A Blockchain Patient-Centric Records Framework for Older Adult Healthcare

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Abstract. Patient-centric medical record systems provide patients control over their health data versus electronic health record (EHR) systems that are health provider based and typically geared around bill presentment and payment. There are several limitations in current EHR systems, such as details of healthcare not making it into the system, the loss of out of network healthcare and potential for malicious cyber exploitations. This research effort posits the potential of utilizing blockchain to support a patient-centered personal health record (PHR) system focused on the healthcare needs of older adults. Such a system expands the data collected to include every source of healthcare provider from optometrists to chiropractors to oncologists. Blockchain technologies would provide architecture and security for such a system.

Specifically, we present the framework geared to track older adult health records including modules that provide early disease detection and drug-drug interaction for the top chronic diseases experienced by older adults using various machine learning classification algorithms. The algorithms evaluate the entirety of diagnoses and symptoms to find co-morbidities that may be an indicator of latent disease such as early signs of dementia and Alzheimer's diseases. The patient's health information is interpreted by a nurse practitioner or hospitalist who can determine if a specialist needs to be involved to evaluate the predicted disease. The proposed approach will provide a secure way to have a comprehensive view of the patient's health data and arm the patient with the most inclusive set of information for doctors to provide the best health care.

Keywords: Blockchain · Older Adults · Patient-Centric · Machine Learning · Proxy Re-encryption

1 Introduction

The objective of Electronic Health Record (EHR) systems is to deliver high quality and accessible patient care services, a better use of resources and improved outcomes. Additionally, healthcare records are supposed to meet strict Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR) Act 2018 security and privacy guidelines. EHR records contain such personal data as names, addresses, social security numbers, insurance information and medical history.

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Unfortunately, any kind of third-party record repository can be corrupted by system failures, design failures, human mischief or errors. Hospital records are also becoming the target of cyber criminals. In 2021, for example, there were 686 healthcare data breaches during which 44,993,618 healthcare records were exposed or stolen [1]. As recently as August 2023, a cyberattack disrupted hospital computer systems across the United States which resulted in forced emergency room closure along with ambulances being diverted to other hospitals [2]. The healthcare processes of contemporary times particularly with chronic diseases require the collection of massive amounts of data so that doctors can make plausible healthcare decisions to care for their patients, manage patient care, communicate with partner organizations and meet regulatory standards.

1.1 Older Adults and Co-morbidities

Multimorbidity tends to be a common occurrence in older adults due to underlying conditions (e.g., physiological issues such as hypertension, atrial fibrillation and diabetes) and (unhealthy) behaviors (e.g., tobacco use, insufficient physical activity or an unhealthy diet). The relationships between multiple health problems and their impact on quality of life and life expectancy needs to be carefully studied and managed. Along with multiple health issues exists the problem of mood and anxiety disorders which are common in many older adults, particularly women, and are highly treatable at any age. Mental health disorders contribute to chronic diseases and vice versa and both need to be addressed. Health decline features typically present before the onset of a symptomatic disease.

There are many early warning symptoms of chronic disease that are so subtle that patients would not see a doctor when they occur until a dangerous, potentially deadly disease event occurs. For example, some of the early warning symptoms of coronary artery disease are fatigue, back pain, and shortness of breath. Early signs of chronic obstructive pulmonary disease, (COPD) include cough, wheezing or recurrent respiratory infection. The early warning symptoms of heart failure are breathlessness, fatigue and swollen limbs. Evidence suggests that when considering potentially early warning symptoms of disease, older adults tend to 1) discount them as normal or 2) reserve judgment as to the significance or 3) attribute them to other problems such as fatigue. Early symptoms of dementia would not necessarily require medical treatment such as aggression, depression, a personality change and sleep disturbances that taken together could lead to an earlier diagnosis and treatment. While research concerning the role of early treatment leading to a better dementia prognosis is limited, an early diagnosis could help the family make more informed decisions particularly about long-term care while the patient can contribute to the conversation. A more comprehensive view of patient care is particularly important in the case of dementia where co-morbidities may be mistaken for features of dementia. Unless the variety of features are understood to be early features of dementia and the general health declines addressed there could be an increased chance of poor outcomes and decreased quality of life [4]. Additionally, older adults with complex healthcare needs can get overwhelmed trying to determine which kind of doctor for them to see leading 22% of Americans to report that they avoid medical care of all kinds for either its high cost or because of the diseases that abound and inconvenience of the waiting room process.

