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Blockchain Framework for Cognitive Sensor Network Using Non-Cooperative Game Theory

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ABSTRACT The incorporation of technology in healthcare and hospital management has given a new perception to the medical procedures, and drug management for patient-centric care. Emerging technologies like blockchain, Internet of Things, and cognitive computing are most adaptable for designing smart healthcare systems. However, due to the diversified tasks involved, a design approach with broader understanding involving multiple factors that represent each area of the healthcare is the need of the hour. Game theory has gained prominence in modeling multi-player problems designated by strategic interdependency. This paper proposes a non-cooperative game strategy between players (stakeholders) to inspect how rationality is exhibited among the players who seamlessly try to get benefitted from the actions of other players. To evaluate the feasibility of the proposed model, a prototype was designed based on Ethereum permissioned blockchain employing Raspberry pi IoT devices and sensor-based cognition. Use of blockchain brings in trust, security and transparency to the system. The simulation results show that the proposed model provides better outcomes in terms of latency ($\approx$15 min), throughput and scalability with an increased number of transactions. The comparative analysis elucidates the fact that the proposed method outperforms the existing healthcare systems with a significant improvement of 10-15% in terms of resource utilization and provides faster and accurate patient-centric services.

INDEX TERMS Blockchain, cognitive sensors, game theory, healthcare, Internet of Things, security.

I. INTRODUCTION

Cognitive computing is a self-learning framework that recreates the human perspectives using automated models. Attention, language, learning, memory, perception and thought are the processes that fall under cognition. Cognition computing can offer both hardware and software services. Technologies such as natural language processing, deep learning, context-aware processing and query-based methods are widely used in cognition. Applications such as virtual nursing assistant, fraud detection, and risk assessment are the most commonly used ones based on cognitive computing. Healthcare is one of the vital domains to maintain or restore human health. Pandemics like COVID-19 has resulted in rapid changes in the health care systems and has put an excessive burden on them. The policy-makers are trying to take the healthcare system to new frontiers for the betterment of the people who access it.

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Cognition in healthcare can provide intelligence to the emergency or life-support medical equipment with the help of sensors. They support monitoring of patient's body vital parameters either from bedside or from remote location. For example, a drop in the oxygen level in the patient body can immediately trigger a signal to turn on the oxygen supply. With cognition, useful information from medical records or healthcare monitoring devices can be effectively captured. All the structured and unstructured data related to healthcare can easily be analyzed and the relationship between the data and patients correlated so that effective treatments could be devised.

Data security and privacy is a huge concern in the healthcare data networks. Complex data encryption algorithms require heavy processing and memory. Since, IoT devices are constrained in terms of processing speed, memory and power, accommodating heavyweight encryption algorithms on such devices is not feasible. Patient-centric treatments, payments processing, treatment-based billing, administration cost reduction and insurance claim processing are major hurdles in healthcare sector that require immediate attention. Since healthcare requires interaction among different entities involved in the process, a strong coordination and trust is required between these entities. Game theory is useful to understand the interactions among stakeholders (players) in action. It provides sustainable gains to the players and reduces administration costs. This paper focuses on creating a trusted platform using blockchain wherein sensor-based cognition is used to identify changes in a patient's body and trigger corresponding medical services. IoT devices can store data with ensured privacy. The whole process inside the system is transparent and game theory-based strategies help in achieving the best possible outcomes for all the stakeholders in the system.

The rest of the paper is structured as follows. Section II discusses the relative works. In section III, the strategic game design, queuing and traffic models for patients are elaborated. In section IV, the hardware and software-based results are evaluated and major advantages of the proposed models are discussed and comparisons are drawn between the existing and proposed works. Section V provides the conclusive remarks.

II. RELATED WORKS

A comprehensive investigation of cognitive computing is proposed in [1]. Various evolutionary stages of cognitive computing for human-centered and cloud-assisted computing are described. The major aspects related to cognitive system architecture namely networking, analytics and cloud computing are elaborated with reference to human-centered cognitive applications. Cognition is an important component in building mash-up applications where data from multiple sources are combined into a single application that supports new services. A centralized mash-up service for environmental monitoring using cognition is presented in [2]. An Internet of Multimedia Things (IoMT) application is developed to detect hazardous patterns using wavelet transforms. Internet of Things (IoT) [3] has been used widely in providing many intelligent applications, such as smart cities, smart agriculture, smart environmental monitoring and smart healthcare. However, due to the increased IoT applications globally, optimized access control, efficient information processing and sharing is the need of the hour. Adaptation of IoT devices into the new intelligent system is a challenge. The key challenges related to the incorporation of cognition in IoT, security and privacy issues and key infrastructural details are elaborated in [4]. An ankle surgery monitoring system using convolutional neural network (CNN) architecture is proposed in [5]. This system monitors ankle features after surgery and uses cognition derived from deep learning algorithm-based classifications. Sensors play a vital role in the cognition-based architectures. A cognition module can be developed using sensors, such as Electroencephalogram (EEG), to provide state-of-the-art monitoring system for healthcare [6]. Protocols mentioned in [7] can help in identifying data loss inside the network. Efficient transmission mechanisms are essential in cognitive IoT networks to improve the throughput and reduce packet delays and losses [8]. Communication technology, security and privacy are of a huge concern in the IoT networks. The devices used in IoT networks have limited memory and processing capabilities and are battery operated. As such, powerful encryption algorithms cannot be implemented. Since the devices are heterogeneous; the use of common communication protocols between different device networks is not possible. Blockchain [9] is a powerful technology that has the potential to provide security for sensitive data networks, such as banking and healthcare [10].

Blockchain is a decentralized, distributed and trustworthy platform technology that records transactions which are immutable and shared amongst legitimate users. The information stored on the blockchain is updated regularly and all the nodes in the blockchain can view this. Scalability is a major constraint in the blockchain-based healthcare systems. By carefully optimizing the storage mechanisms and redesigning the blockchain, scalability of the overall system can be improved [11], [12]. Shard-based transactions processing, wherein the transactions are split among multiple committees, will increase the transaction throughput and scalability of the blockchain because of the parallel transactions processing. However, the processor strategic behavior is one aspect that needs to be addressed during modeling of such systems. A non-cooperative game strategy-based incentive mechanism is designed in [13] to enforce cooperation amongst processors for optimal incentive distribution. Blockchain can be used for efficient spectrum management when integrated with IoT based healthcare system [14]. The header generation time, block preparation time, data duplication and approximation errors can be reduced by using edge-based decoupled healthcare blockchain [15]. Supply chain management in healthcare is vital for effective functionality and provides cost-benefits, vendor's selections and volume discounts. Blockchain-based supply chain management provides economical and feasible solutions [16]. Blockchain based insurance processing can assess potential high-risk and low-risk patients to determine the insurance rates transparently [17]. Cognition in IoT is not a new science and finds many applications [18], [19]. Incorporating game theory in cognition based IoT healthcare systems improves the performance of the healthcare system [20].

