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SECURE DECENTRALIZED DECISIONS IN CONSOLIDATED HOSPITAL SYSTEMS: INTELLIGENT AGENTS AND BLOCKCHAIN

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SECURE DECENTRALIZED DECISIONS IN CONSOLIDATED

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Abstract

Shared decision making has become a very important solution in order to build a consolidated healthcare system. While there is some research in the healthcare literature discussing the advantages and disadvantages of the shared decision making, its efficiency has not been addressed quantitatively. In this thesis, we propose a universal decentralized decision-making architecture utilizing the Blockchain Technology and Machine Learning (predictive and prescriptive analytics) to address the compelling need for coordination among healthcare providers and patients in an efficient and integrated manner. The healthcare process considered is the assignment of a patient to the best physician and hospital in consolidated hospital systems. After designing Decentralized Patients Assignment System (DPAS), the model is simulated using Agent-based models (ABM). The ABM consist of 4 agents including patient, physician, hospital and miner (assignment algorithms) which interact inside a decentralized integrated system. The proposed mechanism introduces the importance of interoperability between healthcare agents in the decision making process created by Blockchain Technology. To illustrate the model efficiency, two scenarios have been simulated and the results are compared. The results demonstrate the proposed model efficiency in terms of the assignment rate, computational time, and cost.

Keywords— Hospitals Consolidation, Blockchain Technology, Machine Learning, Agent-Based Models

1 Introduction

One of the most important processes in consolidated hospital systems has been the assignment/referral of the patient with a certain level of illness severity to the best available physician at a hospital with the required facilities. This is a dynamic problem in nature which needs interoperability among healthcare providers such as hospitals and the physicians. In addition, multiple important parameters will define the decision-making process of patients' assignments, such as the patient's severity of illness, cost of transferring by ambulance, physicians' availability, the consent of healthcare providers and patients on sharing data and making the final decision together. Currently, the major concern in this process is geared towards the coordination and integration of the patients' referral system. In a non-coordinated system, the goal is maximizing the individual's objective; however, in a coordinated system, the goal is maximizing the whole system since locally optimal solutions do not guarantee quality health services in the whole system. Hence, the coordination level of the referral system will characterize the quality of the patients' assignment, which is to fulfill patients' needs in the right time and in an integrated manner. (Mohebbi, 2015).

A new solution to the patients' assignment problem, proposed by the literature, is the shared decision making process in which multiple healthcare parties such as physicians, practitioners and patients make decisions jointly, using the best available evidences (Bai et al., 2014a). Shared decision making can improve both the efficiency of the decision making and the ethical imperative due to the patient's rights, while it reduces unwarranted healthcare practice variations (Légaré et al., 2014). However, shared decision making can be effective only when the healthcare providers can access the data in-time and they can collaborate through a fast and trustable channel. This process will become more difficult if the health providers use different health systems, databases, and communication network. Therefore, lack of data availability and interoperability between healthcare providers are still the huge hindrances to the effectiveness of shared decision making for the patients' assignment problem. To tackle these issues, this paper is proposing a Decentralized Patients Assignment System (DPAS) framework utilizing Blockchain Technology and Machine Learning techniques (predictive and prescriptive analytics). DPAS will employ Blockchain technology to make a decentralized decision system which has secure data sharing, flexible interoperability, and the fast assignment mechanism. Fig. 1 shows the analytical framework which is followed to build the DPAS architecture. The goal is to assign a patient to the right physician and right hospital, with the minimum cost while the severity of illness is taken into account. For this purpose, DPAS consists of two main design levels, including Patient Centric Model (PCM) and the Blockchain Architecture. PCM will result in the optimized assignment and Blockchain will make the assignment process efficient by increasing the coordination and transparency. PCM contains two sub-level designs, including the Machine Learning algorithms to identify the severity of the illness (predictive analytics) which will be fed into the mathematical model (prescriptive analytics), and the TOPSIS Matching Algorithm to rank the best physicians to be assigned to the patient. The output of both sublevel algorithms will be used as an input to the optimization model which will minimize the cost of patients' assignment and the average cost of losing patients (the optimization model will be the mining algorithm in the smart contract design). On the other parallel level, Blockchain Architecture contains several smart contract layers which are used for gathering, sharing and saving data generated by DPAS. By embedding the optimization model as the mining process into the Blockchain architecture, the smart contract can be ready to give the patient data to the mining process and get the mining results (assignments solution) from the optimization problem which is run by miners.

The analytical framework is modeled and implemented using the Agent-Based models in Python. It considers the patients, physicians, hospitals and the miners as the interacting agents. To build the Blockchain architecture, Ethereum platforms which is based on smart contracts is utilized. The designed system will employ Blockchain to connect multiple decision makers agents in a decentralized-transparent environment. This will facilitate the coordination and the integrity of the system. In addition, the optimization model will guarantee the quality of the patients' assignment process.

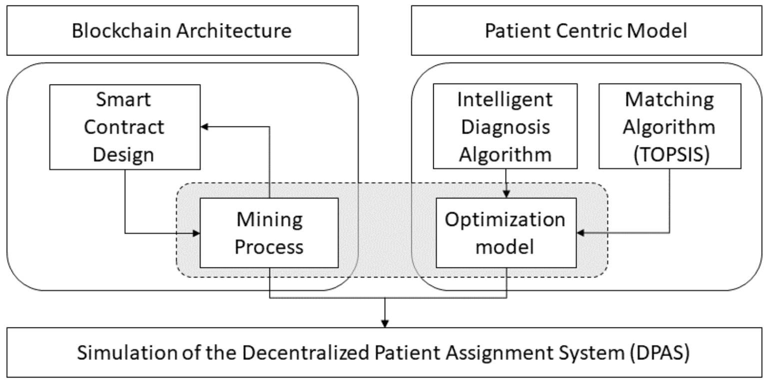

Figure 1: Analytical Framework for DPAS design

Following this section, the remainder of the work is organized as follows: In section 2, the literature on three main streams of healthcare research including Advanced Analytics, Blockchain Technology and decentralized systems, and Agent-based Simulation is reviewed. Section 3 is devoted to defining the methodology and the proposed DPAS framework. Section 4 provides the performance evaluations of the DPAS framework for two scenarios. Finally, section 5 will give insights and discussion about the cons and pros of the proposed framework and will provide concluding remarks, limitations, and the future research directions.

2 Literature Review

This study is focused on three main streams of healthcare literature: Advanced Analytics, Blockchain Technology, and Agent-based Simulation. The healthcare literature in Advanced Analytics presents two main categories : Prescriptive Analytics and Predictive Analytics. The most employed techniques for simulation are based on Markov chain and Agent-based simulation.

