to suggest these ingredients and adoption of these techniques because they are commensurate with the nature of the clinical data generated from EMR systems used by Hebron hospitals in Palestine. Also, the technologies used are among the most modern. The model is also designed in such a way that it may be utilized for data interchange if all hospitals use the same EMR system.

We implemented the islEHR and succeeded in sharing data out from a clinical database in FHIR format, where it can be used by any data user (hospital, clinic, AI system, etc..). Total time of execution and accuracy were measured. Experimental results were good enough to say that usage of the islEHR represents a promising solution for reaching eHealth interoperability in the Palestinian community.

7.3. Limitations

We encountered various limitations during our research, which we have stated below:

1. We were unable to cover other cities in the West Bank owing to the Corona pandemic, the difficulties of moving between cities, and the curfew, so we had to include the Hebron community as part of Palestine as a whole. Furthermore, Gaza is under blockade, and we are unable to reach it.
2. We only have limited access to realistic clinical data generated by existing EMR systems. This is due to hospitals policies restricting data sharing and protecting patients' privacy.

7.4. Recommendations

In Palestine, eHealth should be improved as much as possible. This could be accomplished through investments in this sector such as:

- Develop clear strategies for improving health information systems in general and EMR systems in particular and develop them to higher levels that matched the EMRAM model. Also, conduct annual assessments to track progress and identify roadblocks.
- Producing high-quality clinical data while adhering to international terminology and interoperability standards.
- Invest more in eHealth interoperability solutions and technologies. Hence, moving toward interoperable EHRs in Palestine should go hand in hand with protecting data security and privacy.
- Developing policies related to the exchange of EHRs such as a policy of patient consent to share data.
- Provide more training for employees and motivate them to follow new developments regarding eHealth.
- Increase community awareness about health information sharing and its benefits to all parts of the community including healthcare providers and individuals.
- Establish a relationship with educational and research institutions to get benefited from educated and professional human resources.

7.5. Future Work

The focus of this thesis was on EHRs interoperability among different hospitals in Palestine County. The author worked hard to find a suitable solution for these healthcare companies to achieve interoperability and exchange medical data. The author believes that her proposed model will be useful, but it still requires further testing to prove its validity and applicability in real-world scenarios. Also, semantic and structural ambiguity of medical phrases represents a significant issue to be addressed in future work. As well as working on expanding our prototype to include structured and standardized data and evaluating the results of merging various types of data. We will endeavor to increase the accuracy as well.

7.6. Summary

The thesis' general conclusions on establishing eHealth interoperability in the Palestinian community were covered in this chapter, which included a discussion of the key findings, a suggested model, and prototype development. Furthermore, we have made some suggestions in this regard. Introduce upcoming works as well.

References

Adel, E., El-Sappagh, S., Barakat, S., & Elmogy, M. (2018). Distributed electronic health record based on semantic interoperability using fuzzy ontology: A survey. *International Journal of Computers and Applications*, *40*(4), 223–241. https://doi.org/10.1080/1206212X.2017.1418237

Adel, E., El-Sappagh, S., Barakat, S., & Elmogy, M. (2019a). A unified fuzzy ontology for distributed electronic health record semantic interoperability. In *U-Healthcare Monitoring Systems* (pp. 353–395). Elsevier. https://doi.org/10.1016/B978-0-12-815370-3.00014-1

Adel, E., El-Sappagh, S., Barakat, S., & Elmogy, M. (2019b). Ontology-based electronic health record semantic interoperability: A survey. In *U-Healthcare Monitoring Systems* (pp. 315–352). Elsevier. https://doi.org/10.1016/B978-0-12-815370-3.00013-X

Alshenqeeti, H. (2014). Interviewing as a Data Collection Method: A Critical Review. *English Linguistics Research*, *3*(1), p39. https://doi.org/10.5430/elr.v3n1p39

Azungah, T. (2018). Qualitative research: Deductive and inductive approaches to data analysis. *Qualitative Research Journal*, *18*(4), 383–400. https://doi.org/10.1108/QRJ-D-18-00035

Babic, K., Martincˇic-Ipšic, S., Meštrovic, A., & Guerra, F. (2019). *Short texts semantic similarity based on word embeddings*. 7.