1.2 EHR Gaps

The typical healthcare networks are composed of doctors, patients, medical and drug suppliers, insurance companies, third-party logistics (3PL) providers, and regulators. This leads to many and varied feature requirements. An EHR system focused only on delivering the best healthcare must be comprehensive and should include a formulation of the problem list, careful analysis of abnormal findings along with symptomology and diagnostics. Current EHR systems fall short of this standard and therefore have many problems delivering comprehensive healthcare data. One reason is that the healthcare data systems utilize non-standard data which is generally hard to comprehend, use and share. Another gap is that many EHR systems struggle when trying to share information across different states or to providers in rural areas that are not as computerized as larger suburban providers. Because patient records are typically stored in different databases across different service providers, it becomes difficult to get a comprehensive picture of the patient's health as control rests in the hands of each service provider [32]. Other problems involve getting the complete diagnostic dataset into the EHR system. Only the patient and/or their primary caregiver knows the breadth of their healthcare and treatment.

Physicians are so busy they do not use the online entry mode of the system so an assistant transcribes notes either from the doctor or as the doctor is speaking. These fragmented health records lead to uneven healthcare service delivery and to an inequitable allocation of resources. An even larger problem with network centric systems is that patients are given care typically only for their presenting problem and doctor visits are brief. Those with chronic versus acute disease may not receive instructions concerning how to care for their diseases on a day-to-day basis. A study of 516 patients found that EHR systems lack data as only 62.3% of diagnoses were recorded for the patients [5]. A different examination of 1347 breast cancer health records found either gaps in treatment or gaps in recording treatment as approximately 7% were missing the ejection fraction (EF) studies that are required for breast cancer chemotherapy treatment [6]. Healthcare systems today also do not provide a means for patients to control access to their health records.

1.3 A Case for Patient-Centric Healthcare

The typical doctor sees approximately 76 patients per week and spends approximately 13 to 24 min with each patient. Older adults with comorbidities do not normally offer the breadth of their health issues within the short time they have to spend with a doctor concerning the problem at hand. Many older adults are being treated by multiple subspecialists that each prescribe medicines, therapeutics and other treatments which cannot be conveyed within a single doctor's visit. Each doctor could deliver better health care if provided a more complete and comprehensive representation of the patient's health. Current clinical decision support tools have limited support for patients with co-morbidities. Comprehensive care is critical for the older adult patient as the effect of co-morbidities is generally related to mortality and/or a greatly diminished quality of life.

Nurse practitioners (NP) and hospitalists (HSP) are known to have the ability to deal with a breadth of medical issues and often coordinate the care of a variety of specialists. Both positions provide diagnosis, order labs, and prescribe medications. The nurse practitioner holds an advanced nursing degree and for many communities address the shortage of physicians and bring down healthcare costs [7]. The hospitalist treats an array of different medical conditions and rose in importance because primary care providers were not able to take time away from their offices to treat hospitalized patients. NPs working in conjunction with hospitalists have been able to close the healthcare gap particularly in rural communities where some hospitals are at risk of closing due to lower funding levels, lower patient volumes and decreased hospital revenue.

Wang et al., [8] identifies five capabilities of Big Data analytics implementations in healthcare: unstructured data analytical algorithms, care pattern analytics, predictive capabilities, decision support functionality and traceability. The proposed three-pronged technology solution for comprehensive care of older adults is 1) assemble a thorough collection of symptoms, therapeutics, all known diagnoses for the top ten health problems of older adults; 2) use analysis and predictive analytics to find potential problems from the breadth of patient data and 3) a trusted agent - nurse practitioner and/or hospitalist – who can review the output of the system, the symptoms/therapeutics that lead to a potential diagnosis and may then determine the next healthcare steps to take. The system acts as both an early warning system to healthcare problems along with providing a comprehensive health review of why the system believes there to be a problem. Additionally, to better prepare for a doctor visit, the patient can print out a report detailing their health history and prescribed drugs giving their physician a more complete view of their health status.

Blockchain has been described as a suite of technologies based on a means to get a network of computers to trust the state of a distributed ledger. The ledger is updated and maintained via a consensus protocol which is executed by the participants. It acts as a distributed transactional database which has the security of cryptography and a consensus mechanism as its authority. Blockchain provides transparency, security, and privacy using consensus-driven decentralized data management on top of peer-to-peer distributed computing systems. Blockchain solves many of the data requirements for health organizations including privacy, system security, authentication, interoperability, data sharing, data access, trust, visibility, and mobility. Each block can represent a variety of data types including currency, digital rights, identity, transactions of almost any kind and is said to disrupt all industries. Blockchain represents a structured approach to medical health records as it provides security and privacy for patients and an infrastructure for data collection and exchange.

This paper proposes a blockchain-based EHR system geared to the health needs of older adults. The features of the system are described in Sect. 3 including the framework, the workflow and the participants in the system. In Sect. 4, the prototype components and methods to evaluate each are defined. Contributions include a system focused on the healthcare needs of the most vulnerable members of our population who likely have the most healthcare problems and are prescribed more drugs than any other segment of the population – 85% of adults 60 years of age and older have used one or more prescription drugs in the past 30 days [10]. We will review the extant literature in the next section.

2 Review of Literature

This section presents the related works that are classified into five technology categories: blockchain applications in healthcare, blockchain frameworks and platforms, analytics and machine learning in healthcare, proxy re-encryption (PRE) and blockchain framework evaluation strategies.