2.1 Prescriptive Analytics Review

Prescriptive analytics recommends a course of action and remains the most widely used techniques in healthcare literature. Many attempts have been conducted to improve the existing systems from different perspectives. Some research focused in increasing the security of information-transition among the healthcare providers while optimizing the healthcare workflow task assignment. This can be done by using two-stage optimization methodology to minimize the information disclosure risk via a workflow system with optimal efficiency of the workflow task assignment and a viable and effective control scheme (Bai et al., 2014b). The results showed that it is possible to identify this risk, but the solution remains partial because it does not propose a direct solution to tackle the security issue. Another area of Advanced Analytics focuses on optimization techniques to optimally manage healthcare processes. Bastian (2015) compared different decision-making tools applied to optimize the accuracy and the fastness of the management in military healthcare. Applying mathematical modeling to complex problems is sometimes limited by the assumption made in the modeling even if it improves the existing system by proposing a data-driven managerial support to the military healthcare decision makers. Another study applied a game theory framework to consolidated hospital systems with a central referral center to enhance the coordination among physicians and hospital managers (Mohebbi, 2015). Other studies utilized metaheuristic algorithms for accepting and scheduling patients dynamically for home healthcare or patient flows in hospitals by using variables among nurses, patient, task and time (see Demirbilek et al. (2018); Niroumandrad and Lahrichi (2018)). Metaheuristic approach offers an adaptable and fast method for integration in healthcare process and for the large-scale patient flow problem. The aforementioned works have bridged some gaps in the literature. However, they are mainly built on the assumption of a central decision making procedure.

2.2 Predictive Analytics Review

Predictive analytics tries to address the literature gaps using real time data-driven approaches. It uses statistics to analyze past and current facts hidden in the data to make prediction about the future. Ganguly and Nandi (2016) proposed statistical techniques to develop a forecasting model, using ANOVA techniques, for optimal staff scheduling in healthcare organizations based on patient arrival rates. It was found that personnel allocation can be anticipated, and the staff was correctly allocated by analyzing patient arrival rates. Other applications, based on Machine Learning techniques, offer unlimited possibilities for analyzing different data models less visible or hidden to common analysis techniques to forecast, put diagnose, and set treatments for patients in healthcare organizations (see Agarap (2018); Hijazi et al. (2016); Ţăranu et al. (2016)). The outcomes reach very high accuracy, near to 97 to predict disease. Nevertheless, the results remain very basic, because the models only predict binary outcomes: if there is an illness or not. The level of gravity of the disease could be predicted also using multi integer outcome algorithms. Many attempts were conducted to improve the decision making process using prescriptive and predictive analytics and have shown great results to improve existing solutions or to create new ones. However, these works mainly deal with centralized decision-making processes and avoid the involvement of other actors such as patients. Thus, the secure decentralization of the decision process could bring an acceptable solution to involve more actors in an integrated decision-making framework.

2.3 Blockchain Review

Demand for decentralization of the digital information system (Al-Megren et al., 2018) is growing in different domains including healthcare systems. There are several decentralization mechanisms which have their own pros and cons, but the current literature stream offers a new compelling secure way of decentralization known as Blockchain technology. Blockchain technology proposes a peer to peer system which guaranties a highly secured and fast transaction process (Nakamoto, 2008). The technology was first introduced by Bitcoin as a cryptocurrency asset. Later, with the creation of Ethereum (Buterin et al., 2014), Blockchain got the ability to represent the ownership protocol by implementing “smart-contract” which define “smart properties.“ It supports a built-in fully-fledged Turing-complete programming language to create “contracts” that can be used to encode arbitrary state transition functions. This new technology has been adapted to many other field in industry and especially in the healthcare industry. Blockchain is a revolutionary technological breakthrough which has triggered a wide research interests in finding the ways to integrate existing healthcare processes (Alla et al., 2018). The healthcare community has established multiple metrics to define the expectation regarding to the Blockchain-based healthcare systems(Zhang et al., 2017a). Based on these metrics, Blockchain with healthcare application must comply with the following rules: the entire work flow is HIPAA compliant, the framework employed needs to support Turing-complete operations, the support for user identification and authentication must be significant, the support for structural interoperability must be respected, the scalability across large populations of healthcare participants is compulsory, the cost-effectiveness side must be reasonable and the support must be a patient-centered care model. It proposes a set rules to respect for any Blockchain related works in healthcare. E-health Blockchain (Liu et al., 2017), MedShare (Xia et al., 2017) and MedRec (Ekblaw et al., 2016) are some examples of the Blockchains were developed. E-health Blockchain proposes to build the chain of blocks for each provider, but also each block is chained among providers to follow the exact path for each patient through the network of providers. Regarding MedRec, it gives patients a comprehensive and immutable record and easy access to their medical information across providers and treatment sites. Nevertheless, none of those new Blockchains respects completely the metrics. The e-health Blockchain remains too provider-centered to record patient but presents a structural interoperability, while the med-rec presents a reasonable patient-centered skill but few structural interoperability when it comes to release inputs for Intelligent Systems. Thus, many researches focus on the decentralization of healthcare process and Blockchain technology has been adapted to tackle this major issue. Nonetheless, existing works struggle to be validated by the two most important metrics, which are the patient centered and structural interoperability criteria simultaneously. To address this gap, we propose a new Blockchain architecture responding to those two major requirements in hospital networks.

2.4 Agent-Based Modelling Review

The third stream of the healthcare literature is the modeling and simulation of the healthcare processes. As discussed before, it is recommended to test the resilience and the scalability of the decentralized healthcare systems. Markov chain modeling provides suitable techniques to study the different behaviors of a system under uncertainty. Among other studies, Zhang et al. (2017b) utilized Markov chains to simulate decision making for the treatment decision for a type 2 diabetes. They demonstrated the effectiveness of this decision-making process using variation in a patient's glycated hemoglobin use case, where the transition probability is subject to uncertainty. The study bases its metric on QALYS and Medical Cost to assess its efficiency. Another technique of simulation is Agent-Based modeling. It describes and models a complex system in totality as a set of multiple autonomous agents who have their own objectives, behavior and interactions with other agents and the environment. This set of different individual behaviors generates a global behavior as in the real world. There are a growing number of research works utilizing Agent-Based simulation in healthcare. Liu and Wu (2016) focused on accountable care organization (ACO) in hospital. They developed an Agent-Based simulation model to study ACOs that considers payers, healthcare providers, and patients as agents under the shared saving payment model of care for congestive heart failure. They demonstrated that the major factor of an acceptable ACO is the payment model. When the cost-effectiveness implemented by the ACO varies, the behavior of the medical team varies accordingly. Agent-based simulation has also been utilized to model the interaction of a multidisciplinary healthcare team and its scheduling (see Othman et al. (2016); Wilk et al. (2016)). The simulation process allows the model to be similar to the real world. Lopes et al. (2018) focused on the medical workforce in Portugal using Agent-Based simulation. The study shows that the medical workforce will not be enough to address the aging population issue.

All in all, the analytics stream of the literature has not addressed the decentralization of the decision-making in healthcare processes deeply. In addition, due to the models' assumptions, actors such as patients are mainly overlooked in the modeling process. Blockchain technology literature suggests two most important metrics for Blockchain adoption in healthcare, which are the patient centered and structural interoperability criteria. In an attempt to bridge these gaps in the literature, this paper proposes a Blockchain-based analytics framework for integrated healthcare system. To demonstrate its feasibility and efficiency, we utilize Agent-Based modeling to simulate the interaction among main decision makers, mimicking the real life behavior of the different human or machine, and decision makers.