Over the last couple of years, various game strategies were developed to enhance security aspects, network performance, and energy efficiency in the healthcare domain [21], [22]. Blockchain provides a transparent and trustworthy platform for transaction management and secure data sharing among different stakeholders of the healthcare platform, while cognition using IoT devices provides patient's critical data using sensors and provides knowledge about the processes at the patient's end without human intervention. Blockchain based game theory approaches provide trust amongst the players and immutable record keeping of every event inside the blockchain. Game theoretical approaches also improve the incentive mechanisms and allow other technologies such as IoT to work in conjunction with blockchain [23].

Wireless Body Area Networks (WBAN) provides real-time medical data. A two-stage task and priority-based resource allocation scheme based on game theory is proposed in [24]. Game theory also finds applications in mitigating the interference caused by multiple WBANs [25]. In situations such as COVID-19, where there is a rapid growth in the demand for hospital, game theory-based solutions can become handy [26]. Priority-based local data processing unit (LDPU) systems for critical and emergency care is proposed in [27]. Parameters such as urgency, priority are used to allocate the transmission slots for the LDPUs. Clustering in WBANs improves scalability and game theory-based clustering helps in better scalability with improved power utilization [28]. Cooperative or non-cooperative game theory models can be employed to control the communication between the peers in the WBANs and behavioral models can be analyzed for better controllability [29]. Blockchain based biomedical applications continue to emerge with the increase in demand for data privacy and security [30]. With decentralized systems and edge nodes, the ever-growing data from the IoT networks can be managed [31]. A proof of concept developed in [32] provides a model with off-loading provision to decrease the on-chain process and improve overall scalability of a healthcare system. COVID-19 has changed the lives and living styles of people in many ways. Management of electronic medical records, sharing among different entities while preserving privacy and security is challenging. In [33], authors demonstrate a model that provides a transparent, secured and privacy preserving data sharing and communication platform using blockchain. The impact of resource utilization on the system performance is demonstrated in [34], [35].

The transaction processing capacity and thereby the throughput of the blockchain network is the major issue that limits the scalability and performance of the blockchain. The major challenges associated with IoT and blockchain based healthcare systems that are yet prevailing are:

1. Data Privacy and security: The data stored inside the blockchain is tamper-proof. However, other nodes inside the chain can still have access to this data which is a threat to the privacy of the user.
2. Transparency: The medical processes are complex and require coordination between various entities of the healthcare systems. There should be transparency at levels including treatment, medication, billing and insurance claiming processes.
3. Interoperability: Due to the device heterogeneity inside the IoT networks, the interoperability is a concern.
4. Access Control: Most of the works provide access to legitimate users using encryption and decryption process. Such process is expensive on blockchain platform. Also, key distribution is another problem.
5. Denial/Delay in Insurance Claims: Due to the differences between the actual costs and billed costs or due to the use of unwanted medical processes, the insurance claims may be denied and delayed.

The proposed system addresses the challenges associated with the blockchain based approaches. A novel game theory-based model is designed with the objective of providing scalable, secured, and efficient patient-centric smart healthcare platform using blockchain, cognition and IoT technologies. Use of game theory in the healthcare helps to model strategies among the different entities such as patient, doctor, insurance companies and hospitals where actions of individual entities affect the actions of others. Non-cooperative game theory incorporates competition into the system wherein every player in the system autonomously strives to maximize his payoff abiding to the strategies formulated thereby providing the best possible outcomes. IoT devices deployed on-site collect patient body vital parameters and blockchain provides a trusted platform for data storage and to facilitate interactions amongst different stakeholders. The contributions of this paper are:

1. To design and develop a non-cooperative game-theory based strategy for various players in the healthcare sector in such a way that all the players compete with each other using a non-cooperative game strategy to maximize his benefits.
2. To model a secured and trustworthy platform using blockchain for immutable data storage using lightweight smart contracts-based access control for the patient's data.
3. To ensure ensures faster claims as all the records are readily available and are tamper-proof.
4. To design and evaluate the performance of the complete system prototype built using embedded processor based IoT devices and Ethereum-based blockchain platform.

III. METHODOLOGY

Figure 1. illustrates the overall processes involved in the proposed model. While developing game theory models for healthcare, most of the attention is paid towards developing quantitative relationships between a set of variables and corresponding outcomes. In the proposed healthcare model, a chain consisting of a group of hospitals, a group of insurance companies (insurers) and a group of patients is considered. The strategy adopted is non-cooperative, meaning that the players in the game are competitive and try to maximize their own profit. Internet of Medical Things (IoMT) is a common term used for IoT device networks in medical applications. Each patient that joins into the system is allotted an identification number (PID) which is unique. The patient-end devices are connected through wireless networks, such as Wi-Fi and can access the healthcare system. All the data from the IoT devices is collected by a central processing module which runs on a high-end processing machine. The central processing module is responsible for managing the different participation groups. It manages the three different groups present in the system and performs adding, deleting and