2.1 Blockchain Applications in Healthcare

The underpinning technology of blockchain makes it valuable within a medical setting given the amount of coordination and data security that must be administered between various outside parties. Blockchain solves the trust problem between decentralized nodes via its verification and consensus mechanisms. Data can move from a single and proprietary siloed system to one that is distributed across many computers and servers. Data may be exchanged into or outside of the network EHR system without a trusted third party. One means that provides trust to data exchange within a blockchain-based system is a transaction-based smart contract - a means for multiple parties to stipulate that the terms of some agreement are met [11]. For the healthcare patient, smart contracts are regularly used to allow such events as patients providing permission to a third party to access their personal healthcare records. Blockchain healthcare use cases include electronic medical records (EMR), drug and pharmaceutical supply chain transactions, remote patient monitoring, health insurance claims and health data analytics with EMR representing the most common use case.

Some examples of healthcare applications built using blockchain technologies include solutions like MedRec EHR management system that offers patients some degree of control of their health data by providing a means for them to share data with professionals or not. MedRec is based on Ethereum, it uses proof-of-work as the consensus method (how all parties agree that the transaction is valid) which is extremely costly and energy inefficient [12, 13]. OmniPHR is a patient-centered application concerning electronic health records (EHR) storing records in blocks signed by the provider. FHIRChain is another blockchain solution geared around the need for standardized and secured shared clinical data with the goal of overcoming lack of trust relationships between healthcare entities and scalability concerns [14]. Both FHIRChain and MedRec store data off-chain. Data is accessible through pointers and smart contract-controlled access tokens.

2.2 Blockchain Frameworks and Platforms

Blockchain platforms provide the development environment for blockchain-based applications. Its plethora of technologies and implementation variations allow it to be used in finance, healthcare, governance, retail and more. The underlying principles of a BC framework are based on its application objective. However, some technologies lack a stable design and/or an established user base so there still is much research to be done [3]. Every part of the blockchain framework and development platform has different advantages and disadvantages. It is important for designers and developers to analyze each aspect of BC technology to determine its suitability for a specific application.

Table 1. Variety of Blockchain Framework Features

Application Category	Key Concern	Network	Consensus	Security /Privacy Protocol	Data Transfer	Citation
Secured Insurance	Fraudulent Transactions	Private Ethereum	PoA	Internal Validators	IPFS	Hassan et al. 2021
Diabetes Detection	Prediction/Security	BC Public key/PCCH	BC	PCA	IPFS	M. Chen et al. 2021
Patient Portal	Longitudinal Data Curation	Private	Hyper-ledger Fabric	Proxy Re-encryption (PRE)	FHIR	Hylock & Zeng 2019
Health Insurance	Fraudulent Transactions	Private – Invite Only	PBFT	Internal Validators	N/A	Ismail & Zeadally 2021
Health Oriented BC	Improve Scalability, Broader BC Adoption	Variable	Variable	Variable	OCSB	Miyachi & Mackey 2021
Transfer Patient Care	Scalability, Trust	Go Ethereum	PoA	DApp	DApp	Lo et al. 2019

This research effort includes a review of blockchain-based frameworks focusing specifically on healthcare applications. Depending on the application, the breadth of block chain technologies is varied. One blockchain-enabled system has been designed to detect diabetes in which blockchain utilizes a distributed ledger for storing smart contracts between the physician and the patient via the EHR system in combination with machine learning classification algorithms [15]. A different BC framework utilizes a decentralized application (DApp) for patients to interact with the national healthcare record system upon physician referral [16]. A blockchain based insurance application utilizes smart contracts and Proof of Authority (PoA) consensus algorithm to ensure secure fraud-free transactions covering client registration, policy issuance and refund settlement [17]. A similar blockchain based insurance fraud detection system, this one concerning healthcare, is a peer to peer private system with several layers of authorization and utilizes machine learning to detect fraud [18].

Other research efforts are designed to test various blockchain elements to ascertain their feasibility for use in any sort of application. One such research effort tested Hyper-Ledger Fabric using a variety of test scenarios to determine if it was a useful tool in the healthcare industry [12]. Off-Chain Blockchain Systems (OCBS) were similarly evaluated for healthcare records. Often a health record needs to move out of its home network and technologists were seeking a means to securely transport information without the need to pass the entire health record from one blockchain based system to another. The outcome provided a modular and flexible system architecture that allows secure data transfer - see Table 1: Variety of Blockchain Framework Features for comprehensive features of each blockchain application described above.

