Towards a Blockchain based Fall Prediction Model for Aged Care

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ABSTRACT

Falls are one of the major health concerns for the elderly people. These falls often result in severe injuries which lead into huge medical expenses. Over the recent years, many ICT based fall detection and fall prevention solutions emerged to address the risk factors associated with falls. However, despite of these research studies, predicting the likelihood of falls still remains as a huge challenge in both medical and IT research domains. Data related to these risk factors being scattered among different healthcare providers can be attributed as a main reason for this challenge. This is further amplified by healthcare providers being reluctant to disseminate the data beyond their entities due to the security and privacy concerns. However, in recent years, blockchain has been proven as a promising technology to address the security and privacy challenges in healthcare data exchange as it provides a shared, immutable, and transparent audit trail for accessing data. Therefore, in this paper, we are going to propose a conceptual blockchain based fall prediction model leveraging smart contracts and FHIR (Fast Healthcare Interoperability Resources) standard to identify the elderly people who are at a higher risk of falling.

CCS CONCEPTS

• **Information systems** → *Data exchange.*

KEYWORDS

Healthcare, Fall Prediction, Blockchain Technology, Smart Contracts

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1 INTRODUCTION

According to the World Health Organization (WHO) the falls can be defined as 'unintentionally coming to rest on the ground, floor or other lower level' [57]. This definition has been used as a standard definition throughout healthcare and aged care facilities to develop consistent set of frameworks and guidelines [5]. However there are many definitions for 'Falling' in different stakeholder groups. The elderly people define fall as 'losing their balance' while healthcare professionals expect them to cause injuries or ill health to be defined as a 'fall' [57]. According to Zecevic et al. [80], both elderly people and the healthcare professionals define 'falling' considering the background conditions and consequences of falling while researchers mainly define it based on the incident itself.

WHO has recognized 'falls' as the second leading cause for unintentional fatal injuries which is accounted for nearly 646000 deaths worldwide [58]. Annually 30 percent of the older adults experience falling and this includes the adults who belong to the older age groups that need assistance and suffer from various medical conditions [29]. The highest number of fatal falls are reported from the adults who are 65 or above [12, 58]. 37.3 million fall related incidents have resulted in requiring immediate medical attention because most of those fall injuries have lead in to broken hips or head injuries [58]. In the US, direct medical costs for fatal fall related injuries incurred during 2015 was 637.5-754 million USD and for the non-fatal injuries it was 31.3-50 billion USD [14, 24, 25]. For non-fatal falls, 58 percent of the cost has been covered by the Medicare, 17.5 percent of the cost has been covered by the Medicaid and the remaining cost has been covered by other payers [24]. According to the Centres for Disease control and prevention, the fall death rates of older adults in the US has been increased by 30 percent from 2007 to 2016 and it has the potential to further increase into 7 deaths per hour by 2030 [26]. According to the Australian Government Department of Health and Ageing (DoHA), the fall related medical costs would increase up to 1375 million AUD per year by 2051 and in order to avoid that, fall related injuries should be reduced to 66 percent by 2051 [51]. In order to address these concerns, one viable approach is to prevent the falls by predicting the likelihood of falls and identify the elderly people who have a higher risk of falling.

Significance of this research: Even though there are multiple studies done to detect someone after the fall has happened, less research has been carried out in predicting the likelihood of fall before it happens. According to the authors [61], few research gaps in this domain would be lack of a comprehensive fall prediction system addressing multiple risk factors, lack of user friendly interfaces and feedback techniques, not empowering patients to actively engage with fall prevention and the inability of visualizing the health data to assess the risk. However, as the data related to these risk factors are scattered and stored in traditional distributed databases, it has been difficult to build solutions to predict the likelihood of falls by accumulating the data. Therefore, it has been identified that by incorporating blockchain distributed ledger technology with the existing data storage structures, it would be possible to aggregate the data stored in various data sources while enhancing the data provenance, data availability, security and privacy through decentralized management and immutable audit trail [39].

In this research study, we discuss a conceptual blockchain based fall prediction model incorporating smart contracts and FHIR standards to address the identified design parameters accessibility, accuracy, interoperability, security, traceability and legal compliance. Moreover, smart contracts will facilitate the administration by minimizing the human interference while the blockchain will provide the immutable audit trail to ensure secure data exchange and access control. Moreover, the existing fall prediction models and techniques are currently limited to capturing only the medical factors. The extrinsic factors such as behavioral and environmental factors are not being considered when assessing and predicting the risk of falls.One of the other contributions of our work will be to develop the model with incorporating both intrinsic and extrinsic risk factors related to fall.