Bauer, M., Baqa, H., Bilbao, S., Corchero, A., Daniele, L., Esnaola, I., Fernandez, I., Osten Franberg, Garcia-Castro, R., Girod-Genet, M., Guillemin, P., Gyrard, A., Kaed, C. E., Kung, A., Jaeho Lee, Lefrancois, M., Wenbin Li, Raggett, D., & Wetterwald, M. (2019). *Towards Semantic Interoperability Standards based on Ontologies*. https://doi.org/10.13140/RG.2.2.26825.29282

Blackman-Lees, S. M. (2018). *Towards a Conceptual Framework for Persistent Use: A Technical Plan to Achieve Semantic Interoperability within Electronic Health Record Systems*. Hawaii International Conference on System Sciences.

Blobel, B. (2018). Interoperable EHR Systems—Challenges, Standards and Solutions. *European Journal for Biomedical Informatics*, *14*(2). https://doi.org/10.24105/ejbi.2018.14.2.3

Bojanowski, P., Grave, E., Joulin, A., & Mikolov, T. (2017). Enriching Word Vectors with Subword Information. *ArXiv:1607.04606 [Cs]*. http://arxiv.org/abs/1607.04606

Borah, A., Barman, M. P., & Awekar, A. (2021). Are Word Embedding Methods Stable and Should We Care About It? *ArXiv:2104.08433 [Cs]*. http://arxiv.org/abs/2104.08433

Brayda, W. C., & Boyce, T. D. (2014). So you Really Want to Interview Me?: Navigating “Sensitive” Qualitative Research Interviewing. *International Journal of Qualitative Methods*, *13*(1), 318–334. https://doi.org/10.1177/160940691401300115

Calders, T., & Daelemans, W. (2004). *A Formal Framework for Evaluation of Information Extraction*. 13.

Cho, J. Y., & Lee, E.-H. (2014). *Reducing Confusion about Grounded Theory and Qualitative Content Analysis: Similarities and Differences*. 24.

do Espírito Santo, J. M., & Medeiros, C. B. (2017). Semantic Interoperability of Clinical Data. In M. Da Silveira, C. Pruski, & R. Schneider (Eds.), *Data Integration in the Life Sciences* (Vol. 10649, pp. 29–37). Springer International Publishing. https://doi.org/10.1007/978-3-319-69751-2_4

Dong, X., Chowdhury, S., Qian, L., Li, X., Guan, Y., Yang, J., & Yu, Q. (2019). Deep learning for named entity recognition on Chinese electronic medical records: Combining deep transfer learning with multitask bi-directional LSTM RNN. *PLOS ONE*, *14*(5), e0216046. https://doi.org/10.1371/journal.pone.0216046

Ed Hammond, W. (2017). Standards for Global Health Information Systems. In *Global Health Informatics* (pp. 94–108). Elsevier. https://doi.org/10.1016/B978-0-12-804591-6.00005-7

European Medicines Agency. (2016). *Introduction to ISO Identification of Medicinal Products, SPOR programme*. 12.

Everitt, B. S., & Skrondal, A. (2010). *The Cambridge Dictionary of Statistics*. 480.

F.H. Aljazairi, A. (2019). Triage. In O. Karcioglu & M. Günalp Eneyli (Eds.), *Emergency Medicine and Trauma*. IntechOpen. https://doi.org/10.5772/intechopen.86227

Gansel, X., Mary, M., & van Belkum, A. (2019). Semantic data interoperability, digital medicine, and e-health in infectious disease management: A review. *European Journal of Clinical Microbiology & Infectious Diseases*, *38*(6), 1023–1034. https://doi.org/10.1007/s10096-019-03501-6

Garets, D., & Davis, M. (2006). Electronic Medical Records vs. Electronic Health Records: Yes, There Is a Difference. *HIMSS Analytics*.