2.3 Analysis and Machine Learning in Healthcare

Machine learning (ML) and artificial intelligence (AI) algorithms have been used in a variety of ways in healthcare. For example, they allow hospitals to diagnose and customize medical care and follow-up plans to get better results. During the COVID-19 pandemic various ML models were used to predict symptomology and spread [19]. The diabetes detection system utilizes machine learning (ML) to classify diabetes using decision trees (DT), k-nearest neighbors (KNN), random forest (RF), linear regression (LR), and support vector machines (SVM) [15]. Natural Language Processing (NLP) has been used to find inconsistencies in surgical details or pathology reports [20]. Logistic regression and classification has been used to find care gaps within the treatment of cardiac patients, finding that 95.3% of the patients studied has one or more cardiometabolic care gaps during the period of the study [21]. Another combination of machine learning and blockchain technologies are used to model the risk of readmission across a variety of hospitals while the blockchain portion of the solution protected patient privacy [22]. Neural network algorithms have also been used to detect Parkinson's disease [17].

Drug contraindications (also called drug-drug interactions (DDI)) are problematic for older adults even with the wealth of information available about each drug. NLP techniques have been used in the past to consolidate such information for healthcare providers. Organizations like the World Health Organization (WHO), the Food and Drug Administration (FDA), the European Medicines Agency (EMA), and the Medicines and Healthcare products Regulatory Agency (MHRA) maintain a reporting system that enables individuals to spontaneously report any experienced adverse effects related to the use of medicines or healthcare products. Mei & Zhang report that DDI are typically uncovered using one of three methods: similarity-based methods, networks-based methods and machine learning algorithms [23]. Han et al. notes that DDI currently are found by two methods: 1) to summarize DDI from literature, electronic medical records, and spontaneous reports; 2) use known DDI to predict unknown DDI [24]. Disease information is typically organized by the pharmaceutics and often found to be queried together with Chemical/Drug or Gene/Protein information. Because the system described in this paper is focused only on the top ten diseases for older adults, the universe of drugs and potential interactions can be captured and contained from what is currently known with backup support from the NP/HSP.

2.4 Proxy Re-encryption

The Cloud computing paradigm has released data from legacy systems allowing the data to be securely held and accessed. Healthcare data are usually encrypted before uploading to the cloud server though this impedes data sharing between different medical institutions. The question becomes how to share patient data with outsiders in a secure manner without giving full access to all the patient data. How can the data stay secure as it passes from patient to nurse practitioner or hospitalist? The solution for this kind of data exchange is to be able to do so without a 3rd party encryption solution or exposing the encryption keys of the patient. Proxy Re-Encryption (PRE) provides a solution to this problem.

Proxy re-encryption allows a proxy to take Alice's ciphertext (the patient) into one that can be opened by Bob's (NP/HSP) secret key. PRE has been deployed in a variety of architectures including in the cloud, as part of a network storage system, in distributed file systems, as a function for email forwarding and in other various information exchange capacities. PRE has been found to be an important and secure scheme for handling IoT healthcare data such as data from glucose and blood pressure monitoring devices. It allows for off-chain data collection (regular glucose and BP statistics) while avoiding encrypting all of the data in the block which increases communication and computation costs over the cloud. Another solution for transferring patient records from one EHR system to another used PRE – it kept the disease itself invisible while transferring other data which protected the patient's privacy.

2.5 Blockchain Application Evaluation Strategies

Blockchain features in healthcare face a unique set of challenges compared to applications in other sectors of the economy [25]. One needs to consider all the participants of the block chain system, the feature set, the data flow, security needs, and in the case of healthcare governance and privacy – typically HIPPA and GDPR. In choosing the features of the framework, the individual elements of the system require an evaluation process appropriate for that feature of blockchain. The literature shows that both qualitative and quantitative methods have been used to evaluate frameworks [3] which varied based on the technology used within the framework.

Blockchain Technology Evaluation Strategies. One of the pressing problems with blockchain in general concerns performance. All transactions/every entry on a blockchain requires every node to process it and therefore not only slows down transactions but also creates scalability problems. Because of this, several researchers focused on performance and throughput to evaluate their frameworks. Another EHR solution first created a proof of concept then tested the system in a variety of configuration models to ascertain its performance within each configuration. Several research efforts added scalability and security to the list of evaluation measures [15, 18, 26]. Antwi added regulation compliance and flexibility given that many healthcare applications will need to connect with legacy applications [12]. Ateniese et al. evaluated Proxy re-encryption (PRE) by creating a suite of benchmark tests using a variety of types of content and measured functionality, performance and scalability [27].

Feature Function Evaluation Strategies. Other evaluation strategies focused more on features and functionality, even creating new evaluation frameworks. Miyachi & Mackay created a novel evaluation framework built on Yusif et al. [28] for performance features and evaluation topics to include technology purpose and accessibility and language to evaluate technology fit [29]. When evaluating permissioned blockchain framework solutions, Polge et al. started with a literature review then evaluated the technology based on the number of people using that particular technology (demand), community activity, adoption, privacy features along with scalability, throughput and latency [9]. Chowdhury used both qualitative and quantitative measures to evaluate a distributed ledger technology as a platform [26]. Peng et al. also evaluated on-chain/off-chain technology by creating an evaluation matrix of quantitative and qualitative features for permissionless blockchain [30].