The remainder of this paper is structured as follows. We discuss related work in section two followed by the research methodology and design principles of our approach. In addition to that, we also provide justifications for selecting blockchain technology to design this solution. We discuss the risk factors associated with falling and data sources of these risk factors under the data analysis in section four and describe the system design in the next section. Finally we conclude the paper by summarizing our contribution to the fall prevention in aged care domain and discussing our directions as future work.

2 RELATED WORK

2.1 ICT based fall detection solutions

There are many fall detection techniques and devices which are built leveraging wireless sensor networks. These sensor networks can be used in smart homes to gather environmental and physical data from the sensor nodes by monitoring sleeping patterns, walking styles and various other motions inside smart homes [72, 73]. Some sensor based systems which have been developed are wearables, those are not very convenient for elderly people [20]. However, in order to address that issue, Ariani et al. [3, 4] developed an unobtrusive fall detection mechanism using the passive infrared sensors and pressure mats which can detect a fall by analysing the captured data . Several camera based systems are also proposed to detect falls among elderly people. In one of the prior studies, multiple camera systems have been used to gather video data while using image processing techniques to analyse images to identify the movements of shapes and positions of people to detect falls [6]. In another study, inexpensive cameras have been used to identify body sway parameters which can be used to assess the stability and the balance of elderly people which have a direct co-relation with risk of falling [76]. Content-independent image processing systems also have been designed to detect falling [41] while camera based systems also have been developed to analyse the captured images using machine learning techniques to classify the falls at high accuracy level [10]. There are applications designed to detect falling by leveraging the accelerometers that are embedded in to personal devices such as smart phones and wearable devices to capture body movements [38].

2.2 ICT based fall prediction solutions

Compared to the amount of research studies conducted on fall detection, so far there are no seminal work done in the fall prediction in ICT domain. However, Volrathongchia et al. [75], has proposed a fall prediction model by applying the data mining techniques to predict the likelihood of falling among the elderly people who reside in the long term elderly care facilities. In this analysis, authors have discovered that the most associated risk factors for falling are previous falls within a month, antipsychotic and hemiparesis. They have also identified that the mode of expression (writing) or hearing does not have a positive correlation with falling. One of the man limitations of this study was restricting their analysis in to six risk factors.

2.3 Blockchain solutions in healthcare

The blockchain is a relatively new technology which is also known as a peer to peer distributed ledger technology. This technology is initially used in cryptocurrencies such as bitcoin [53]. Blockchain can be considered as a distributed database which can record time stamped digital transactions while organizing them in blocks. The blocks are linked together and create a chain of blocks which is known as blockchain. The blockchain networks can be structured as public and permissionless enabling anyone to participate or limit the participation by designing the blockchain as 'private' and 'permissioned' where only the invited participants can be joined to the network. The blockchain 2.0 emerges with the smart assets (digital assets that are managed by the blockchain technology) and the smart contracts (computer codes which are deployed on the blockchain to manage the smart assets) to extend the blockchain technology beyond the finance domain [16]. This has been possible due to the smart economies that emerged through blockchain platforms such as Ethereum [22] and Neo [54] which provide the opportunity to develop decentralized applications on top of their platforms.

Recently, numerous research studies were conducted in the healthcare context addressing many healthcare challenges through blockchain technology. One of the initial attempts in introducing blockchain technology to healthcare is known as 'Medrec' which is a decentralized record management system to handle Electronic Medical Records [7]. The solution has been proposed with a modular infrastructure to enhance the interoperability. It has been designed based on the proof of work consensus mechanism and the medical stakeholders such as researchers and the medical institutions act as the miners who would receive the aggregated medical data as their reward. After this successful attempt, many researchers have discussed the importance of developing more secure, inter-operable and scalable blockchain based solutions in healthcare [63]. As a result, blockchain based privacy preserved patient centric healthcare data management systems, new blockchain based architectures, secure key management schemes and new access permission handling mechanisms have been developed [1, 68, 83].