Gligic, L., Kormilitzin, A., Goldberg, P., & Nevado-Holgado, A. (2020). Named entity recognition in electronic health records using transfer learning bootstrapped Neural Networks. *Neural Networks*, *121*, 132–139. https://doi.org/10.1016/j.neunet.2019.08.032

Gomes, F., Freitas, R., Ribeiro, M., Moura, C., Andrade, O., & Oliveira, M. (2019). GIRLS, a Gateway for Interoperability of electronic health Record in Low-cost System: Interoperability between FHIR and OpenEHR Standards. *2019 IEEE International Conference on E-Health Networking, Application & Services (HealthCom)*, 1–6. https://doi.org/10.1109/HealthCom46333.2019.9009602

González Bernaldo de Quirós, F., Otero, C., & Luna, D. (2018). Terminology Services: Standard Terminologies to Control Health Vocabulary: Experience at the Hospital Italiano de Buenos Aires. *Yearbook of Medical Informatics*, *27*(01), 227–233. https://doi.org/10.1055/s-0038-1641200

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (Seventh Edition).

HIMSS. (n.d.). *Interoperability in Healthcare*. https://www.himss.org/resources/interoperability-healthcare

HIMSS Analytics. (n.d.-a). *Electronic Medical Record Adoption Model (EMRAM)*. https://www.himssanalytics.org/emram

HIMSS Analytics. (n.d.-b). *Stage 6 & 7 Achievement*. https://www.himssanalytics.org/stage-6-7-achievement

HL7 International. (n.d.-a). *Health Level International Standards*. https://www.hl7.org/

HL7 International. (n.d.-b). *HL7 FHIR*. http://hl7.org/fhir/

Hong, N., Wen, A., Shen, F., Sohn, S., Wang, C., Liu, H., & Jiang, G. (2019). Developing a scalable FHIR-based clinical data normalization pipeline for standardizing and integrating unstructured and structured electronic health record data. *JAMIA Open*, *2*(4), 570–579. https://doi.org/10.1093/jamiaopen/ooz056

Iroju, O., Soriyan, A., Gambo, I., & Olaleke, J. (2013). *Interoperability in Healthcare: Benefits, Challenges and Resolutions*. *3*(1), 10.

ISO. (2015). *International Standard 2382: Information technology—Vocabulary*. https://www.iso.org/obp/ui/#iso:std:iso-iec:2382:ed-1:v1:en

ISO 13606 community. (n.d.). *ISO 13606 standard for Electronic Health Record Communication*. http://www.en13606.org/

ISO Technical committees. (n.d.). *ISO/TC 215 Health Informatics*. https://www.iso.org/committee/54960.html

Khattak, F. K., Jeblee, S., Pou-Prom, C., Abdalla, M., Meaney, C., & Rudzicz, F. (2019). A survey of word embeddings for clinical text. *Journal of Biomedical Informatics: X*, *4*, 100057. https://doi.org/10.1016/j.yjbinx.2019.100057

Kiourtis, A., Mavrogiorgou, A., Menychtas, A., Maglogiannis, I., & Kyriazis, D. (2019). Structurally Mapping Healthcare Data to HL7 FHIR through Ontology Alignment. *Journal of Medical Systems*, *43*(3), 62. https://doi.org/10.1007/s10916-019-1183-y

Lancaster, G. A., Dodd, S., & Williamson, P. R. (2004). Design and analysis of pilot studies: Recommendations for good practice: Design and analysis of pilot studies. *Journal of Evaluation in Clinical Practice*, *10*(2), 307–312. https://doi.org/10.1111/j..2002.384.doc.x

Lange, K. (2019). *The Little Book on REST Services*. 31.