Data-base Evaluation Strategies. Zhang used two different cancer patient databases to evaluate feature function and control logic along with technologies related to token retrieval and event logs. A fully functional system was developed that included a DApp and it was tested with actual patients in four hospitals measuring usage statistics [16]. Antwi utilized test cases to evaluate Hyperledger Fabric [12]. To ascertain performance of machine learning algorithms to detect diabetes, M. Chen used the Pima Indian Diabetes Disease Dataset (PIDDD) and the typical machine language performance measures of accuracy, precision, recall, Matthews Correlation Coefficient (MCC) and receiver operating characteristic curve (ROC) [15]. Another machine learning healthcare algorithm used 5-fold cross validation and ROC curve and Area Under The Curve (AUC) scores to determine performance of Drug Drug Interactions [23].

3 Proposed System

3.1 The Framework

The outcome for this proposed healthcare application is for the patient to be the owner of a comprehensive collection of their entire health landscape. Institution-centric EHRs introduce barriers that hamper patient engagement, data portability and information exchange [31]. The proposed blockchain architecture involves four distinct members (agents) of each patient's healthcare ecosystem with the patient being the chief administrator / data owner. The patient is in control of their own health data including requesting data from the disparate EHR systems to be added to their private patient healthcare record or adding any additional information which pertains to health even those not part of a diagnosis such as reading glasses or chiropractic visits. The choice of framework requires consideration of the feature and functionality of the system and the types of blockchain technology that best supports those features. Some of the technological issues to address are its decentralization features, transaction speed, security, auditability and control - see Fig. 1: Patient-Centric EHR System Framework.

3.2 The Agents

In this patient-based system, every kind of health event is entered into the care system as a transaction. The data is accessible by the patient and stored in unalterable blocks. Each new transaction is added to the system after approval by the patient. As new symptoms, prescriptions or treatments are added, the ML modules analyze all the data to determine if there are drug contraindications or signs of a new or alternative diagnosis not already in the system - see Table 2: Agents and Roles.

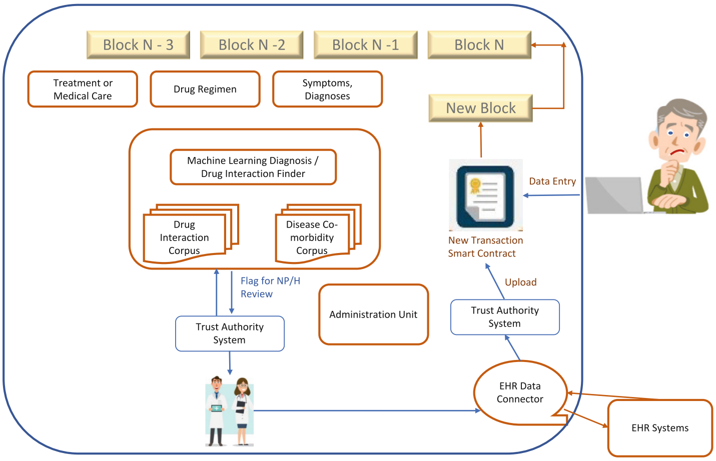


Fig. 1. Patient-Centric EHR System Framework

3.3 The Workflow

Data Collection Workflow. All system data entry is either manual entry by the patient or by a data connector from an EHR system. The data connector would have interoperability features for any kind of standard EHR system and convert the data to a standard format aligned with the patient's system.

Table 2. Agents and Roles.

Agent	Relevant System Data/Actions
Patient (or Caregiver)	Symptoms, Prior/current diagnoses, Therapeutics related to any diagnosis, Pharmaceuticals, supplements and drug regimens, Prior relevant heath concerns, Relevant diagnoses from family members
Network EHR	Relevant data to be added to the patient data such as Diagnoses, Prescriptions and Therapies by Category
Nurse Practitioner/Hospitalist	Receives reports from the system to be considered for future evaluation
External Health Data	Data outside of any EHR system (to be entered by the patient, caregiver, nurse practitioner / hospitalist including diagnostic testing such as auditory, chiropractic care, podiatrist, over the counter (OTC) medications, vitamins and supplements

Data Exchange. The patient desires to send some portion of their healthcare record to a NP/H. The system will give the patient the means to select one or more health records marked by a unique identifier and will transfer just that information to the NP/H.

Additionally, the patient may have a healthcare visit in which their medical information is in a hospital network EHR system. The patient desires to gather that information to be included in their private healthcare system. The system will allow the patient to connect to the EHR system using their EHR system credentials. Once the patient selects the records to download, the system will collect the data and add it to the next block of the blockchain that encompasses the patient's health records.