3 Analytical modeling

The proposed Decentralized Patient Assignment System (DPAS) connects different intelligent systems which boost the interoperability between differeFnt healthcare providers while it enables considering the patient preference in the decision-making process. In fact, the Blockchain architecture is added to the patient assignment/referral system designed to bridge two main aforementioned gaps in the literature. As shown in Fig. 1, DPAS consist of two design layers; Blockchain Architecture and the Patient Centric Model which are integrated to create a decentralized, secured, optimal and patient-involved assignment system.

3.1 Blockchain Architecture

Blockchain technology is defined as distributed ledger technology, which records transactions in a secure, transparent, decentralized, and efficient manner with low cost. The Blockchain is the technology underlies bitcoin, which was introduced by pseudonym Satoshi Nakamoto in 2008 (Nakamoto, 2008). The idea of applying Blockchain to the healthcare systems stems from the need for decentralization of referral systems and efficient decision-making process. Blockchain can distribute the decision process by connecting decision makers to the distributed healthcare network including patients, hospitals, and physicians. This will create a transparent system in which all the healthcare actors are involved in decision making, confirming and implementing it. The overall mechanism of Blockchain architecture and the roles' distribution is as follow. The hospitals focus on gathering and computing local data for the patient transfer process and they make these data accessible to miners. The role of the miners is to bring consensus and find the best assignments solution by solving the consensus problem. The first miner who finds the solution, publish it to the network. When the generated solution is confirmed by other miners in the network, the solution is accepted, and the miner gets a reward in Ethereum. At this point, patients assignment happens according to the validated solution, and a new block (including the data about the assignment solution and process) will be generated and chained to the previous latest block. As shown in Fig. 2, the proposed Blockchain architecture is built on the Ethereum which uses multiple layers of the smart contract such as Blockchain state contract (BSC), network state contract (NSC) and Transfer Block Contracts (TBC).

The BSC is a unique smart contract which stores the block's information on the Blockchain. In other words, it keeps the address of the latest block chained to the Blockchain and the address of the potential new block. The NSC is also a unique smart contract which detains all the information about the hospital and physicians. For instance, it contains the number of patients that we can attribute to a physician in the current block, the number of beds available per hospital, the service that each hospital and the physicians provide in the hospital. Finally, the TBC is not unique and it contains the address of the previous TBC and all the patients' data and their transfer requests' information, such as the ambulance cost or the physicians matched with each patient. Every hour a new smart contract, which defines a new Blockchain for patients transfer among hospitals in the network, is created and published. The information shared on each smart contract is not sensitive information; hence, the privacy concern is fulfilled. Moreover, the confidentiality of the information is fulfilled by the actor's authentication and authorization in the network. For instance, hospitals are only allowed to submit the patient's information to the Blockchain system. The consensus protocol, defined in the smart contract, pushes the solution given by the miners to be always cross-checked. This process is a validation of the global solution which satisfies all parties in the network. Miners will solve the mining problem (Nakamoto, 2008) which is the optimization model derived from the patient centric model (PCM) described in the next section.

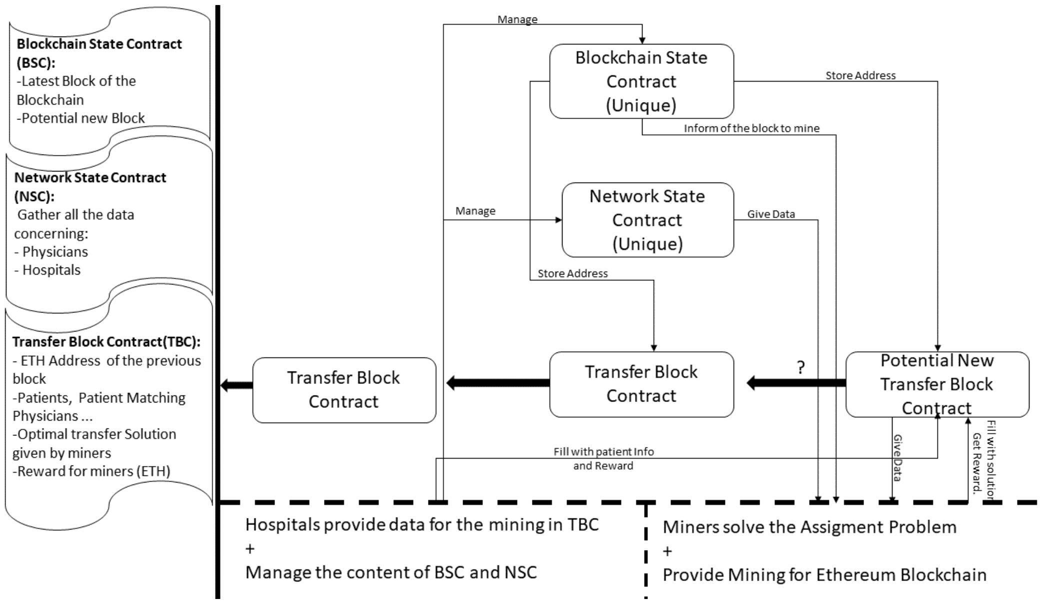

Figure 2: Blockchain Architecture

The Blockchain architecture is HIPAA (Health Insurance Portability and Accountability Act of 1996) compatible as it offers a high flexibility to fit with a patient centered decision-making framework. Also, this architecture is cost-effective, as it attempts to give an optimal solution to the assignment problem minimizing the cost for the hospitals and patients. Hence, this system is a secure decentralized patient-centered decision-making process providing patients with the best possible physicians, while taking into account their decisions and the involved costs.

3.2 Patient Centric Model (PCM)

Patient centric model is a mechanism to find the optimal assignments minimizing the cost of assignment and losing patients. PCM contains three layers; TOPSIS matching algorithm, Machine Learning algorithm (predictive analytics), and the optimization model which combines the first two algorithms to reach the optimal solutions.