As most of the healthcare providers currently store their patient data on cloud based storages, multiple research studies have been conducted on addressing the challenges in that domain as well. Xia et al. [77, 78] proposed a blockchain based solution to enhance the data provenance and auditing over the medical data that shared among the big data entities in cloud environments.This solution has been designed to monitor and identify the data accessed by the malicious users. Using the immutability of the blockchain, the access logs are built in a tamper-proof manner. Therefore, the malicious entities can be detected and their access can be revoked. This would minimize the privacy issues in exchanging medical data with research and medical institutes. Esposito et al. [21] also discussed about the potential of implementing blockchain based solutions to secure the data hosted within the cloud storages.

Few research studies also have been conducted on addressing the challenges arisen with the rapid increase in mobile and medical wearable technologies through blockchain. In order to address the issues in secure transmission of personal healthcare data generated through mobile and wearable devices, Liang et al. [44] introduced a blockchain based patient centric data sharing mechanism . This has been designed using a permissioned blockchain considering the data privacy, identity management and the data integrity aspect of the personal medical data. When developing this solution, scalability and the performance requirements also have been taken in to the consideration. Zhang et al. [82] also proposed a blockchain based data exchange protocol for the pervasive social network (PSN)-based healthcare which emerged with the mobile and wearable technologies.

There are blockchain applications that have been developed to address the challenges in specific healthcare domains as well. One of the examples is to design a patient specific techniques for the classification of arrhythmias [37]. As the technique requires the access to the large amount of data, blockchain technology has been used to facilitate access control as well as secure real time data access for the classifier for the external data storages.

Dubovitskaya et al. [19] proposed a blockchain based data sharing mechanism to enhance the decision making for cancer patient care as well as to reduce the overall costs. Nugent et al. [55] introduced a blockchain based solution to enhance the credibility of the clinical trials by incorporating the smart contracts to manage the trial data by controlling the unauthorized manipulations to data records. One of the key reasons for using blockchain in healthcare data exchange is its ability to provide the immutability for preservation of data security and privacy. Therefore, leveraging this specific blockchain property, Zhang et al. [81] proposed a secure and privacy preserving patient health information sharing mechanism specifically focusing on the diagnosis improvements of e-Health systems. In their solution, they have used a private blockchain to store the personal healthcare data and a consortium blockchain to maintain the secure indexes for the personal data stored in private blockchain.

3 METHODOLOGY

In this study, "Design Science" has been used as the research paradigm. 'Design Science' is known as the problem-solving paradigm which addresses the research through the building and evaluation of artifact [33].

- Problem Statement: The problem we are going to address in this research study is the inability to predict the elderly people who are in risk of falling due to the scattered personal, medical and environmental data.
- Solution Postulated : In order to address this critical multi factorial problem, we have investigated and designed a solution to integrate the different data sources to build a predictive model for fall prevention leveraging blockchain technology.
- Development of solution: The solution has been developed through different tasks.

(1) Identifying the various risk factors that lead in to falling by literature analysis and the priority of each risk factor by weighing them against the amount of evidence
(2) Verifying the identified risk factors and the priorities by conducting discussions with domain experts who have firsthand clinical experience as well as research experience in fall prevention and aged care domain
(3) Identifying the data sources for each risk factor
(4) Identifying the meta requirements against each design principle
(5) Designing a conceptual data prediction model addressing the meta requirements using the identified data sources for the each risk factor

- Evaluation: The proposed solution would be evaluated after the prototype is built and deployed in a test environment.

3.1 Design principles and meta-requirements for the proposed solution

In order to develop this solution, we were able to derive 20 Meta Requirements (MR) representing six Design Principles (DP) addressing accessibility, accuracy, interoperability, security, traceability and legal compliance parameters.

- Accessibility : DP01 - Information should be easily accessible

(1) MR01 - Multiple access levels should be defined
(2) MR02 - Registration process should not be complex
(3) MR03 - Accessibility through mobile and web platforms
(4) MR 04 - Real time fall prediction alerts
(5) MR 05 - User Friendly GUI

- Accuracy : DP02 - Fall prediction should be accurate

(1) MR06 - Identifying the correct risk factors and the priorities
(2) MR07 - Retrieving data from the reliable data sources
(3) MR08 - Risk prediction based on the verified data

- Interoperability : DP03 - Data should be retrievable from multiple data sources

(1) MR09 - Supporting the open interoperability standards such as 'FHIR'
(2) MR10 - Reducing the amount of data mapping between the systems
(3) MR11 - Reducing the integration complexities among systems

- Security : DP04 - Data should be securely sharable among the systems

(1) MR12 - Accessibility of data is limited to the registered users
(2) MR13 - The person under care or her representative should be able to control the accessibility of the data to the other stakeholders
(3) MR14 - Using cryptographic techniques such as hashing and encrypting for the data transmission
(4) MR15 - Offchain verification for the user identities