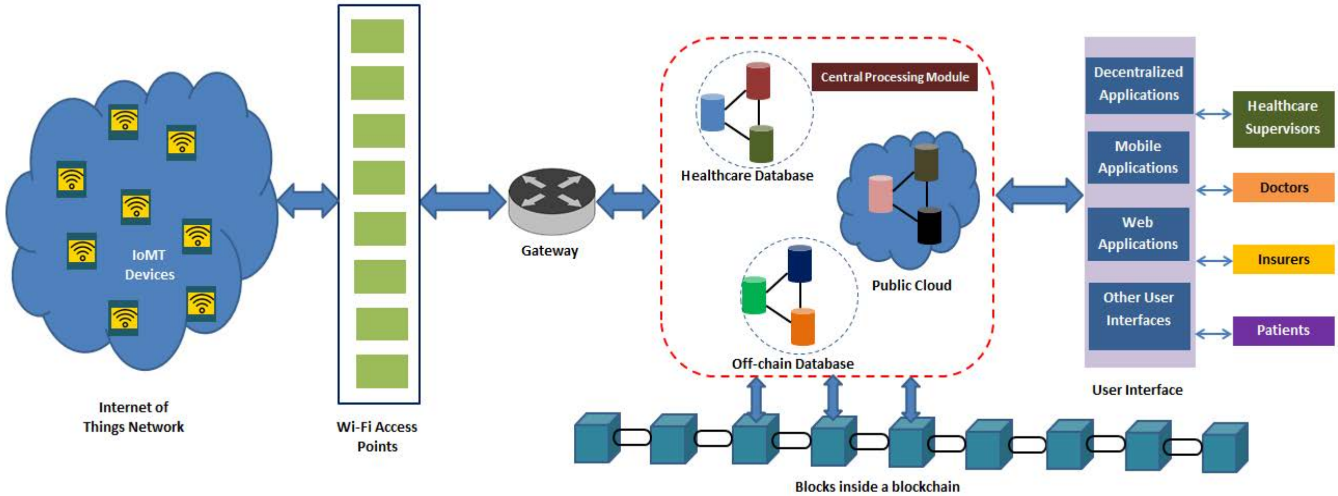

FIGURE 1. Overview of the proposed model.

report generation tasks. Rankings to hospitals and insurance companies are based on the reports generated by blockchain.

Every event in the system, such as patient admit, medication, bill processing, insurance claiming, claim processing, bill settlements, are recorded in the blockchain as a transaction. Since the platform is immutable, transparency can be maintained throughout the system. The performance of the healthcare management in terms of patient arrival, departure and resource utilization can be best assessed using queuing and traffic models. In this section, queuing and traffic models along with the game theory-based strategy are elaborated. The queuing models can be used to model the objects that seek entry and exit into the system and traffic models are used to analyze the transactional events. Following this, the technology used in the system implementation is detailed.

A. QUEUING AND TRAFFIC MODELING

The queuing and traffic models usually concentrate on understanding wait time and locating the points of congestion within the system. To develop the queuing and traffic models, the pattern in which the objects enter into and exit from the system are to be identified. The M/G/1 model proposed by Kendall [36] is apt for a generalized healthcare system. The state of the system at time t is represented as $\{M(t), t \geq 0\}$ process and $X(t)$ represents the service time. The arrival times and service times of the objects are stochastic and Poisson distributed represents the probability of a series of consecutive independent events. In this case, $p_n = d_n = a_n$, where p_n is the probability of n number of objects existing in the system, a_n and d_n are the number of objects arriving at and departing from the system. With the Poisson distribute input processes arriving at a rate λ and service times independently and identically distributed with mean $\frac{1}{\mu}$ following a general distribution $B(t)$.

Least Slack Time of $B(t)$ be represented as

$$B^*(s) = \int_0^\infty \frac{e^{-\lambda t}(\lambda t)^r}{r!} dB(t) \tag{1}$$

and

$$B^{*\,(1)}(0) = \frac{1}{\mu} \tag{2}$$

Let k_r represent conditioning on the duration of the service time of a unit and A be the number of arrivals during that particular service time of a unit. Then

$$k_r = \Pr\{A = r\} = \int_0^\infty \frac{e^{-\lambda t}(\lambda t)^r}{r!} dB(t), \quad r = 0, 1, 2, 3 \ldots \tag{3}$$

The probability generator function (PGF) of $\{k_r\}$ is given by

$$K_s = \sum\nolimits_{r=0}^{\infty} k_r s^r \tag{4}$$

$$= s^r \sum_{r=0}^{\infty} \int_0^\infty \frac{e^{-\lambda t}(\lambda t)^r}{r!} dB(t)$$

$$= \int_0^\infty e^{-\lambda t} dB(t) \sum_{r=0}^{\infty} \frac{(\lambda t s)^r}{r!}$$

$$K_s = B^*(\lambda - \lambda s) \tag{5}$$

Also,

$$E\{A\} = K'(1) = -\lambda B^{*(1)}(0) = \frac{\lambda}{\mu} = \rho \tag{6}$$

When there are bulk arrivals having a distribution $a_i = \Pr(X = i)$ are arriving at the rate of λ, the PGF is given by

$$K(s) = B * [\lambda - \lambda A(s)] \tag{7}$$

The traffic intensity,

$$\rho = \frac{\lambda E(X)}{\mu} \tag{8}$$

The queue length M can be can be represented in the form of differential equation given by

$$\frac{dM}{dt} = r - s - kM \tag{9}$$

where r is the arrival rate, s is the service rate and $kM = \sigma$ is the drop-off rate and k is the drop-out proportion. If $r > s$, then length of the queue will grow and as M increases, drop-off rate increases. This differential equation (9) has a solution given by

$$M(t) = \frac{r-s}{k}\left(\frac{r-s}{k} - M_0\right)e^{-kt} \tag{10}$$

where M_0 represents the number of individuals in the queue at time 0.

For each individual object/process P in the system, the wait time is given by

$$W_P = t_{qout} - t_{qin} \tag{11}$$

The size of the wait list in front of the individual P at time t is denoted by $Q(t)$ which satisfies (11) when time t is confined to the interval $t_{qin} \leq t \leq t_{out}$.

$$\frac{dQ}{dt} = -s - kQ \tag{12}$$

The solution for (12) is given by

$$Q(t) = -\frac{s}{k} + \left(\frac{s}{k} + Q_{t_{qout}}\right)e^{-k(t-t_{qout})}$$

where $Q_{t_{qout}}$ is the number of people in front of P at time t_{qout}.

Since, $Q_{t_{qout}}$ must be zero, the eq.no reduces to

$$Q(t) = -Q(t) = -\frac{s}{k} + \frac{s}{k}e^{-k(t-t_{qout})} \tag{13}$$

When $M(t_{qin}) = Q(t_{qin})$, $M(t)$ and $Q(t)$ are related as

$$\begin{aligned} M(t_{qin}) &= -\frac{s}{k} + \frac{s}{k}e^{-k(t-t_{qout})} \\ &\Rightarrow M(t_{qin}) = -\frac{s}{k} + \frac{s}{k}e^{-kW_P} \\ &\Rightarrow e^{kW_P} = \frac{k}{s}\left(M(t_{qin}) + \frac{s}{k}\right) \\ &\Rightarrow kW_P = \ln\left(\frac{k}{s}M(t_{qin}) + 1\right) \\ &\Rightarrow W_P = \frac{\ln\left(\frac{k}{s}M(t_{qin}) + 1\right)}{k} \end{aligned} \tag{14}$$

This is a closed form solution for the total waiting time of P when the length of the waiting time during its entry into the queue is known.