3.2.1 Matching Algorithm

Mohebbi (2015) proposed an intelligent matching algorithm to match patients with physicians across the hospitals network. The matching algorithm utilizes two sets of attributes to define the requirements, similarities, and properties of each assignment case: critical attributes and bilateral attributes. The former includes the attributes defining exclusive criteria related to the scope of the hospitals' services so that any decisions are compatible with the critical attributes. The latter are the attributes assigned to the physicians as a common viewpoint about their level of specialty and quality of the services they provide. In this study, we adopt the same health attributes and apply TOPSIS method to rank physicians for each patient. The matching algorithm implement three main steps:

- **Step 1: Defining the relative importance of each criterion**

  Let $E = \{e_1, e_2, \ldots, e_n\}$ be the set of physician, $C = \{c_1, c_2, \ldots, c_m\}$ the set of criteria for treatment choice and $M_{m\times n}$ the matrix defining the relative importance of each criterion. Here, we add the patient P to the set E, as an indicator for the patient preference to choose the physician or the hospital. Therefore, the dimension of the matrix $M_{m\times n}$ changes to $M_{m\times(n+1)}$. Let A be a vector of size m with $a_i \in \{0,1\}$ such that:

$$
\mathrm{M}_{m*(n+1)} = \begin{array}{c} \\ c_1 \\ c_2 \\ ... \\ c_m \end{array}
\begin{array}{c}
\begin{array}{cccc} \qquad p \qquad & \qquad e_1 \qquad & ... & \qquad e_n \qquad \end{array} \\
\begin{pmatrix}
a_1 * x_{11} & (1-a_1) * x_{12} & ... & (1-a_1) * x_{1n} \\
a_2 * x_{21} & (1-a_2) * x_{22} & ... & (1-a_2) * x_{2n} \\
... & ... & ... & ... \\
a_m * x_{m1} & (1-a_m) * x_{m2} & ... & (1-a_m) * x_{mn}
\end{pmatrix}
\end{array}
$$

where x_{ij} is the importance of criteria j assigned to each expert i. The importance level is defined based on the verbal definition given by Saaty (1977), but modified to the range between 1 and 5 as follow: Very important (1), Low (2), Medium (3), High(4), Very high(5). Vector A also considers the contribution of the patient preference to the relative importance of each criterion (weights w).

- **Step 2: Prioritizing the physician choice for patient**

  Let $P = \{p_1, p_2, \ldots, p_k, \ldots, p_d\}$ be the set of physicians presenting the specialty required to treat the patient. For each physician, we can define the matrix $M^k_{i,j}$:

$$
\mathrm{M}_{i,j}^{k} = \begin{array}{c c}
 & \begin{array}{cccc} e_1 & e_2 & ... & e_n \end{array} \\
\begin{array}{c} c_1 \\ c_2 \\ ... \\ c_m \end{array} & \begin{pmatrix} x_{11}^{k} & x_{12}^{k} & ... & x_{1n}^{k} \\ x_{21}^{k} & x_{22}^{k} & ... & x_{2n}^{k} \\ ... & ... & ... & ... \\ x_{m1}^{k} & x_{m2}^{k} & ... & x_{mn}^{k} \end{pmatrix}
\end{array}
$$

where $x_{i,j}^{k}$ is the rank of physician k given by the expert i based on the criteria j.

- **Step 3: Matching Patient and Physician**

  In the matching process, TOPSIS method calculates the final ranking of physicians for each patient. Decision matrix is first formed based on the obtained results from the first two steps. The weighted normalized decision matrix is then calculated. The worst and best solutions, closeness to ideal solutions for each physician are calculated based on the TOPSIS method procedure. The physician selected for every patient is the physician with the highest score, presenting the closeness to the ideal solution.

When the ranking of physicians is established, a threshold is set to define the minimum acceptable closeness to the ideal solution. If the physician's rank is larger than this threshold, then she is considered as a candidate to treat the patient. The threshold values are inputs to the assignment problem.

3.2.2 Intelligent Diagnosis Algorithm

The aim of the PCM is to minimize the cost of assignment and losing patients. One of the criteria that can lead to a tremendous cost in the patient assignment problem is the cost of transferring a patient from one hospital to the other hospital. This cost depends on the ambulance type which is chosen based on the patient's severity of illness. In this study, the severity of illness and the ambulance cost are calculated as below.

- **Step 1: Classifying the severity of illness**

  One of the novel aspects of this study pertains to the use of Machine Learning algorithms, as a support tool, for automatic diagnosis of the severity of illness. For each level of acuity, a specific level of medical care is needed, and the level of medical care will determine the necessary ambulance type for transferring a patient. According to the Medicare Payment Advisory Commission (2017), medical care level can range from 1 to 6. In order to get an accurate prediction of the ambulance cost, a classifier is trained to predict the belonging of a new patient to one of these medical cares. Depending on the prediction, established by the classifier, it is possible to find a correspondence between the prediction and the level of medical care as an index of severity of illness. Predicted severity of illness is not a direct input to the assignment problem but remains compulsory to compute the ambulance cost in the next step.

- **Step 2: Computation of the ambulance cost**

Obtaining the level of medical care needed to transfer the patient (Step 1), we can compute the ambulance cost (C). According to the Medicare Payment Advisory Commission (2017), the cost of transferring patient using a specific ambulance type can be calculated as follow:

$$C = RVU * ACF * AGPC + MI * MIR \tag{1}$$

where RVU is the Relative Value Unit (Table 1), determines the level of patient's emergency situation, and is considered as the severity of illness. ACF is the Ambulance Conversion Factor, $AGPC$ is the Adjusted Geographic Practice Cost. MI and MIR are the Mileage and Mileage Rate, respectively.

The intelligent diagnosis algorithm automates the computation of the ambulance cost by classifying the severity of illness accurately.

3.3 Mining Process: Optimization Model

The result of the matching algorithm and the intelligent diagnosis algorithm are input parameters to the optimization model. Having a set of best feasible physicians and the transferring cost for each patient, the mathematical model can be formulated. The global optimization function is defined as a linear mathematical model with the set of parameters, decision variables and constraints which are presented

Service	**RVU**
1:BLS non emergency	1
2:BLS emergency	1.6
3:ALS non emergency	1.2
4:ALS emergency (level 1)	1.9
5:ALS emergency (level 2)	2.75
6:Specialty care transport	3.25

Table 1: Relative Value Unit scale

(ALS: Advanced Life Support, BLS: Basic Life Support)

as follows.

3.3.1 Decision variables

$$X_{ijh} = \begin{cases} 1, & \text{if patient } i \text{ is accepted by physician } j \text{ at hospital } h \text{ during each time block} \\ 0, & \text{Otherwise} \end{cases}$$

$$P_{ijh} = \begin{cases} 1, & \text{if patient } i \text{ is not accepted by physician } j \text{ at hospital } h \text{ during each time block} \\ 0, & \text{Otherwise} \end{cases}$$

3.3.2 Parameters

- I : Set of Patient

- J : Set of Physicians
- F_i: Subset of feasible physicians for patient i
- $W_{i,j \in F_i}$: Weight of physician j if it is assigned to patient i, derived from TOPSIS algorithm. If the physician is not in the subsetF_i, the value is 0
- H: Set of Hospitals
- C_{ih}: Ambulance cost to transfer patient i to hospital h
- ρ_i: Severity of illness for patient i derived from the intelligent diagnosis algorithm. It is equal to 0 if there is no severity of illness. Otherwise, it goes in a range from 1 to 6
- ψ_s: Average cost of losing a patient requiring specialty s
- B_h: Number of bed at hospital h
- m_j: Maximum number of patients to be assigned to physician j at each time block.
- p_s: Number of patient requiring service s.