3.4 Other Building Blocks

Machine Language. Various machine learning classifiers will be used to predict and diagnose current and future health issues based on analysis of co-morbidity features. Included in the design is that the output of a positive potential of disease based on the patient's symptoms will be addressed by a nurse practitioner or hospitalist.

Two corpora will be created: Disease, Symptoms and Features (DSF) and Drug and Contraindications (DC). Initially the DSF will contain the top 10 most common chronic diseases in older adults, specifically: hypertension, lipid metabolism, diabetes, coronary artery disease, cancer, chronic obstructive pulmonary disease, heart failure, stroke, chronic kidney disease and osteoporosis [33]. All symptoms and features associated with each disease will be included in the corpus. The machine learning algorithm will process the patient's reported symptoms and diagnoses and deliver indications of undiagnosed disease in the patient. Should a new diagnosis be detected, the application will create a "potential diagnosis record" that includes the symptoms the patient has and the probability of the undiagnosed disease. The patient can decide if the information is to be sent to the NP/HSP.

The DC corpus will be created from existing drug databases and will only include contraindications at a very high-level rating each if it is a common occurrence or less common occurrence. It will also include over the counter drugs, vitamins and all contraindications of any combination of the drugs and therapeutics. Given that this is a patient-centric application, it shouldn't be considered a medical diagnostics and advice provider. The information is transferred to the NP/HSP to evaluate and determine the course of healthcare.

To evaluate the best algorithm the machine language performance measures of accuracy, sensitivity, specificity, precision, F1, recall, Matthews Correlation Coefficient (MCC) and receiver operating characteristic curve (ROC) will be used. To evaluate the disease or DDI prediction, 2000 dummy patient records will be created and processed with a variety of ML algorithms. The system will create a chart that lists the information (drug, symptoms, prior diagnoses) that ML found as an indication of disease and/or drug interaction. These will be studied independently by 20 experts including pharmacologists, hospitalists, chronic care doctors and geriatric care doctors to assess the accuracy of the system output.

Proxy Re-encryption (PRE) - The Security System. In the proposed system, the patient is the "authority" and chooses to whom and how much information to transmit to the nurse provider or hospitalist. A ciphertext transformation scheme is needed to transfer the owner's data into another ciphertext that the target user can decrypt [34]. For the proposed solution, the patient data is held in the cloud. The patient is prompted by the NLP system to alert the NP/HSP due to potential diagnosis or drug interaction. In this system, the patient desires to transfer some portion of their health record to the NP/HSP. The health record(s) along with a message is combined into a ciphertext. The NP/HSP requests a re-encryption key to facilitate decryption of the patient's ciphertext without exposing the party's private information. The NP/HSP can only see the subset of a patient's healthcare records – only the data that contributed to the alert message – the transferred data records, the output from the ML algorithms (the data that caused the alert) and any message(s) from the patient.

PRE-Summary for the Application

1. The patient desires to send a health record or a collection of health records to the NP/HSP. The data is encrypted with proxy-encryption.
2. The NP/HSP requests access to the patient's data using the patient's public key and their own private key that triggers the system to send the NP/HSP the re-encryption key and the encrypted data to the NP/HSP.
3. The NP/HSP uses the combination of their own private key and the re-encryption key to decrypt the patient's health record(s).

3.5 Security Analysis and Data Accuracy

We examine the patient-centric system based on proxy re-encryption method from integrity and confidentiality perspectives. The patient being the data owner and controller of the information within a private network eliminates many security issues.

Integrity. The nature of blockchain makes the system tamper-resistant and its records tracible. Should the patient detect invalid information such as incorrect data downloaded from a network EHR system, the patient can correct that information to maintain the integrity of the dataset.

Confidentiality. The system transfers data to the NP/H via a unidirectional use of static Diffie-Hellman exchange using a 2048-bit key. As Alice is sending a simple text file of new symptoms or potential diagnosis to NP Bob, it is unlikely that Eve would have a reason to try steal this limited information - that is to go through the effort to solve the discrete logarithm that secures the data. The patient who is uploading their own health records would do so utilizing the network EHR system's security which would be very secure.

Privacy. The only identifying information is the patient record is the patient's name and birthdate which is used to identify the patient to the NP/H upon data transfer. This data remains encrypted within the system so privacy is preserved.

4 Prototype

As this application is designed to be used by older adults, the user interface (UI) should consider potential health limitations and disabilities. Older adults may struggle with blindness or low vision therefore the application interface should feature the ability to change text and font size and overall size of interface screen. Additionally, the system should limit any moving parts unless the speed can be controlled by the user [35]. Older adults who struggle through physical challenges to input data can be supported by Voice UIs (VUIs). Those who are deaf or hard of hearing should be supported by audio prompts that are always accompanied by another visual prompt or notification. Additionally, the application should include assistive technology such as interoperability with screen readers, screen magnifiers along with alternative input devices and work with Windows and Macintosh text-to-speech and speech recognition software.