B. GAME THEORETIC APPROACH

A strategic game model is developed in this paper to provide an interactive and cost-effective healthcare system. Game theory can be an apt solution-provider to non-cooperative behavior in healthcare thereby providing mutual benefits to the stakeholders. Game theory-based strategy is represented using a tuple $\mathbb{G} = \langle I, S_{i\in I}, U_{i\in I}\rangle$ where $I = \{1, 2, \ldots I\}$ is a finite set of players and S is a set of strategies/actions for each player and U represents the utility/pay-off function. The pay-off function maps a strategy to a real number. Nash equilibrium, also known as strategic equilibrium, specifies a strategy for each player in such a way that each player's strategy yields the player at least as high a payoff as any other strategy of the player, given the strategies of the other player. In general, utility function u_i for a player i, a strategy $s_i \in S_i$ yields best response to s_{-i}(s_{-i} indicates set of players except i) if and only if

$$u_i\left(s_{i(Best\ Response)}, s_{-i}\right) \geq u_i(s_i, s_{-i}) \quad \forall s_i \in S_i \tag{15}$$

If (1) is true for all $\boldsymbol{s_{-i}}$, then it is called as dominant strategy. Figure.2. shows the workflow and Figure.3. gives the strategic relationships amongst the three players (Patient, Hospital/Healthcare service, Insurer) in the proposed model. Patients have the option of choosing any hospital or insurance agent, while the insurer tries to cover maximum medical needs of the patient through their services which are subject to change over the course of time. Hospitals provide charge-based medical services and the amount is collected from either patients or claimed from the insurance companies. Table 1 lists the strategies adapted by the players in this non-cooperative game plan. A Central Processing Module (Controller/Central Management System) manages the overall system interactions. The controller is a blockchain management module that enrolls legitimate users to the system. This module is responsible for overall system validation, transactions management, and rank assignments to the hospitals and insurance companies. The rank of the hospitals is

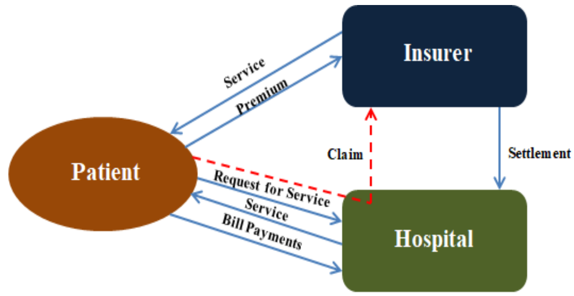

FIGURE 2. Workflow model between three players in the proposed system.

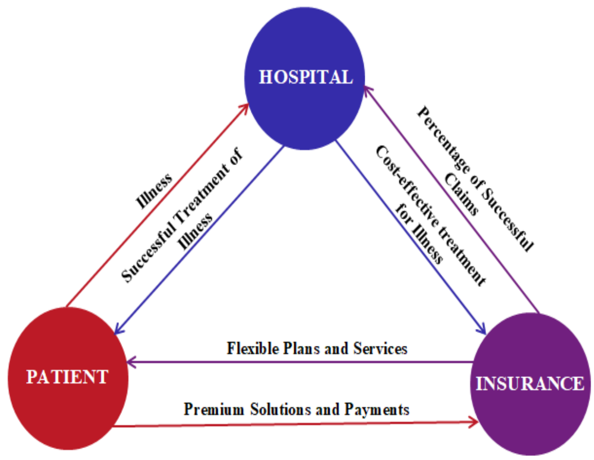

FIGURE 3. Strategic diagram of the proposed model.

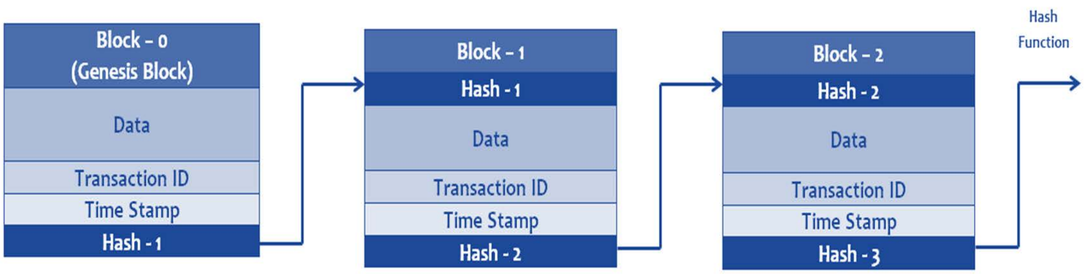

FIGURE 4. Blockchain storage mechanism.

influenced by the cost-effective treatments, success rate in curing the patient's illness and percentage of successful insurance claims made through that hospital. Similarly providing flexible premium plans and time taken for claim processing will dictate the ranking of the insurance companies. Table 2 shows symbols used in the modeling and their description.

The ill-patients' arrivals to the healthcare system are Poisson random distributed with arrival rate λ and successful treatment rate μ,. The probability of illness is determined by

$$P_i\left(N_p, \lambda\right) = \frac{\lambda^{N_p} e^{-\lambda}}{N_p!} \tag{16}$$

and

$$P_{treated}\left(N_{p\_treated}, \mu\right) = \frac{\mu^{N_{p\_treated}} e^{-\mu}}{N_{p\_treated}!} \tag{17}$$

where,

$$N_{P_{treated}} = \sum_{i=1}^{N_h} N_{P_{treated}\, i} \tag{18}$$

Nash equilibrium is established inside the system when

1. $P_i = P_{imin}$ i.e., if the probability of illness is minimum, then the number of patients turning to hospitals becomes minimum; number of claims also becomes minimum.
2. λ should be close to μ, i.e., all patients admitted into the hospital with illness are treated successfully.
3. $N_C \approx N_{Csuccess}$ i.e., all claims raised by the users are successfully processed.

To provide competition between the hospitals and insurance companies, ranking is given to each hospital and insurance companies. The rank of the ith hospital in the chain is given by

$$\Re_{h_i} = F\left\{P_{sH_i}, \mu_{h_i}\right\} \tag{19}$$

For example, during a period, T, let

- Total no of patients in the system, $N_p = 100$
- No of patients selecting the ith hospital $N_{ph_i} = 20$

The rate of selecting the ith hospital in this case is 0.2. The cumulative ratio over the consecutive time durations is given by the sum of the rates in (T1, T2, ...).