Le, Q. V., & Mikolov, T. (2014). Distributed Representations of Sentences and Documents. *ArXiv:1405.4053 [Cs]*. http://arxiv.org/abs/1405.4053

Leavy, P. (2017). *Research design: Quantitative, qualitative, mixed methods, arts-based, and community-based participatory research approaches*. Guilford Press.

Legaz-García, M. del C., Martínez-Costa, C., Menárguez-Tortosa, M., & Fernández-Breis, J. T. (2016). A semantic web based framework for the interoperability and exploitation of clinical models and EHR data. *Knowledge-Based Systems*, *105*, 175–189. https://doi.org/10.1016/j.knosys.2016.05.016

Liyanage, H., Krause, P., & De Lusignan, S. (2015). Using ontologies to improve semantic interoperability in health data. *Journal of Innovation in Health Informatics*, *22*(2), 309–315. https://doi.org/10.14236/jhi.v22i2.159

LOINC. (n.d.). *The international standard for identifying health measurements, observations, and documents*. https://loinc.org/

Luna, D., Campos, F., & Otero, C. (2019). *Interoperability in Digital Health: Reference Material*.

Matney, S. A. (2016). Semantic interoperability: The good, the bad, and the ugly. *Nursing*, *46*(10), 23–24. https://doi.org/10.1097/01.NURSE.0000490225.92179.69

Meng, M., Steinhardt, S., & Schubert, A. (2018). Application Programming Interface Documentation: What Do Software Developers Want? *Journal of Technical Writing and Communication*, *48*(3), 295–330. https://doi.org/10.1177/0047281617721853

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient Estimation of Word Representations in Vector Space. *ArXiv:1301.3781 [Cs]*. http://arxiv.org/abs/1301.3781

Neideen, T., & Brasel, K. (2007). Understanding Statistical Tests. *Journal of Surgical Education*, *64*(2), 93–96. https://doi.org/10.1016/j.jsurg.2007.02.001

Oliveira, D., Coimbra, A., Miranda, F., Abreu, N., Leuschner, P., Machado, J., & Abelha, A. (2018). New Approach to an openEHR Introduction in a Portuguese Healthcare Facility. In Á. Rocha, H. Adeli, L. P. Reis, & S. Costanzo (Eds.), *Trends and Advances in Information Systems and Technologies* (Vol. 747, pp. 205–211). Springer International Publishing. https://doi.org/10.1007/978-3-319-77700-9_21

OpenEHR. (n.d.). *What is openEHR?* https://www.openehr.org/about/what_is_openehr

Patra, S. (2019). Questionnaire Design. In R. N. Subudhi & S. Mishra (Eds.), *Methodological Issues in Management Research: Advances, Challenges, and the Way Ahead* (pp. 53–78). Emerald Publishing Limited. https://doi.org/10.1108/978-1-78973-973-220191005

Payne, T. H., Lovis, C., Gutteridge, C., Pagliari, C., Natarajan, S., Yong, C., & Zhao, L.-P. (2019). Status of health information exchange: A comparison of six countries. *Journal of Global Health*, *9*(2), 0204279. https://doi.org/10.7189/jogh.09.020427

Peck, R., Olsen, C., & Devore, J. L. (2008). *Introduction to statistics and data analysis* (3rd ed). Thomson Brooks/Cole.

Puttini, R. S., Toffanello, A. A., Chaim, R. M., Alves, G., Rotzsch, J. M. P., Carvalho, E. O., Ishikawa, E., Araujo, A. P., & Oliveira, E. C. (2017). Semantic Framework for Electronic Health Records. *2017 IEEE 11th International Conference on Semantic Computing (ICSC)*, 334–337. https://doi.org/10.1109/ICSC.2017.98

Reisman, M. (2017). *EHRs: The Challenge of Making Electronic Data Usable and Interoperable*. 4.

Sekaran, U. (2003). *Research methods for business: A skill-building approach* (4th ed). John Wiley & Sons.