- Traceability : DP05 - All the activities performed by the users should be traceable for the auditing purposes

(1) MR16 - Identities of the users should be verifiable
(2) MR17 - All the actions that user performed in the system should be recorded
(3) MR18 - All the actions should be time stamped in the audit log

- DP06 - Legal compliance : Data exchange process should adhere to the state and government laws and regulations

(1) MR19 - Person under care should be given the access to completely remove their accounts, if required
(2) MR20 - In order to facilitate the right of erasure, none of the personal or medical information of the person under care would be recorded in the blockchain.

3.2 Why blockchain?

By leveraging blockchain technology, we can address the accessibility requirements by using smart contracts on permissioned blockchain to create different access levels based on each user category. Blockchain also provide the ability to retrieve data from distributed data sources in real time while reaching to many number of data sources. Other than that, by developing a consensus mechanism on blockchain that limit the verification process to the person under care and her primary care providers, accuracy of the fall prediction model can be enhanced. With regard to the interoperability perspective, already there are research studies conducted on exploring the ability to integrate FHIR with blockchain [68, 81]. In order to address the security requirements, a consortium blockchain would be used instead of a public blockchain. Therefore the data would be only accessible by the registered users. As the blockchain technology already applies cryptographic techniques such as hashing and encrypting for the data transmission it also fulfills one of the critical security meta requirements. Blockchain is already well known for providing an immutable audit trail to improve the transparency and traceability compared to other technologies and also all the data recorded in the blocks are time stamped. when it comes to legal compliance, we would be able to facilitate the right of erasure (person's right to permanently delete her digital personal records) by selecting a consortium blockchain. In addition to that, by taking a design decision to not to store any medical records on the blockchain (only hashed references would be recorded), we would be able to comply in to the legal requirements as well.

4 DATA ANALYSIS

4.1 Identifying the risk factors associated with falls

There are various conditions that contribute towards increasing the probability of falling. These conditions can also be known as the risk factors for falling. The probability of falling significantly increases as the multiple risk factors are accumulated [52]. According to the WHO, these risk factors can be divided in to four groups as biological, behavioral, environmental and socioeconomic [57].The risk factors can also be divided as intrinsic and extrinsic factors as well [5]. Intrinsic factors are related to human behavior related conditions while extrinsic factors are related to the environment related factors.

An event of 'fall' can be divided into three main phases. The first phase would involve an extrinsic factor such as a wet floor or broken stairs and an intrinsic factor such as foot issue or muscle pain and also a physical activity such as running or rushing. The result of this phase would be losing control over the body. During the second phase, due to the intrinsic factors such as muscles weakness or sensory issue, the person would not be able to gain back the control over body and correct the posture by herself. During the third phase, person would hit the ground which lead in to damages on tissues or organs [11].

There are many research studies conducted on addressing different aspects of falls and risk factors on elderly people. Because of the same reason, conflicting opinions and research findings have been published by various researchers. Thus, the validity and the importance of these risk factors tend to vary and get inconsistent (when evidence are available to both prove and disprove the likeliness of them cause falling) [11]. This suggests that, even though some studies have identified certain risk factors, there is still a possibility to be disproved by new research studies.

- Task 01: Literature Analysis

Search Strategy: In order to identify the risk factors and the amount of evidence to support those risk factors we have conducted a systematic search through literature. As one of the purposes of doing this literature analysis was to understand the latest status of the risk factors, we have decided to place a date restriction on the search results. Therefore, the literature analysis was limited to the latest research studies published from year 2000 to 2018. Only the peer reviewed articles and the reports published from the reliable sources in English Language have been used. Key search terms included the key words 'Fall prevention', 'fall detection', 'fall prediction', 'Older adults', 'seniors', 'elderly', 'and Risk Factors','Risk of falls'.

Inclusion/exclusion criteria: Both systematic reviews on risk factors and also the studies conducted on focusing specific risk factors have been used for the analysis. Papers only focused on the specific age group (older adults) have been selected and the studies that discuss the risk factors on wider audience (Including young adults) have not been included.

Selection Process: First, by going through the titles and abstracts we have identified the papers that discussed about specific risk factors without targeting on fall prevention strategies. After a detailed reading has done to identify the risk factors that paper proves or supports. The risk factors that have been identified and the studies that support those risk factors are recorded in Table 1.