3.3.3 Global objective function

$Min\ Z = A(X) + R(X) + P(X)$,

where,

$$A(X) = \sum_{i,\ j \in F_i, h} X_{ijh} * C_{ih} \tag{2}$$

$$R(X) = \sum_{s} (p_s - \sum_{h,i,j \in F_i} X_{ijh}) \psi_s. \tag{3}$$

$$P(X) = M * \sum_{i,\ j \in F_i} P_{ijh} \tag{4}$$

The global objective function consists of three main terms: $A(X)$ represents the cost of transferring a patient which depends on the distance between a patient and physician's hospital. This cost also includes the ambulance fee given in equation 1. $R(X)$ penalizes the loss of a patient based on a particular specialty/service. Eventually, $P(X)$ penalizes the rejection of patients' transfer. M is a large penalty associated with the slack variable P_{ijh}.

3.3.4 Operational Constraints

The operational constraints are defined to guarantee that (i) beds are available to patients at a hospital after transfer (equation 5), (ii) only one physician can be assigned to the patient from the set of possible physicians (equation 6) and (iii) maximum number of patients assigned to a physician is less than the defined threshold (equation 7).

$$\sum_{i,\ j \in F_i} X_{ijh} \leq B_h \quad \forall h \tag{5}$$

$$\sum_{h,\ j \in F_i} X_{ijh} + P_{ijh} = 1 \quad \forall i \tag{6}$$

$$\sum_i X_{ijh} \leq m_j \qquad \forall j \in F_i, h \tag{7}$$

Since there is a network of hospitals, each hospital tries to use the same variables to solve the model to get the best possible solutions for their patients transfer problem. This will make a challenge for the optimization model as a patient may assign to two different hospitals/physicians. Thus, we must add the consensus concept to the system which ensures that all parties in the network have the most UpToDate results and they confirm that results are valid. The optimization model in the PCM layer plays the role of mining process in the Blockchain architecture. In fact, miners run the optimization model to find the solution for the assignment problem for each patient, and the first miner who find the solution for the optimization model will publish it to the network. Parties in the network will see the results, confirm the optimum solution and take action according to their role as a hospital manager or physician. The assignment process will continue for other patients and the result will form the blocks of the Blockchain.

4 Validation and Performance Evaluation

In order to validate and evaluate the proposed system, an Agent-Based simulation is designed. We define two scenarios: (i) baseline scenario which mimics the current practice for patients assignments (a central referral system handles transfers based on geographical distances and/or the referring physician's suggestion), (ii) proposed scenario which is designed based on the DPAS system. There are four different types of agents which have different attributes and dynamic behavior, and interact through the Blockchain network. The definition of each agent is given below.

- **Patient Agent:** Represents the patient which has specific severity of illness and specific preferences. In the DPAS system, patients can participate in the decision making process and the matching algorithm. They are transferred from a hospital to another after receiving the final assignment decision. In the baseline scenario, patients can accept or reject the assigned physician, according to their preferences.

- **Physician Agent:** Represents the physician who receives the result of patient assignments and decide to accept or reject assigned patients. Physicians participate in the matching algorithm as experts, but cannot take part in the intelligent diagnosis of the severity of illness.

- **Hospital Agent:** Represents the hospital which is in charge of submitting patient data to the Blockchain network. Matching algorithm and the intelligent diagnosis algorithm is run by the hospitals and the result will be sent to a library which interact with the Blockchain (see algorithm 1). Afterwards, miners will get the data from the Blockchain network according to the smart contract protocol . Physicians and patients can be in different hospital agents.

Procedure: Committing Hospital Nodes to Patients

Request Physicians with the required specialty on the Blockchain;

for *All patients to be transferred to this hospital* **do**

  Perform the TOPSIS analysis for the patient;

  Issue the severity of illness and compute the ambulance cost ;

  Commit the results on the Blockchain;

end

Algorithm 1: Hospital agent

- **Miner Agent:** Represents the miner which is in charge of solving the optimization problem/ mining algorithm and sending the solution back to the Blockchain network according to the smart contract protocol (see algorithm 2). Each hour, a new problem is solved, and a new block of solutions will be published. The first miner solving each problem will publish the new block and gets the reward in Ether. Every result is verified by ten other agents. If ten other agents get the same result, then the result is accepted (they reach to consensus) and added to network as a new block. The hospital agent and miners are both nodes of the network that have the right of sending and getting data from the Blockchain network (see Fig. 3).

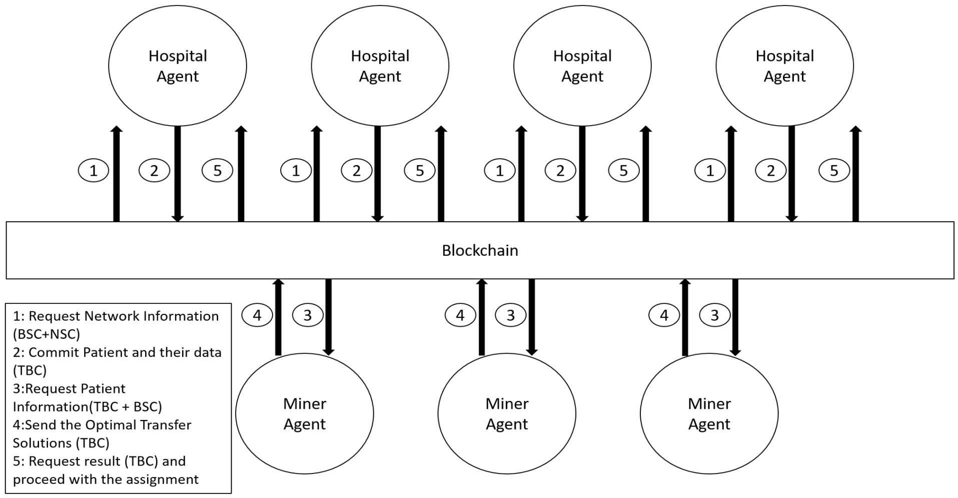

Figure 3: Blockchain and Agent-Based framework

In this study, two sets of data (Oncology and Cardialogy) are used in the simulation model. The oncology data, derived from the Breast Cancer Wisconsin (Diagnostic) Data Set from the UCI Machine Learning Repository, is reviewed to assess the possibility of the automated computation of severity of illness. The features are the characteristics of the cell nuclei presents in the breast image. Ten values are computed from the nuclei like the radius of the nuclei or the perimeter. The target variable is the nature of the tumor which is either malignant (1) or benignant (0). When predicted, the result would be matched with the necessary ambulance service. Malignant would raise the level of medical care to an ALS non-emergency while a benignant tumor would match it with a BLS non-emergency. The cardiology data, derived from the Heart Disease Data Set from the UCI Machine Learning Repository, is also reviewed to assess the possibility of finding several levels of illness in the targeted prediction. The features are mainly about characteristics of the patient as the age, the pain location, if the patient has antecedent, and etc. The target variable is a level of illness between 0 and 4, that can be segmented in three different levels. The level of ambulance service can be adjusted to the level of acuity. For the level of 1 to 2, we can match it with an ALS non-emergency, if the level is 3, then it is identified as an ALS emergency (level 1) and if the level is 4, it is an ALS emergency (level 2). According to El-Bialy et al. (2015), the accuracy of the prediction heart illness is up to 78% with decision tree.