Singh, S. (2018). Natural Language Processing for Information Extraction. *ArXiv:1807.02383 [Cs]*. http://arxiv.org/abs/1807.02383

SNOMED International. (n.d.). *SNOMED CT*. https://www.snomed.org/

The Medical Imaging Technology Association. (n.d.). *Digital Imaging and Communications in Medicine*. https://www.dicomstandard.org/

Thompson, S. K. (2012). *Sampling* (3rd ed). Wiley.

Torregrossa, F., Claveau, V., Kooli, N., Gravier, G., & Allesiardo, R. (2020). *On the Correlation of Word Embedding Evaluation Metrics*. 9.

WHO. (n.d.). *EHealth* [Http://who.int/ehealth/en/].

World Health Organization. (n.d.). *Classifications: Classification of Diseases (ICD)*. https://www.who.int/classifications/icd/

Zitouni, I. (Ed.). (2014). *Natural Language Processing of Semitic Languages*. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-45358-8

APPENDIX A: SEMI-STRUCTURED INTERVIEW GUIDE

* Note: This guide only represents the main topics to be discussed with the participants.

Introduction

Thank you for agreeing to participate in the interview. We are interviewing you to assess the condition of available EMR systems in our community. The interview should take between half an hour and an hour and a half depending on how much information you would like to share. With your permission, I would like to audio record the interview because I don't want to miss any of your comments. All responses will be treated with complete confidentiality and only for scientific research purposes.

Are there any questions about what I have just told you?

May I turn on the audio recorder?

Build A Rapport

Before we begin, it would be nice if you could tell me a little bit about yourself. Tailor a general question. For example: how long have you been working here?

Common Information

Tell me a little about the used EMR system within your institution?

> **Prompts:** What Electronic Medical Record (EMR) system you are responsible for?
>
> **Prompts:** How long this system has been used?
>
> **Prompts:** What kind of data does it record (e.g., health, financial, managerial)?

EMR Adoption

What clinical ancillary department applications are installed (laboratory, pharmacy, radiology)?

> **Prompts:** How can physicians access (i.e., medical images, etc..) created and stored by (i.e., radiology application, etc..)?
>
> **Prompts:** Is (i.e., radiology application, etc..) connected/feeding a central clinical data repository (CDR)?

Is nursing health documentation (e.g., vital signs, flowsheets, nursing notes, nursing tasks, care plans) electronically implemented? If so, is it integrated with a CDR?

> **Prompts:** If yes, how often it is used?
>
> **Prompts:** If yes, is it used in the emergency department (ED)?
>
> **Prompts:** If yes, does the hospital has the ability to track nurse task completion?

Can physicians access a national or regional patient database to support decision-making (e.g., medications, images, allergies, lab results, etc.)?

Prompts: If yes, can you explain how data is exchanged?

Do physicians place medical orders using a Computerized Practitioner Order Entry (CPOE)?

Prompts: If yes, is it used in the ED?

Prompts: If yes, can you give a scenario of its use?

Is physician documentation (e.g., progress notes, consult notes, discharge summaries, problem/diagnosis list, etc.) electronically implemented?

Prompts: If yes, is it implemented with structured templates?

Let us talk about Clinical Decision Support (CDS), how does it apply within the hospital system?

Prompts: Whom it supports? What tasks does it support? Where it is used?

What privacy and security procedures are implemented to protect patients' information (e.g., role-based access control, encryption, antivirus/anti-malware, etc..)?

Prompts: For example: if a portable device (e.g., laptop, tablet) is stolen, is it possible to wipe information stored on it remotely?

Prompts: For example: if an attacker threatens the system with a cyber attack, is it possible to detect it? If so, is it possible to prevent threats?

Prompts: Does the hospital conduct annual security risk assessments?

How the hospital manage blood products?

Prompts: Tell me about blood specimen collection and tracking?

What about health information exchange, is it possible to exchange information with other entities that are authorized to treat the patient (e.g., other non-associated hospitals, outpatient clinics, employers)?

Prompts: If yes, could you explain how the exchange takes place?