- Task 02: Analysing the opinions gathered from the domain experts

As the next step, we have gathered the clinical opinions of the domain experts to verify the importance of the risk factors.

Selection of experts: Two domain experts were selected. One domain expert is a clinical consultant in aged care domain who has more than 10 years of experience with clinical consulting on fall prevention strategies in aged care facilities. The other domain expert is a medical doctor and a professor who has conducted extensive research on fall prevention, aged care and related research domains.

Structure of the discussion: Two separate discussions were conducted with the selected domain experts. Each session started with discussing about risk factor groups (Medical, Environmental, Demographic, Cognitive and Behavioral) followed by a discussion on specific risk factors under each group. The discussions were mainly focused on the likelihood of causing fall due to each risk factor. In addition to that, the domain experts were given the time to come up with any other risk factors that have not been identified through the literature analysis as well. During the discussions, we also found certain contradictory ideas among the published literature and the expert opinions. As an example, even though the tripping and slipping have considered as environmental risk factors, based on the expert opinions they are only two mechanisms of falling thus can not be considered as direct risk factors.

Accumulating the results: After conducting both discussions according to the opinions gathered in the session 02, the risk factors have been categorized as 'Strong', 'Moderate' and 'Weak'. After that, by comparing the results achieved through both discussions, the highest category given for each risk factor has been chosen as the final category for each risk factor. The accumulated risk factor category for each risk factor is recorded in Table 1.

When selecting the risk factors to build the predictive model, we will give the first priority to the risk factors categorized as 'Strong' in both instances. Secondly, the risk factors categorized as 'Strong' at least in one instance. Finally, the risk factors categorized as 'Moderate' in both instances. The risk factors categorized as 'Weak' at least once in any instance, will be ignored for the first iteration.

4.2 Identifying the data sources associated with risk factors

After identifying the importance of each risk factor through evidence based and opinion based approaches, as the next step, we look at the various data sources to map with the identified risk factors. In order to do that, first we have divided the identified risk factors in to two main groups as static and dynamic as illustrated in the Figure 1. In this research study, static factors represent the factors which are not continuously changing. In contrast, dynamic factors represent the factors with fast changing values.

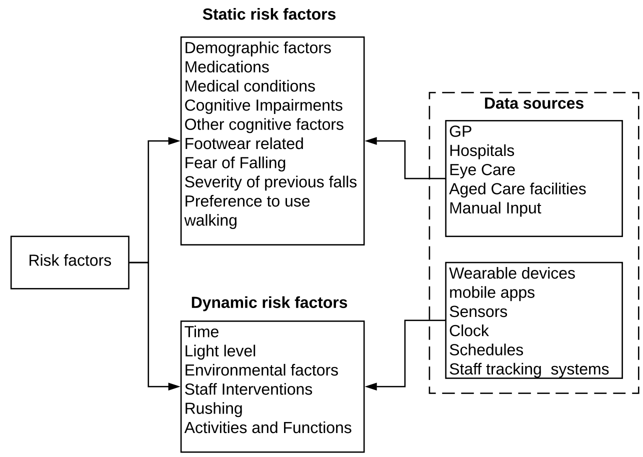

Figure 1: Data sources of identified risk factors

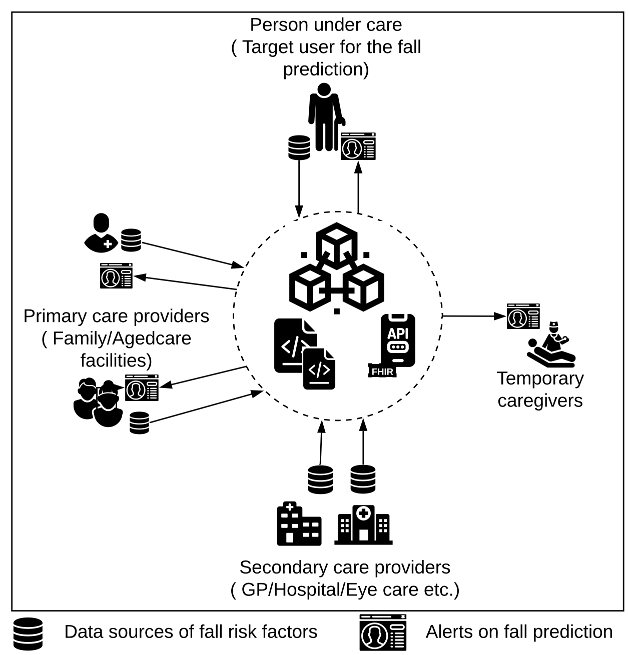

Figure 2: High level system design

5 SYSTEM DESIGN

In this section, we discuss about the main components of the system design. A high level overview of the system design is illustrated in Figure 2.