If the number of patients treated successfully by the ith hospital be $N_{p\_treated\_h_i} = 18$, then the success rate for the

TABLE 1. Strategies of individual players in the proposed game theory model.

	Strategies		
S. No	Patient	Hospital	Insurer
1	Probability of Illness.	Success rate in treating illness.	Probability of illness to be minimal.
2	Minimal premium plan	Cost-effective, Treatments, Super specialty Diagnosis (optional), Percentage of successful claims with insurer.	Flexible Premium cost.

hospital is given by $\mu_{h_i} = \frac{18}{20} = 0.9$. Similarly, for insurance company

$$\Re_{I_i} = F\left\{P_{sI_i}, N_{Csuccess}\right\} \tag{20}$$

C. COGNITION, BLOCKCHAIN, AND INTERNET OF THINGS

In the recent times, game theory use cases for blockchain has gained significant momentum as game theory helps in developing applications with optimum incentives. A processing model using game theory for blockchain is developed in [37], [38]. Off-chain processing reduces the burden of intensive computing on-chain thereby providing a lightweight infrastructure for cost-effective application development. Mining is one mechanism in which game theory can be applied. As the mining process not only depends on the computational resources of the miner but also on the resources of the other miners, a non-cooperative game strategy can be modeled to derive an efficient solution for earning rewards [39]. It can also be applied on the financial applications based on blockchain such as Bitcoin cryptocurrency. In [40], game theory-based resource mining strategy is developed to invest electricity for mining Bitcoin.

In critical applications such as healthcare, data is critical to derive insight resulting in effective decision-making. Cognition can be incorporated into the healthcare system in order to get information about the patient condition, and the resultant medical processes to be implemented. The IoT devices installed at the patient-end (wearable devices or bed-side installations) continuously monitor the patient-end activities and the data collected through sensors is stored off-chain.

The sensors connected to the IoT devices provide cognition about the environment around the patient. In the blockchain, the transactions are signed using the hash of the node address. A special node called miner will validate these transactions and stores them inside the block, periodically and adds the blocks to the previous blocks, as shown in Figure. 4. The first node in the chain is called genesis block. The data structure inside the blockchain is organized as a binary Merkle tree, as shown in Figure 5. It is evident from the structure that any fraudulent action can easily be traced back and such a transaction will automatically be discarded from the blockchain record.

Every event at the patient's end (such as opening oxygen supply valve for patient with breathing difficulty) is recorded in the blockchain as a transaction along with digital prescriptions, patient body vital parameters, and medical records. The blockchain and IoT technologies have bought revolutionary changes in the transformation of healthcare systems. Blockchain provides secure data sharing, and unaltered medical record keeping resulting in faster claim processing and treatment-oriented billing. Smart contracts are employed to provide access control to the patient's medical records and other relevant data. A smart contract is a digital agreement comprising a set of rules that all the nodes in the blockchain agree upon. Smart contracts avoid the need for employing complex consensus mechanisms to validate transactions. Solidity is the official programming language for writing smart contracts. Smart contract algorithms for patient event recording and insurer modules are shown in listings 1 and 2, respectively.

Listing 1 Algorithm for Storing Patient Events in the Blockchain

```
Input: PID, patient-event
Output: Event information is stored in the off-chain
database and Transaction is recorded.
pragma solidity ^0.7.4;
mapping (address => bool) authenticated_Patients;
 if (verifyPatient(PID))
record the details of the event in corresponding in the off-
chain
event is recorded as a transaction in the blockchain;
store the transaction hash and block number in the patient
record;
}
 else
Revert the transaction;
function public (verifyPatient(address PID) public view
return (bool approved)
 {
     return authenticated_Patients[PID];
 }
```

Listing 2 Algorithm for Insurer During Claim Processing

```
Input: PID, IC_ID
Output: Returns the patient's medical records and bills.
pragma solidity ^0.7.4;
mapping (address => bool) authenticated_Insurer;
 if (verifyInsurer(PID))
Allow access to the medical records and bills of the patient
to the insurer.
    transaction is recorded in the blockchain;
store the transaction hash in the blockchain.
}
 else
Revert the transaction;
    function public verifyInsurer(address PID) public view
                        return (bool approved)
{
 if(msg.sender == authenticated_Insurer(PID))
        return true;
    else
        return false;
}
```

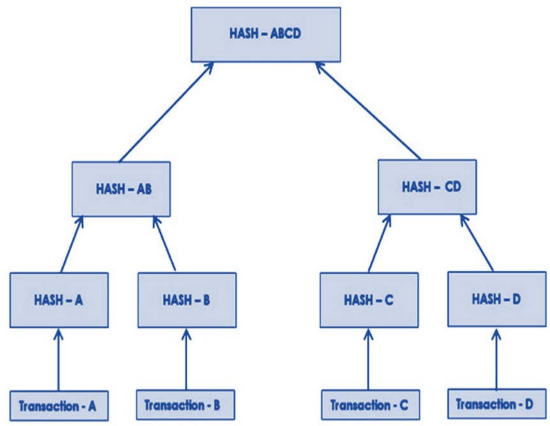

FIGURE 5. Merkle tree structure.

Smart contracts use Solidity's mapping data structures that associate address of the node to a Boolean which returns true when the user is legitimate to access the resource and false otherwise. Pysolc and Web3.py are used to access the contracts from the Python APIs. Smart contracts require less computational process in comparison to consensus mechanisms hence are able to provide economical transaction validations. Data storage is validated through smart contracts and hence only legitimate transactions are recorded. At the same time, only authorized insurance agents, hospitals and doctors can access the patient medical records hence data privacy is preserved. The conjunction of blockchain, IoT and cognition technologies makes the transactions non-fraudulent, traceable and improves the efficacy and the efficiency of the system. In the next section, a healthcare prototype is designed to evaluate the proposed design methodology. A comparative

TABLE 2. Symbols used in the modeling.