Does the hospital employ data warehousing to support analytical reporting?

Prompts: If yes, can you give an example of its use?

Standards Compliance

Does the hospital information system follow any of the health informatics standards (i.e., ICD, HL7, SNOMED CT, LOINC, DICOM, ISO)? If so, mention them.

Prompts: If yes, talk a little about its use?

Conclusion

Is there anything else you want to add to our discussion today?

Thank you for your time and the information you shared with me.

APPENDIX B: QUESTIONNAIRE

An Electronic Health Records Interoperability Model Among Hebron Hospitals In Palestine

I'm Arwa Najjar, a master's student in information technology and systems management. At both Hebron University and Atlantica University. I'm researching to investigate the current condition of the available Electronic Health Record (EHR) systems in Palestine and find out the most appropriate eHealth interoperability model to be applied in this community. As part of this research, I'm surveying to explore interoperability conditions, obstacles, driving forces, and requirements from a doctor's perspective. This questionnaire targets physicians who work in different hospitals located in Hebron. Only hospitals with Electronic Health Record Systems (EHR) are included.

We have high confidence in you and your keenness in supporting scientific research. So we kindly ask you to complete the attached questionnaire. The collected data will be pivotal and important to the success of this work, so please be precise answer the paragraphs shown in the attached pages. Your answers will be treated with complete confidentiality and only for scientific research purposes.

-- Key Terms

01. Electronic Health Record (EHR) is a repository of information regarding the health status of a subject of care, in computer processable form.

02. Interoperability is the ability of different information systems to access, exchange, integrate, and cooperatively use data in a coordinated manner.

* Required

1. Demographic Information

1. Gender *

select one option

- Female
- Male

2. Age *

select one option

- <30
- 30-39
- 40-49
- >50

3. Medical specialty *

select one option

- Internal medicine
- Surgery and its subspecialties
- Obstetrics and Gynecology
- Emergency medicine
- Pediatrics
- Ophthalmology
- Otorhinolaryngology
- Neurology
- Radiology
- General medicine

4. Place of getting the medical specialty *
select one option

- Palestine
- One of the Arab world countries
- USA
- Canada
- One of the European Union countries
- One of East Asia countries
- One of the Soviet Union countries
- Turkey
- Australia

5. Place of work *
select one option

- Al-Ahly Hospital
- Al-Amera Alia Hospital
- Palestine Red Crescent Society Hospital
- Al-Meezan Hospital
- Al-Shaheed Abu Al-Hassan Al-Qasem Hospital
- St John Hospital

6. Years of experience (post-internship) *
select one option

- 1-4
- 5-8
- 9-12
- >12

7. Years of using an EHR system *

select one option

- <1
- 1-4
- 5-8
- >8

2. Part 1: Data Exchange Condition

8. Physicians can electronically acquire the information they need from other hospitals with the same EHR system? *

select one option

- Yes
- No

9. Physicians can electronically acquire the information they need from other hospitals with different EHR systems? *

select one option

- Yes
- No

10. Outside patient information is typically sent and received from other hospitals with different EMR systems in Hebron using? *

select one option

- Paper
- Fax
- Email
- Computer System

11. Outside patient information mostly used in the case of? *
select one option

- Day to day life
- Referral
- Consult

12. The usual time frame for receiving information? *
select one option

- Within 30 minutes
- Within 24 hours
- From 2 to 3 days
- More than 3 day

3. Part 2: Interoperability Barriers

13. In your opinion, what barriers prevent you from electronically acquiring the information you need from other hospitals with different EHR systems? *
select one option per row

	Strongly Disagree	Disagree	Agree To Some Extent	Agree	Strongly Agree
There is no electronic system for connecting different EHRs					
There is no infrastructure for information exchange					
Hospitals prefer to depend on their internal sources of information					
This may cause some leaks of patients' private information					
Increase in information system costs					
The hospital has strict policies regarding information sharing					