5.1 System users

In this proposed fall prediction model, four types of user roles have been defined based on the tasks they are allowed to perform. The four user roles are; person under care, primary care provider, secondary care provider and temporary care giver.

- The person under care

Table 1: Risk factors and likelihood of falling

Risk factor	Based on evidence	Based on expert opinions
MEDICAL FACTORS		
Gait,mobility and balance disorders [5, 9, 15, 64]	Strong	Strong
Diabetes [34, 45, 59, 65, 74]	Strong	Moderate
Pain (Leg muscle weakness and deconditioning) [43, 50, 67]	Strong	Strong
Cardiovascular conditions and syncope [13, 70]	Moderate	Moderate
Foot issues [48, 50]	Moderate	Strong
Urinary incontinence [13, 69]	Moderate	Moderate
Vision Impairments [13]	Weak	Strong
Somatosensory [8]	Weak	Weak
Dizziness and vertigo [47]	Weak	Strong
Depression [40]	Weak	Weak
Stroke [46]	Weak	Strong
Dementia [49]	Weak	Strong
Postural (orthostatic) hypotension	Weak	Strong
Urinary tract infections (UTI)	Weak	Strong
Delirium	Weak	Strong
Eye Health	Weak	Strong
Vestibular	Weak	Moderate
Hearing	Weak	Weak
ENVIRONMENTAL FACTORS		
Footwear related [5, 13, 27, 32]	Strong	Moderate
Tripping [5, 15, 17]	Strong	This is a way of falling. Cannot consider as a risk factor
Slipping [5, 17, 27]	Strong	This is a way of falling. Cannot consider as a risk factor
Lack of staff intervention [31, 56, 66]	Strong	Strong
Light level [5, 27]	Moderate	Moderate
Friction level of the floor, carpet, tiles (supporting the surface) [79][39]	Weak	Strong
Time (day, night) [27]	Weak	Moderate
Grip of the footwear	Weak	Moderate
DEMOGRAPHICS		
Age [12, 29, 58]	Strong	Strong
Gender [14, 25]	Moderate	Moderate
Fall frequency [35, 60]	Moderate	Strong
BEHAVIOURAL FACTORS		
Medication (Polypharmacy) [5, 13, 42, 62, 71]	Strong	Strong
Rushing [15, 69]	Moderate	Strong
Nutrition(eg: Vitamin D) [13, 30]	Moderate	Strong
Severity of previous falls [60]	Weak	Strong
Function(Exercising,walking) [27]	Weak	Moderate
Choosing to not to use Walking aids [28]	Weak	Strong
COGNITIVE FACTORS		
Fear of falling [18, 27, 36]	Strong	Weak
Cognitive Impairments [2, 13]	Moderate	Strong
Patient willingness to ask for help from staff	Weak	Strong
Patient willingness to wait for help once requested	Weak	Strong
Patient desire to be independent	Weak	Moderate
Patient self-awareness of functional ability	Weak	Strong

This solution is based on the patient centric healthcare. The patient or the elderly person that targeted on the fall prediction is known as the 'person under care'. In this research, we will consider anyone who is aged 65 or above as an elderly person irrespective of their gender. This user would act as a data provider for the prediction model through data sources such as mobile and wearable devices which can be used to gather real-time patient generated data especially related to gait and balance problems. This user also will be able to manually input the certain data related to risk factors and get notified on the prediction of falls.

In the consortium blockchain, this user will be authorized to participate in data verification process to reach in to the consensus.

- The primary care provider

Primary care providers would include the long term care providers such as family members of the person under care and the care givers at his/her assisted living facility. The primary care providers will be responsible for providing the falls risks related data as well as retrieving the accumulated data that predict the probability of falling. Electronic healthcare systems that are deployed in the aged care facilities will be considered as one of the main data sources to gather data related to the identified risk factors in Table 1. This user also will be able to manually input the certain data related to risk factors and get notified on the prediction of falls on the people under their care.

This user also will be authorized to participate in data verification process to reach in to the consensus.