Symbol	Description	Significance	Dependency		
			Patient	Hospital	Insurer
N_p	No of Patients	No of patients currently active in the system.	✓	●	●
N_h	No of Hospitals	No of hospitals in the chain.	●	✓	●
N_i	No of Insurers	No of Insurance companies registered inside the chain.	●	●	✓
$N_{p\_treated}$	No. of patients treated	No of patients treated from any of the hospitals registered inside the chain.	✓	✓	●
$N_{p\_insured}$	No of Patients insured	No of patients insured from any of the Insurance companies registered inside the chain.	✓	●	✓
T	Time interval under consideration.	–	✓	✓	✓
λ	Arrival rate of the patient into the healthcare system	The arrival rates are Poisson distributed random function.	✓	✓	●
μ	Successful treatment rate/Curing rate of illness within the healthcare system.	This rate will define the amount time spent by the patient in the system.	✓	✓	●
$P_i(N_p, \lambda)$	Probability of illness	The probability of illness	✓	●	✓
P_{imin}	Probability of illness minimum	When the probability of illness is minimum, no. of ill patients decreases and this allows insurance companies to provide competitive premiums.	✓	●	✓
P_{sH}	Probability of selecting a particular hospital.	The probability of selecting the hospital is influenced by rating/ranking of a particular hospital (R_H) provided by the controller.	✓	✓	●
P_{sI}	Probability of selecting a particular Insurance provider.	The probability of selecting the insurance company is influenced by rating/ranking of a particular hospital (R_I) provided by the controller.	✓	●	✓
N_C	No. of claims	No of claims made by the insurance holders in a unit time interval.	✓	✓	✓
$N_{Csuccess}$	No. of successful claims	No of claims processed successfully by the insurance companies.	✓	✓	✓
$\Re_h$	Rank of the hospital	Rank of the hospitals depends on (P_{sH_i}, μ_{h_i}) where P_{sH_i} is the probability of selecting i^{th} hospital and μ_{h_i} is the i^{th} hospital's success rate in treating patients.	✓	✓	●
$\Re_I$	Rank of the insurance company	Rank of the insurer depends on $(P_{sI_i}, N_{Csuccess})$where P_{sI_i} is the probability of selecting i^{th} insurance company and $N_{Csuccess}$ is the no. of successful claims processed by that insurance company.	✓	●	✓

analysis is made at the end, showcasing the results derived from hardware and software implementations.

IV. RESULTS AND DISCUSSION

A. RESULTS

A healthcare system prototype is developed to evaluate the performance of the proposed model, with patient IoT devices, hospital management and insurers as players. The prototype uses Raspberry Pi 3 model B+ [41] boards as IoT devices on which various sensors are interfaced. A few switches are configured and attached to the bed to indicate the status of life-support systems. Ethereum [42] based permisioned blockchain is created and the IoT devices are attached to this network. A high-end computing system with 32 GB RAM and 2 TB secondary storage acts as the miner, as well as the central controller, to validate the transactions in the system. The miner uses Ubuntu 18.04 operating system, and computations are carried out using core-i7 processor clocking at 2.2 GHz. Every event, such as patient admit, medication process, digital prescriptions, storing of patient body vital parameters, are recorded as a transaction in the blockchain.

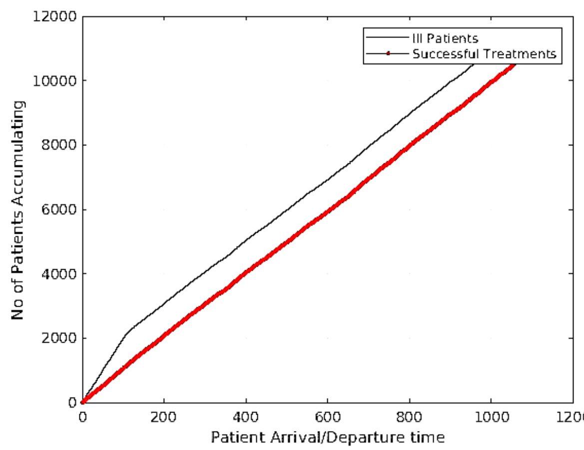

FIGURE 6. Patient arrivals and departure times in the healthcare system.

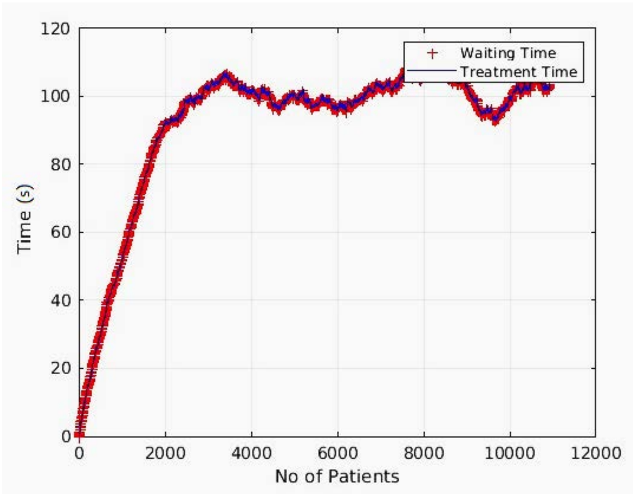

FIGURE 7. Average waiting and treatment times in the proposed system.

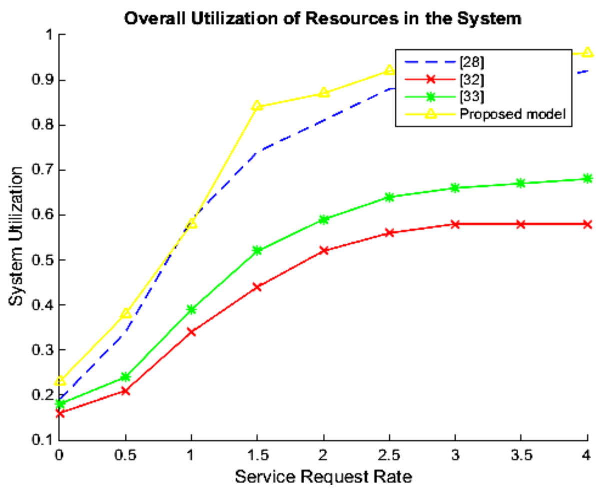

FIGURE 8. System utilization as a function of service request rate.