Procedure: Mining Process

Request information about patients to be transferred from the TBC on the Blockchain ;
Request physicians information on the network from the NSC on the Blockchain ;
Request hospitals information from the NSC on the Blockchain ;
for *All Patients* **do**
    Request the outcomes of the matching algorithm from the TBC;
    Request the calculated ambulance costs from the TBC;
end
for *All Hospitals* **do**
    Request hospital's capacity from the TBC ;
    Request services each hospital can provide from the NSC;
    for *Each hospital's service* **do**
        Request physicians information providing the required service ;
    end
end
for *All Services* **do**
    Request costs of losing a patient;
end
for *All Physicians* **do**
    Request the maximum number of patients to be accepted per physician;
end
Compute the optimal transfer solutions ;
Send Back the result on the Blockchain;

Algorithm 2: Miner agent

Multiple software packages are connected and used to model different layers of the proposed DPAS. The intelligent diagnosis algorithm and Agent-Based simulation are coded in Python. For building the Blockchain architecture, Python (for building the Blockchain), Solidity (for building smart contract) and Geth (command line interface to run the Ethereum Blockchain) are used. The optimization algorithm is solved by the Gurobi platform.

4.1 Performance of intelligent diagnosis algorithm

The intelligent diagnosis algorithm from the PCM layer predicts the nature of a tumor (malignant or benign) as the level of acuity. We applied four different supervised machine classifiers (logistic regression, decision tree, random forest, gradient boosting) to the dataset, and selected the best model which has the best performance.

4.1.1 Data Preparation

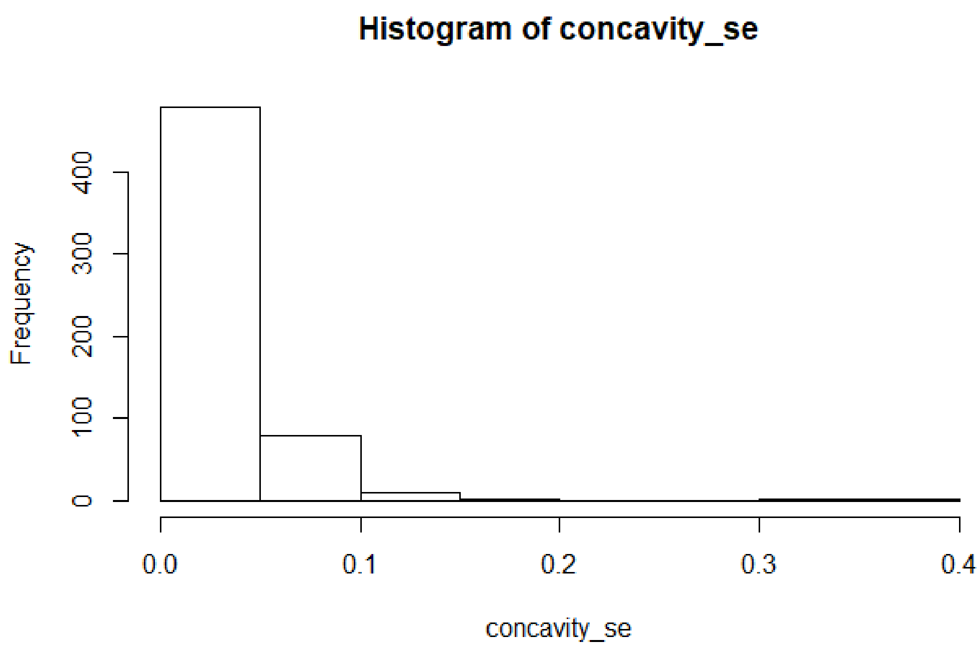

Figure 4: concavity_se distribution before transformation

The first part of this task was to prepare the data. We analyzed it and transformed it if necessary. First,there was no missing data.Concerning the distributions of the variables, a few were skewed on the the left. For example, one of the variable distribution, concavity_se, was very skewed on the left (Figure 4). Thus, it was necessary for this one to apply a log transformation to tend to a normal distribution (Figure 5).

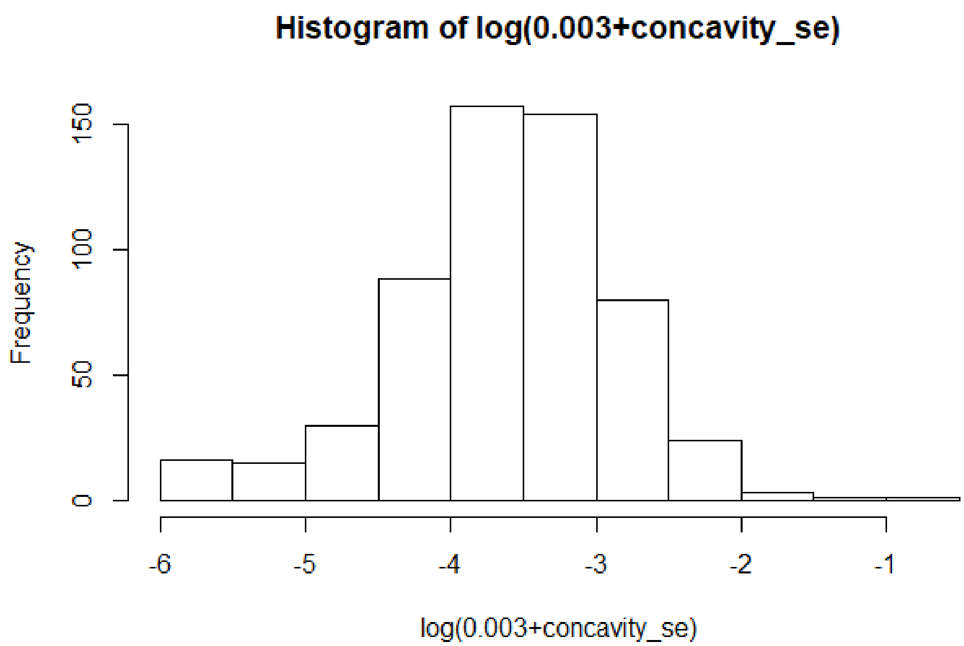

Figure 5: concavity_se distribution after transformation

Moreover, we studied the correlation among the data. After noting some high correlations (>0.75), it was decided to remove one of the two variable among the correlated couple.

Concerning the Heart Data values, no special transformation were necessary, because the variable weren't correlated, there was no missing data and there was no need to transform it because the distribution were all similar to normal distribution.

4.1.2 Training Phase

For the Breast Cancer, the results are assessed by full 10 folds cross validations and as it is shown in Table 2, Boosting Tree is giving 99 % accurate prediction on the training set.