- The secondary care provider

We have defined the secondary care providers as the entities that provide short term or temporary care for the person under care. Examples for secondary care providers would be Hospitals, General Practitioners, Allied professionals, Physiotherapy and Eye care etc. These users will be added in to the network upon the consent of the person under care or a primary care provider.

Currently, these entities are maintaining their own electronic health record management systems. However, these systems consist of the data related to the identified risk factors as well. Therefore, these users will be considered as data sources for the prediction model. The secondary care providers will also be able to manually enter data related to the selected risk factors. However, all the data that are added through the secondary care providers will go through a verification process before getting added into the blockchain. This data will be verified by the patient under care or her primary care providers. This user will not be authorized to participate in data verification process to reach in to the consensus.

- The temporary care giver

This user role represents the interested parties who are expecting to get the alerts on fall prediction on the people under their care on limited personal and clinical information. This user will not be considered as a data source to get data related to the risk factors. However they will be granted the limited viewing privileges to get notified when the people under their care is in risk of falling. These users also will be added in to the network upon the consent of the people under their care or the primary care providers. This user also will not be authorized to participate in data verification process to reach in to a consensus.

5.2 Blockchain for fall prediction

The blockchains can be classified in different ways. Considering the level of participation and tasks they are authorized to do, it can be divided as public, consortium and private or as permissioned and permissionless. As an example, bitcoin is known as a public and permissionless blockchain because anyone with the internet connection can download the open source project and join with the block creation and verification process. In contrast, on private and consortium blockchains, only the authorized parties would be able to join with the network and participate in the verification process. In this solution, we are going to use a permissioned consortium blockchain, as we need to restrict the access to the data, only to the known parties. However, the data will be kept in the existing data storages without replicating or moving them in to the blockchain. Only the hashed references to data will be stored in the blockchain.

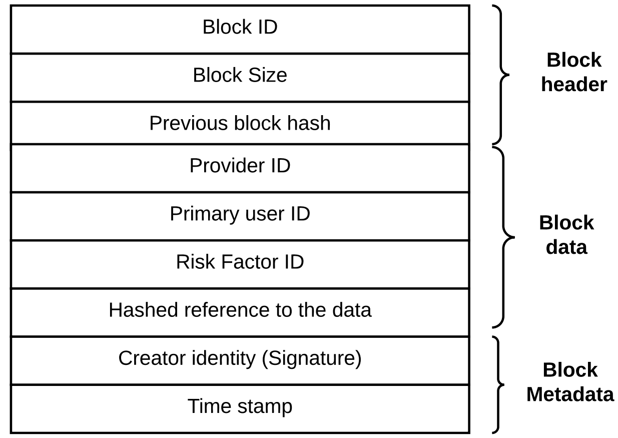

Figure 3: The block data structure

Figure 3, illustrates the block architecture of this blockchain. The high level block data structure can be divided in to three main sections as block header, block data and block metadata. The block header consist of Block ID, Block size and the previous block hash to create a chain of blocks. The content of the block has the provider Id to identify the person who created the block, and the owner of the data would be identified using the Primary user Id. The specific risk factor related to the dataset and the hashed link to the dataset is also available. In order to verify the block, the signature of the provider and the time stamp of the block is also included. In our proposed system, every block will be limited to data about one patient on one single risk factor. The main reason for that is to reduce the unnecessary complexities in data retrieval and verification.

5.3 Designing smart contracts

Smart contracts are set of codes with data that resides at a specific address in a blockchain and its execution would be cryptographically validated by the network [55]. As illustrated in figure 4, we will utilize four smart contracts to execute the fall prediction and related tasks.

- User Registration (UR)

This smart contract facilitates the user registration. As this is a patient centric system, identity management is also important. All four types of users should be registered by this smart contract. This smart contract connects with two other smart contracts, Permission contract and the Patient- Provider contract.

- Permission Contract (PM)

Permission contract facilitates the granting, denying and revoking the permission on the fall risk profiles. This also determines the level of information should be displayed for each user on different primary user risk profiles.