The next step of the application is approval of the features by a hospital or geriatric medical practice. The goal is to find a group that could most benefit from such an application who will provide medical oversight and recommendations during the development process. With the medical team in place the application prototype can be developed. To evaluate the features, functions and UI, the system will be tested by 100 adults aged 60–75 who will receive training from an organization that specializes in teaching software applications to older adults such as OASIS or OATS. The class will last for one day. The instructors will walk the older adults through all the features of the product. The last class exercise is for each older adult, with the help and oversight of the trainers, to set up their own PHR system, import data from any hospital network EHR system and be shown how to add data and use the query and reporting system. Additionally, the students will be shown how to access the DDI and potential disease diagnostic algorithms though these will be tested with a dummy test set of health records for the sake of each person's privacy. Lastly, the research team will gather feedback from the older adults including feature satisfaction and recommendations, UI/user experience (UX) and desire to utilize such an application.

4.1 The Agent Panel and Features

The agent panel is how the patient accesses and controls the features of the application. There is a tiered menu system allowing access to features based on the kind of transaction desired. For example, to add a health record manually, the patient chooses the type of medical care from a drop-down box (or "Other" in the event the type of healthcare is not in the drop-down box). The patient is then provided a blank health record entry form customized to the type of healthcare or a generic form to be completed should the patient select the "Other" option.

4.2 Data Transfer

In the patient-centric healthcare record system, the patient is the governing authority for data moving to and from the system. The patient initiates the data transfer from their personal system to the NP/HSP and initiates the request for data transfer from any network that contains the patient's healthcare records. The patient selects the **Data Transfer** option from the home screen then chooses to send or receive health records. Every record in the system has a unique identifier. The patient chooses the records to send based on the unique identifier.

Send Information to NP/H for Evaluation. The patient is given a screen to help them choose which healthcare records to transfer to the NP/HSP. Additionally, the patient can add comments to each record or compose detailed instructions allowing them to communicate either the system findings or their own concerns. The patient is given a variety of ways to sort the health records or a search box to find individual records by word search or date.

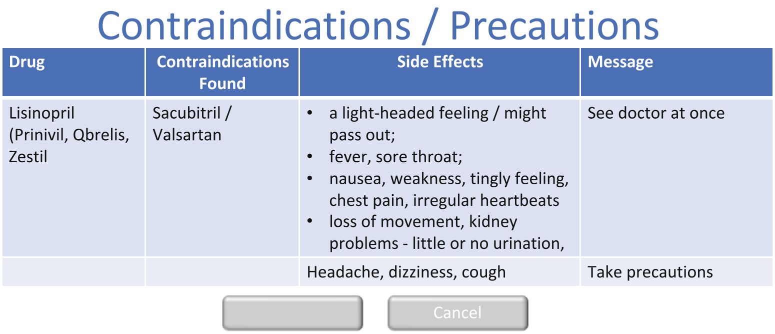
Collect Information from Another EHR Network. The patient is given a screen to help them choose which EHR healthcare record system to connect with, then is taken to that EHR system's credential screen. From there the patient navigates to the specific health record(s) to be transferred. The patient selects the individual records, and the system transfers them by adding them to the blockchain with the next unique identifier for each record. This feature relies on the patient having credentials for a hospital network EHR system and uses Fast Healthcare Interoperability Resources (FHIR) standard for exchanging digital health data.

4.3 Algorithms

The purpose of the ML algorithm system is to act as an early warning system to the patient that there may be a health problem. Given the number of diseases experienced by older adults and the number of medicines and therapeutics older adults take, these features could alert the patient and their healthcare provider before the health problem harms the patient. Each time a new prescription, vitamin or other therapeutic is added to the healthcare system, the Drug Contraindications Algorithm (DCA) processes the patient's prescribed drugs, supplements and therapeutics through the drug contraindication corpus. The system then delivers a list of contraindications of the drugs prescribed to the patient.

Drug Contraindications. As the patient updates their medical record, the DDI algorithm will process the patient's current prescription list and generate a notice to the patient that there may be a DDI. The system will offer a screen to indicate which drugs are involved, some of the symptoms and if the patient should seek immediate medical care - see Fig. 2: Patient Notice of Drug Contraindication. Additionally, the patient can run the algorithm from the main menu. If the patient chooses to provide the information to the NP/HSP, the system will create a health record with the information required for an NP/HSP to provide further guidance such as a new prescription for a drug that doesn't have DDI.

Disease Prediction. As the patient updates their medical record, the Potential Disease algorithm will process the patient's current symptoms with all symptoms and diagnoses in the patient health record system. Should the system detect the symptoms of a disease not currently in the patient's health system, the application will generate a report like Fig. 3: Indication of Potential Disease Report. Additionally, the patient can run the algorithm from the main menu. The patient is given the option to send the health record to the Nurse Practitioner or the Hospitalist on that screen. If selected this information will be sent to the NP/HSP connected to the patient.