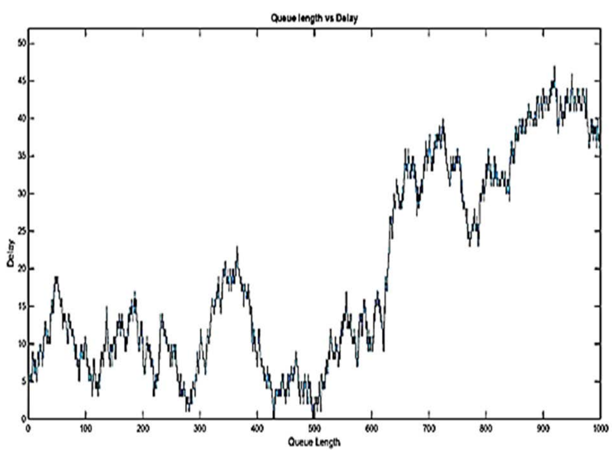

FIGURE 9. Queue length vs delay.

To increase the scalability of the overall system, only transactional information is stored in the blockchain and other data is stored in a secured off-chain storage. As the data on chain can

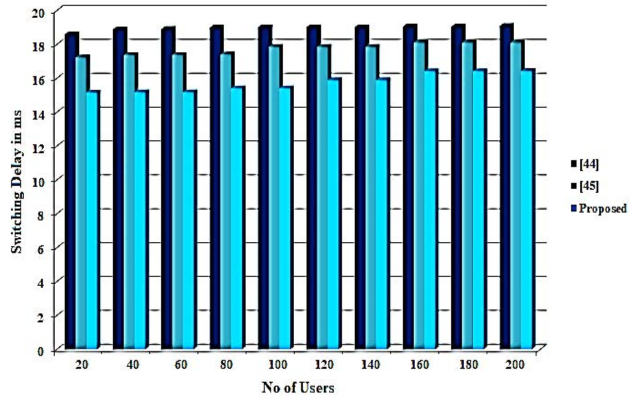

FIGURE 10. Switching delay in the network.

TABLE 3. List of packages and libraries used in the implementation.

Package / Library	Version
geth	1.9.6
ethereum	1.0.8
eth_abi	2.0.0
ethjsonrpc	0.3.0
Truffle	5.3.1
Solidity	0.7.4
Py_solc	3.2.0
Node	8.10.0
Web3.js	1.3.5
Python	3.7.3
go	1.14.2

TABLE 4. Cost involved in accessing various elements of blockchain.

Smart Contract	Cost
authenticate_patient ()	0.00271812 ETH
doctor_contract ()	0.00388938 ETH
insurer_contract ()	0.00426938 ETH
Single transaction	$\approx$ 0.000535060 ETH

be accessed by any legitimate user in the blockchain network, off-chain storage protects the privacy of the users.

Truffle [43] is one of the smart contract provisioning framework used in Ethereum Virtual Machine (EVM). This framework generates an executable byte code for smart contracts written in Solidity. Truffle supports rapid prototyping and testing of smart contracts. Using interfaces such as Web3.py, nodes can access the smart contracts. The list of packages and libraries used in the prototype are listed in Table 3. Each transaction results in consumption of gas and gas price is fixed for every transaction.The units of gas price

TABLE 5. Calculated parameters for various number of transactions.

No of Transactions	Processing Time (Sec)	Latency (Sec)	Avg. Throughput
500	0.91	7.1	674
1000	1.62	79.6	1200
1500	2.79	194.2	1600
2000	4.81	246.8	2008
2500	5.47	328.6	2010
3000	6.89	368.9	2197
3500	7.02	420.9	2350
4000	7.87	516.8	2400
4500	8.46	589.4	2610
5000	8.97	621.6	2624
6000	9.21	710.2	2741
7000	9.76	784.1	2804
8000	10.08	811.2	2985
9000	11.9	946.7	3000
10000	12.47	1021.8	3111

are *gwei* and 1 gwei $= 10^{-9}$ETH (Ethers) on an Ethereum platform. The gas price is fixed at 20 gwei in the proposed blockchain model.

The cost of a transaction is calculated as $Cost = Gas\ Spent \times Gas\ Price$. This cost becomes significant when the testing chain is connected to the public Ethereum chain. Every transaction and every access to smart contract has associated cost. Table 4 gives the costs for accessing various contracts in the implemented blockchain network. The system is considered to be stable when $\lambda < \mu$. If $\lambda > \mu$, the queue inside the system grows longer and it takes larger time interval to reach stationary distribution. Figure 6. shows the patient arrival and successful treatment timing in the healthcare system. The average waiting and treatment times are shown in Figure 7.

Figure 8 gives the system utilization and response time as a function of increasing service rates. Factors such as available infrastructure, number of users will impact the response time of the system. In the equilibrium state, the system utilization (ρ) is a measure of how busy the system is during the course of its operation. Bandwidth utilization, accurate communication between entities and use of smart contracts has significant impact on the overall system impact. The utilization provided by the proposed model proves to be superior compared to the existing schemes. For the system to be stable $\rho < 1$. Figure 9 shows the variation of queuing delay with respect to the length of queue for the overall healthcare system. The longer the patients and other stakeholders are waiting, the longer the delay will be. As the number of users entering the system increases, the amount of time the system takes to enter the equilibrium (stable) state. Latency is another important parameter that hinders the overall performance of the blockchain network, latency in blockchain is the amount of time it takes to broadcast the validated transactions to all the peers in the network. The variation of switching delay in the network is shown in Figure 10. The switching delay increases with the increase in the switching from one process to the other process and the longer these delays, the slower the network becomes. It is evident that the switching delay is less compared to the existing similar methods because the

TABLE 6. Comparison of proposed model with the existing similar woks in the healthcare domain.

Method	Description	Blockchain	Smart Contracts	IoT	Game Theory
[20]	Provides a secured and auditable healthcare platform using blockchain	✓	×	✓	✓
[21]	Two stage computing offloading strategy for resource allocation with task and user priorities in WBAN.	✓	×	✓	✓
[24]	Framework for producing secured and auditable record sharing.	✓	×	✓	✓
[25]	Blockchain based healthcare management with access control using smart contracts	✓	✓	✓	×
[26]	Cooperative game theory model designed to solve demand-supply management in multi-hospitals scenario.	×	×	×	✓
[27]	Resource allocation based on criticality of the patient in IoT based healthcare system	×	×	✓	✓
[28]	Game theory-based clustering for better scalability	×	×	✓	✓
[29]	Use of behavioral model for controlled communication in WBANs	×	×	✓	✓
[31]	Edge based scalable data management system with blockchain for scalable IoT networks	✓	✓	✓	×
[32]	Scalable integration of blockchain and IoT in healthcare	✓	✓	✓	×
Proposed Model	Provides secured trusted platform for privacy-preserved data access	✓	✓	✓	✓