- Patient - Provider Contract (PPC)

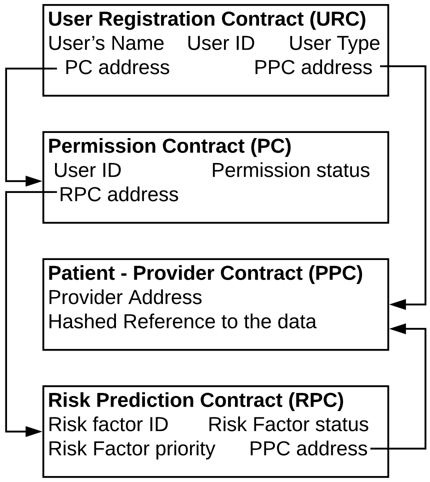

Figure 4: Smart Contracts

This contract manages the data sources and the hashed data links to the provider data storages. As all the data providers are also registered users, there is a link between the user registration contract and this contract.

- Risk Prediction Contract (RPC)

Risk Prediction Contract manages the risk values and the priority against each risk factor. This is mainly responsible for the risk prediction calculation and alerting. As the data related to the risk factors are coming from the data sources of the providers, it has a link to the Patient - Provider Contract as well.

5.4 Designing a consensus mechanism

When the new blocks are generated with the new patient information, the blocks need to go through a verification process before adding them in to the blockchain. In this solution, when the new block is added, primary user or the primary care providers will be responsible for the block verification. This is because in this consortium blockchain solution, only the person under care and the primary care providers can be considered as trusted verifiers.

5.5 FHIR integration

When designing solutions that need to communicate with other entities of the healthcare ecosystem, it is vital to adopt universal healthcare formats and structures. As the different providers are storing the medical data in various formats and data structures, it would be highly difficult for this solution to interpret and integrate data, retrieved from various other data sources. Therefore, one of the meta requirements of this solution is to support the Fast Heath Interoperability Resource (FHIR) standards [23]. This is one of the standards created as the extension of HL7, to facilitate the data exchange among legacy healthcare systems and this format is also compatible with multiple devices such as wearables, health applications, mobile and medical devices. It consists of REST APIs and the secure data exchange would be facilitated through OAuth, OpenId and UMA protocols. Many of the key players in EHR such as Epic and Cerner are already adopted the FHIR services. Therefore, the system design is consisted with FHIR clients and APIs.

5.6 A user scenario

Assume that a registered elderly person (The person under care) has been hospitalized for a week. In the hospital (The secondary care provider) Electronic Medical Record (EMR) system , the medications that the hospital prescribed for the patient is recorded. After getting the treatments, this person would arrive back to the aged care facility (The primary care provider) she resides in. After arriving, she is planning to take another medicine that she was taking regularly which is recorded in the aged care EMR system. This lead in to a condition that related to the risk factor 'medication' which is known as 'polypharmacy' that is directly associated with risk of falls. The proposed fall prediction model would retrieve the prescribed medication data related to this person from the EHR of the hospital and the aged care facility and alerts the person under care, her primary care providers as well as any temporary care givers about the predicted risk.

6 CONCLUSIONS

Every fall has the potential for high cost outcomes. These include but are not limited to; physical (pain and longevity), emotional and economic. As the prediction is a pathway to prevention (a care giver at the side of a resident before a fall), the impact of this research to the health and aged care sectors will be remarkable. Amongst the stakeholders are the benefactors; the people under care, the family, the healthcare providers, the government and the taxpayer. The associated economic value (taxpayer and consumer) on its own would be significant. Beyond that are the positive social and moral outcomes. The well-established paradigm of the ageing population merely serves to escalate the benefits of the research.

Therefore, in this research study, we have identified risk factors associated with falls by conducting a literature analysis and also we have evaluated our findings through experts opinions. Without restricting in to the intrinsic factors, we have included the extrinsic factors such as behavioural and environmental factors also in to the data model. We have derived 20 meta requirements covering five design principles addressing accessibility, accuracy, interoperability, security, traceability and legal compliance parameters. In order to cater the identified meta requirements, a fall prediction model has been proposed using the consortium blockchain. A set of smart contracts have been introduced to securely retrieve the data from the different entities that belong to the healthcare ecosystem. In addition to that, using smart contracts, the data related to the risk factors will be processed and prediction will be made on the likelihood of falling. The model will achieve interoperability among different healthcare systems by leveraging FHIR and the predictions would reach to the end users as alerts.

7 FUTURE WORK

As the next step, we will develop this proposed fall prediction model and deploy the smart contracts. And we will evaluate this model on a test healthcare ecosystem. Few of the limitations of deploying this model in a real healthcare eco-system would be inconsistent and conflicting opinions on risk factors in clinical community, sudden data structure changes in entities, retrieving data from the entities that do not agree to follow FHIR standard and also changing the mindset of people towards blockchain solutions.

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