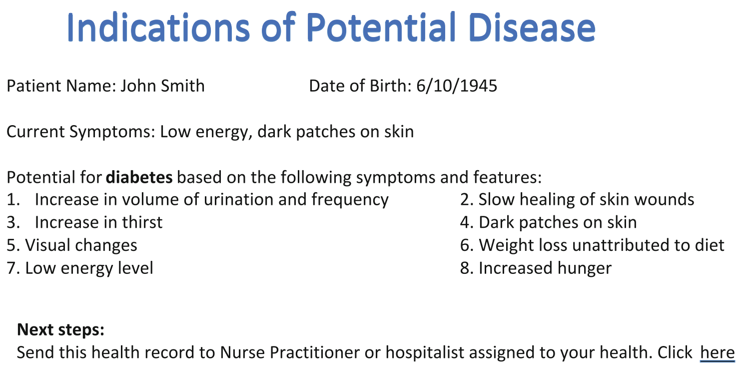


Contraindications / Precautions

Drug	Contraindications Found	Side Effects	Message
Lisinopril (Prinivil, Qbrelis, Zestil	Sacubitril / Valsartan	• a light-headed feeling / might pass out; • fever, sore throat; • nausea, weakness, tingly feeling, chest pain, irregular heartbeats • loss of movement, kidney problems - little or no urination,	See doctor at once
		Headache, dizziness, cough	Take precautions

Cancel

Fig. 2. Patient Notice of Drug Contraindication



Indications of Potential Disease

Patient Name: John Smith Date of Birth: 6/10/1945

Current Symptoms: Low energy, dark patches on skin

Potential for **diabetes** based on the following symptoms and features:

1. Increase in volume of urination and frequency
2. Slow healing of skin wounds
3. Increase in thirst
4. Dark patches on skin
5. Visual changes
6. Weight loss unattributed to diet
7. Low energy level
8. Increased hunger

Next steps:
Send this health record to Nurse Practitioner or hospitalist assigned to your health. Click here

Fig. 3. Indication of Potential Disease Report

4.4 Queries

The query feature of the system is important to help patients provide doctors with a comprehensive review of their health status. To prepare for any doctor's appointment, the patient can choose Records & Reports and create a comprehensive report or filter the information between dates, by diagnosis, or by bodily organ.

The Medical Record Report will provide a complete history around the query topic that includes diagnoses, drugs, dates and symptoms. The patient will be given the opportunity to enter new symptoms to be added to the report see -Fig. 4: Sample Comprehensive Medical Report.

Medical Report

Patient Name: __________________________ Date of Birth: __________________________

Current Symptoms:____

____

____

Prior diagnoses:

1. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Maecenas porttitor congue massa.
2. Nunc viverra imperdiet enim. Fusce est. Vivamus a tellus.
3. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Proin pharetra nonummy pede. Mauris et orci.

Current Prescriptions & Over the Counter Drugs and Supplements

1. ipsum dolor sit amet	Dosage:	Frequency:
2. viverra imperdiet'	Dosage:	Frequency:
3. Maecenas porttitor	Dosage:	Frequency:
4. nonummy pede	Dosage:	Frequency:

Fig. 4. Sample Comprehensive Medical Report

5 Conclusion

According to the Centers for Disease Control and Prevention, by 2040 the number of older adults is expected to reach 80.8 million [39]. The current US healthcare system reportedly struggles to accommodate the breadth of problems to properly care for older adults. For many diseases, early detection can bring about earlier treatment and less intrusive impact on health such as prolonging a patient's level of function in the case of Alzheimer's disease. Having a system that provides an early warning to health problems while providing doctors with a more complete picture of the patient's health for medical visits can provide many benefits for both the patients and the medical care givers. Further research efforts include expanding the number of diseases for the disease detection algorithm, to expand the predictive feature to include what is known for indications of disease for different demographics and to collect information such as weight, number of hours of sleep and mental state on a regular basis to add to disease prediction function. Lastly, the system could be evaluated for research purposes as such will have a substantial amount of health data for longitudinal studies of health needs for older adults.

Some of the barriers to success and wide adoption are matters concerning perception, the age and abilities of the patients and other EHR organizations will see this effort as competition. The current perception by EHR developers is that health records are the purview of the medical community. Patients and their caregivers are considered passive participants in personal healthcare data that should not have control over the information [36]. Another barrier evolves from the fragmented healthcare system of the United States with private practices, public and private hospitals and hospital networks creating a barrier for a standardized system of patient healthcare record. Another concern is both the technical prowess and medical understanding of the older adult leading to low quality data and the potential of misinterpretation [37]. Given that the expected number of people aged 60 years and over will reach 2.1 billion by 2050 and that some of these diseases share modifiable lifestyle-based risk factors, a systemic approach to early diagnosis and treatment of catastrophic disease could benefit families by providing a higher quality of living for older adults along with reduced medical expenditures over their lifetime [38].

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