Algorithms	**AUC Scores**
Logistic Regression	**0.9881348**
Decision Tree	0.9245608
Random Forest	0.9804228
Boosting Tree	0.9784824

Table 2: 10-fold cross validated AUC scores on the training set

The results are very close and highly accurate. To assess the superiority of the Boosting Tree over the Logistic Regression model, we performed a re-sampling on the results and a statistical t-test. The null hypothesis refers to the equal mean. The p-value (Table 3) suggests the rejection of the null hypothesis. Therefore, the results of the two methods are statistically different and the Boosting Tree model is selected as the most accurate model.

p-value	**Mean Logistic Regression**	**Mean Random Forest**
p<2.2 e-16	0.9948313	0.9846181

Table 3: Statistical Analysis of the AUC scores with resampling

NB: the results presented in Table 3 are issued after resampling to fall in a normal distribution.

Concerning the Heart Diseases dataset, we perform the same method but the results remained very different and this time the cross validation is performed with 5-folds. We based our metric on the accuracy measure this time. The task was a little bit harder because it is a multiclass prediction task.

Algorithms	**Accuracy Scores**
Logistic Regression	0.6447368
Decision Tree	0.6052632
Random Forest	**0.6710526**
Boosting Tree	0.6578947

Table 4: 5-fold cross validated Accuracy scores on the training set

Those average scores from the scores on the validation set of each rotation for each classifier show that this multitask classification is not very efficient (Table 4). We never have higher score than 0.7, wich is quite low for classifier. Nevertheless, we also checked the accuracy score to assess whether the binary classification (0 = No Heart Disease / {1,2,3,4}= There is an Heart Disease) is doable.

Algorithms	**Accuracy Scores**
Logistic Regression	0.8684211
Decision Tree	0.7368421
Random Forest	**0.8815789**
Boosting Tree	0.8815789

Table 5: 5-fold cross validated Accuracy scores on the training set for binary classification

Here we can see that the accuracy scores are pretty high so our problem is mainly about the few number of data (Table 5). The use of neural network was irrelevant also regarding the quantity of data. Actually, this kind of technic remains very gourmand in data to outperform more "classics" technics.

4.1.3 Testing Phase

As show in Figure 6, the best number of iterations for the Boosting Tree method is 15064 and this method can predict the severity of the breast cancer efficiently. To confirm the high efficiency of this model, we applied it a final time on the testing set. The result was an AUC score of 0.9760522, which is still very high.

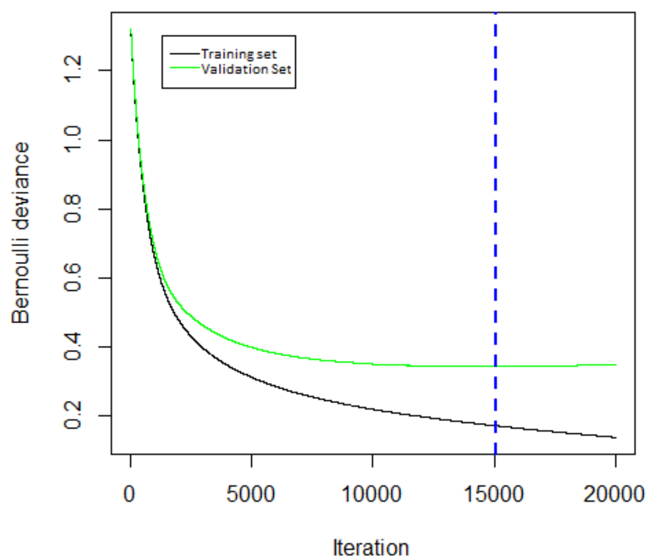

Figure 6: Bernoulli Deviance for Boosting Tree model

Concerning the other dataset, as the scores for multitarget claassification reamined low, it was judged irrelevant to go further without more data.

4.2 Performance of Mining Algorithm

We assume that the hospitals only provide two types of services, cardiology and oncology, the number of physicians in the network is 5 times the number of the hospitals, and they are distributed randomly at each hospitals (Table 6).

Specification	**Values**
Specialty	$\{Oncology, Cardiology\}$
Number of Hospitals	n
Number of Physician	$n * 5$
Distance Between Hospitals in miles	uniform $[\|10, 20\|]$

Table 6: Network Specifications

Concerning the computational power, we assume that the power of computation for the baseline scenario is inferior to what miners could provide. Hence, the baseline scenario for this experiment is run with a processor, less powerful than that of the proposed scenario. For the proposed scenario, miners are competing to get the rewards and they always try to provide the highest computational power possible. Intel Core I7-8550U with a frequency of 1.8GHz is chosen for the baseline scenario, and Intel Core Xeon E5-16070 with a frequency of 3.1 GHz is chosen for the proposed scenario.

For the baseline scenario, the objective function only includes the transportation cost and the penalty associated with the slack variables. We assume that a nurse, in charge of the diagnosis, determines the severity of illness (urgent or non-urgent) and assigns only one physician to each patient. The nurse can be doubtful about the real acuity with the chance of 10%. As a result, the maximum severity of illness (urgent) will be assigned to the patient. Patients can then accept or reject the assigned physician, according to their preferences.

4.2.1 Computational time

The computational power required by the mining is always provided by miners. The higher power a miner uses, the higher is the chance to find the solution before other miners and get rewards. Here, we compute the time it takes to solve the optimization model (mining algorithm). The parameters used in the model are given in Table 7. Fig. 7 shows the result of computational time for two scenarios when the number of hospitals differ. The proposed scenario, using the Xeon processor, has the shorter computational time for different number of hospitals.

Parameters	**Values**
Hospital	$[\|4, 32\|]$
Patient	5 by hospital $[\|20, 160\|]$
Number of CPU used per processor	1
Beds Available per Hospital	50
Cost of Loosing patient for a Service	$800
Physician Capacity	5

Table 7: Additional parameters for the simulation of computational power

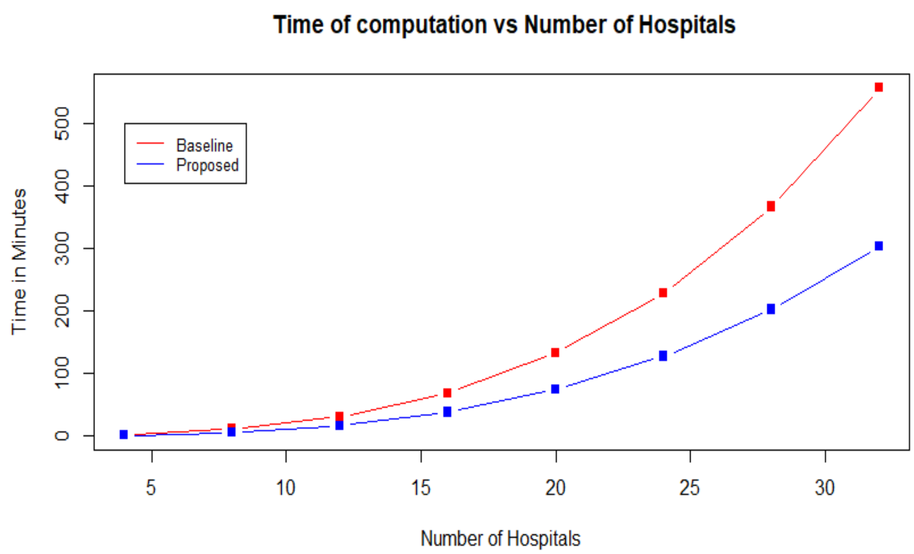

Figure 7: Computational Time for our model with two different processors

To statistically assess the difference, we computed the p-value for the obtained results. It can be observed that there is a significant difference between the baseline and proposed scenarios (Table 8). As a matter of fact, receiving the reward for computing the optimal solution is highly related to the computational power that the miners provide. Hence, the mining process can emulate the competition among the providers of computational power and gives a quality of service to the hospitals.