4. Part 3: Interoperability Driving Forces

14. To what extent would you agree with the need for an eHealth interoperability solution? *
select one option per row

	1	2	3	4	5	
Strongly Disagree						Strongly Agree

15. In your opinion, what benefits will be gained from electronically exchanging patient information between different hospitals with different EHR systems? *
select one option per row

	Strongly Disagree	Disagree	Agree To Some Extent	Agree	Strongly Agree
Having an accurate diagnosis	⬭	⬭	⬭	⬭	⬭
Reducing duplication of lab and imaging tests	⬭	⬭	⬭	⬭	⬭
Preventing of drug–drug interactions	⬭	⬭	⬭	⬭	⬭
Time-saving in patients sessions and treatment decision making	⬭	⬭	⬭	⬭	⬭
Improving decision making	⬭	⬭	⬭	⬭	⬭
Avoiding filling multiple forms	⬭	⬭	⬭	⬭	⬭
Reducing health care costs	⬭	⬭	⬭	⬭	⬭
Increasing in the reputation of hospitals and clinics	⬭	⬭	⬭	⬭	⬭

5. Part 4: Interoperability Requirements

16. What patient information do you want to electronically exchange? *
select one option per row

	Strongly Disagree	Disagree	Agree To Some Extent	Agree	Strongly Agree
Medical history	⬭	⬭	⬭	⬭	⬭
Vital signs	⬭	⬭	⬭	⬭	⬭
Medication list	⬭	⬭	⬭	⬭	⬭
Allergy list	⬭	⬭	⬭	⬭	⬭
Problem list	⬭	⬭	⬭	⬭	⬭
Laboratory results	⬭	⬭	⬭	⬭	⬭
Imaging results	⬭	⬭	⬭	⬭	⬭
Discharge instructions	⬭	⬭	⬭	⬭	⬭
Implanted medical devices list	⬭	⬭	⬭	⬭	⬭
Full record	⬭	⬭	⬭	⬭	⬭

Thanks For Your Response

APPENDIX C: EXAMPLE OF THE ISLEHR OUTPUT


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    "id": "Bundle-21-02331-1",
    "type": "document",
    "timestamp": "2021-06-29T21:33:04.43+02:00",
    "identifier": {
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        "value": "21-02331-1"
    },
    "entry": [
        {
            "resource": [
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                    "resourceType": "Composition",
                    "id": "Composition-21-02331-1",
                    "status": "final",
                    "type": {
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                            {
                                "system": "http://loinc.org",
                                "code": "18842-5",
                                "display": "Discharge summary"
                            }
                        ]
                    },
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                        "display": "Abduljaleel Abdulhakim Ashkar"
                    },
                    "date": "2021-02-11T21:32:44+02:00",
                    "author": [
                        {
                            "display": "Kaamil Rukanah"
                        }
                    ],
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                    "confidentiality": "N",
                    "attester": [
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                            "mode": "official",
                            "time": "2021-02-11T21:32:44+02:00",
                            "party": {
                                "display": "organization"
                            }
                        }
                    ],
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                        {
                            "title": "Final Diagnosis",
                            "code": {
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                                        "code": "29548-5",
                                        "display": "Diagnosis Narrative"
                                    }
                                ]
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                                },
                                {
                                    "reference": "Condition-2"
                                }
                            ]
                        },
                        {
                            "title": "Discharge Medications",
                            "code": {
```

```
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                                    "display": "Hospital discharge medications
Narrative"
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                            ]
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                            },
                            {
                                "reference": "MedicationRequest-2"
                            },
                            {
                                "reference": "MedicationRequest-3"
                            }
                        ]
                    }
                ]
            },
            {
                "resourceType": "Patient",
                "id": "Patient-495336698",
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                        "value": "495336698",
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                            "display": "Government"
                        }
                    }
                ],
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                        "text": "Abduljaleel Abdulhakim Ashkar",
                        "given": [
                            "Abduljaleel",
                            "Abdulhakim"
                        ],
                        "family": "Ashkar"
                    }
                ],
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                        "value": "062-165-5126",
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                        "type": "physical",
                        "district": "Hebron",
                        "country": "Palestine"
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                            "code": "resolved"
                        }
```

```
                    ]
                },
                "verificationStatus": {
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                        {
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                            "code": "confirmed"
                        }
                    ]
                },
                "category": [
                    {
                        "coding": [
                            {
                                "system":
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                                "display": "Encounter Diagnosis"
                            }
                        ]
                    }
                ],
                "code": {
                    "coding": [
                        {
                            "system": "http://hl7.org/fhir/sid/icd-10-cm",
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                            "display": "Transient tachypnea of newborn"
                        }
                    ]
                },
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                    "display": "Abduljaleel Abdulhakim Ashkar"
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                "resourceType": "Condition",
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                        }
                    ]
                },
                "verificationStatus": {
                    "coding": [
                        {
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                            "code": "confirmed"
                        }
                    ]
                },
                "category": [
                    {
                        "coding": [
                            {
                                "system":
"http://terminology.hl7.org/CodeSystem/condition-category",
                                "code": "encounter-diagnosis",
                                "display": "Encounter Diagnosis"
                            }
                        ]
                    }
                ],
                "code": {
                    "coding": [
                        {
                            "system": "http://hl7.org/fhir/sid/icd-10-cm",
```

```
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                        "display": "Bacterial sepsis of newborn, unspecified"
                    }
                ]
            },
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                "display": "Abduljaleel Abdulhakim Ashkar"
            },
            "onsetDateTime": "2021-02-11T21:32:43+02:00"
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            "id": "MedicationRequest-1",
            "status": "active",
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            "medicationCodeableConcept": {
                "text": "Adol"
            },
            "subject": {
                "reference": "Patient-495336698",
                "display": "Abduljaleel Abdulhakim Ashkar"
            },
            "dosageInstruction": [
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                    "timing": {
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                            "frequency": 1,
                            "period": 24,
                            "periodUnit": "h"
                        }
                    },
                    "doseAndRate": [
                        {
                            "type": {
                                "coding": [
                                    {
                                        "system":
"http://terminology.hl7.org/CodeSystem/dose-rate-type",
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                                        "display": "Ordered"
                                    }
                                ]
                            },
                            "doseQuantity": {
                                "value": 2,
                                "unit": "drop",
                                "system": "http://unitsofmeasure.org",
                                "code": "[drp]"
                            }
                        }
                    ]
                }
            ]
        },
        {
            "resourceType": "MedicationRequest",
            "id": "MedicationRequest-2",
            "status": "completed",
            "intent": "order",
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            },
            "subject": {
                "reference": "Patient-495336698",
                "display": "Abduljaleel Abdulhakim Ashkar"
            },
            "dosageInstruction": [
                {
                    "timing": {
                        "repeat": {
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                            "period": 8,
                            "periodUnit": "h"
                        }
```

```
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                        {
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                                    {
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                                "code": "mg"
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                        }
                    ]
                }
            ]
        },
        {
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            "id": "MedicationRequest-3",
            "status": "completed",
            "intent": "order",
            "medicationCodeableConcept": {
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            },
            "subject": {
                "reference": "Patient-495336698",
                "display": "Abduljaleel Abdulhakim Ashkar"
            },
            "dosageInstruction": [
                {
                    "timing": {
                        "repeat": {
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                        }
                    },
                    "doseAndRate": [
                        {
                            "type": {
                                "coding": [
                                    {
                                        "system":
"http://terminology.hl7.org/CodeSystem/dose-rate-type",
                                        "code": "ordered",
                                        "display": "Ordered"
                                    }
                                ]
                            },
                            "doseQuantity": {
                                "value": 11,
                                "unit": "milligram",
                                "system": "http://unitsofmeasure.org",
                                "code": "mg"
                            }
                        }
                    ]
                }
            ]
        }
    ]
}
]
}
```