p-value	**Mean for proposed scenario**	**Mean for baseline scenario**
1.265e-05	302.4114 (sec)	556.1588 (sec)

Table 8: Statistical analysis of the computational time

4.2.2 Rejection rate

Another important measure of the system is the transfer rejection rate as our system is patient-centered. In other words, we measure the ratio of patients that are assigned to a physician and are not rejected by the physician to the total number of patients that need a transfer at a certain time block (equation 8).

$$PAR = 1 - (PAM/TNP) \tag{8}$$

Where PAR is the patient rejection rate, PAM is the number of patients assigned by the model and TNP is the total number of patients to be assigned. We measure the rejection rate over 24 hours for the baseline and proposed scenarios.

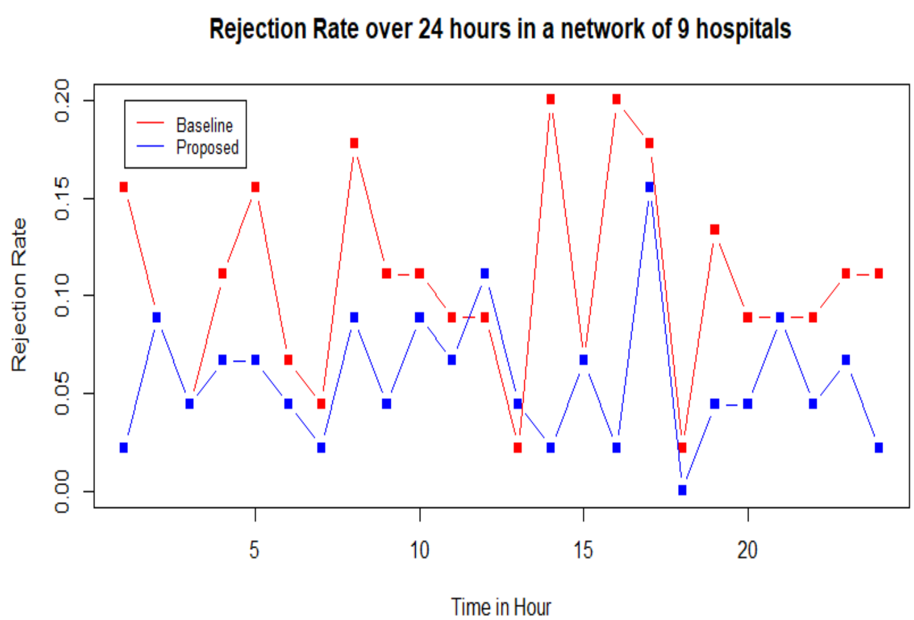

Figure 8: Hourly rejection rate for the baseline and proposed scenarios

Fig. 6 shows the rejection rates for both scenarios. It can be observed that the proposed system has less rejection rate compared to the baseline scenario. This is mainly due to the intelligent matching and diagnosis algorithms, embedded into the Blockchain architecture, which allow for exploring all possible options in the decentralized hospitals network. A *t*-test analysis has been performed to investigate the statistical difference between two scenarios. The results demonstrate that the proposed scenario outperforms the baseline scenario (Table 9).

p-value	**Mean for baseline scenario**	**Mean for proposed scenario**
0.0003646	0.10648148	0.05740741

Table 9: Statistical analysis of rejections rates

5 Conclusion

We designed a secure decentralized patient assignment system using the Blockchain technology, offering several contributions to the literature. The first and main contribution is applying the Blockchain framework to improve the existing patient referral procedures in consolidated hospital systems. In current practices, the referral process begins with receiving a call from referring hospitals. The central referral system processes the request by collecting clinical information. The nurse in the referral system identifies a physician or hospital if the referring physician has not suggested any particular physician. This initial decision can considerably influence the quality of care during the transfer process. Blockchain technology, through its technical features, boosts the security and privacy of the patient information, while it improves the interoperability between different actors in the system. Since all actors are connected in a peer-to-peer manner inside the Blockchain network, the information flow is highly fast. The actors receive the most UpToDate records from the system, meaning that any new patient assignment can be traced by the authorized actor through the Blockchain network. While most works in the literature propose a centralized system to decides about the patients transfer/assignment, our proposed system decentralized the decision making processes by providing access to the consensus algorithm and miner agents. This is accomplished through smart contracts such that all healthcare agents have agreed on its consensus protocol. The protocol is fully defined and controlled by the healthcare agents such as hospitals. Furthermore, the existence of the miners in the network ensures the sustainability of the system as miners invest time and energy to solve the assignment problem in a shorter time. Subsequently, miners get paid for their effort. The second important contribution is designing a patient centric system in which patients are involved in the decision making process. The integration of TOPSIS (to account for patients' preferences) and the Machine Learning algorithm (for automatic and accurate diagnosis of illness severity) results in an enhanced optimal solutions. Machine learning algorithms can help physician with providing more accurate diagnosis based on the data gathered from the previous cases.

In summary, the proposed system is a universal decentralized decision making architecture utilizing the Blockchain technology, relevant predictive and prescriptive analytics for a secure and efficient patient assignment system. Compared to a centralized system with subjective diagnosis system, the proposed system guarantees higher assignment rates and patients' satisfaction. Simulation results demonstrated that the proposed system has a high level of efficiency and accuracy compared to the current practice. Nevertheless, there are some limitations in this study. First, the size of datasets was not large enough (569 observations for the breast cancer data and 303 observations for the cardiology data). Hence, we trained basic algorithms to predict the severity of illness rather than more complex structures (e.g. neural networks). Secondly, the smart contract model on the Blockchain could be expensive in Ethereum if the amount of data skyrockets in real world applications. Therefore, a cost-benefit analysis would be required to ensure the scalability and the proficiency of the proposed system.

Future research may consider improving the the intelligent matching and diagnosis algorithms as well as the mathematical model. For instance, we only considered the cost of losing patients and ambulance costs. The proposed system needs to be investigated within a consolidated healthcare system for an extensive empirical analysis. In addition, more comprehensive behavior for agents involved in the decision process can improve the performance of the DPAS and make the architecture evolve to decrease the smart contract cost on the Blockchain.

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