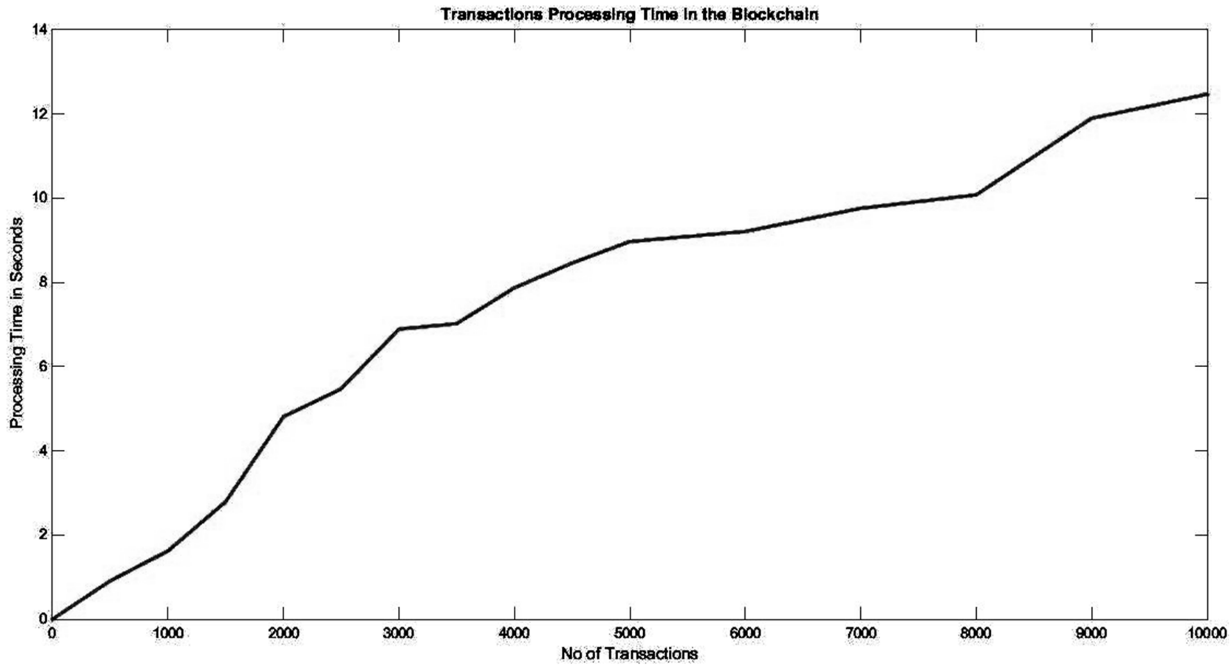

FIGURE 11. Transactions processing time in blockchain.

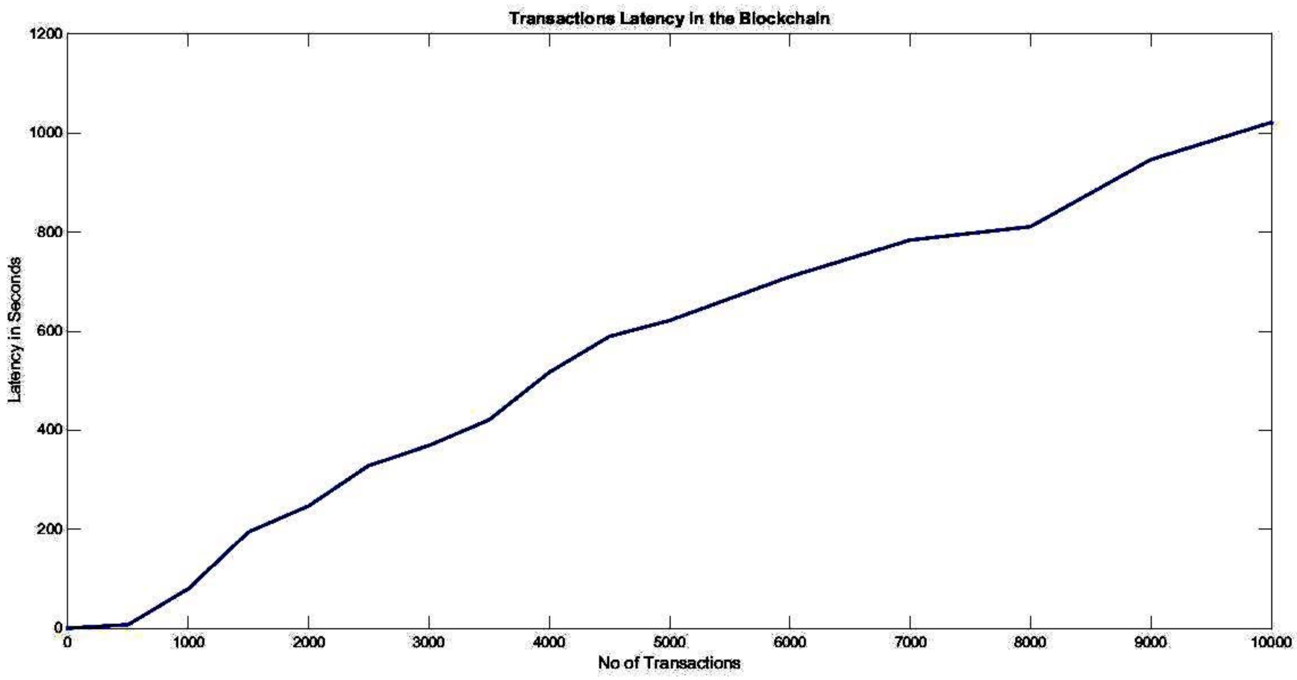

FIGURE 12. Blockchain latency with increased number of transactions.

course of actions and outcomes at each stage are predefined and little process is required at each stage. Figure 11 shows the transaction processing times in the blockchain network. The processing time increases with the increase in the number of transactions but these delays are tolerable and less than 13 seconds in the proposed method, due to the use of smart contracts. Figure 12 shows the latency in the blockchain as a function of increasing transactions. Compared to public Blockchains, latency in the proposed model is less due to the use of permissioned blockchain networks and dedicated bandwidth is available to all the nodes.

Since patient's critical data, medical records and prescriptions are stored off-chain and only transactional references are stored in the blockchain which reduces the gas

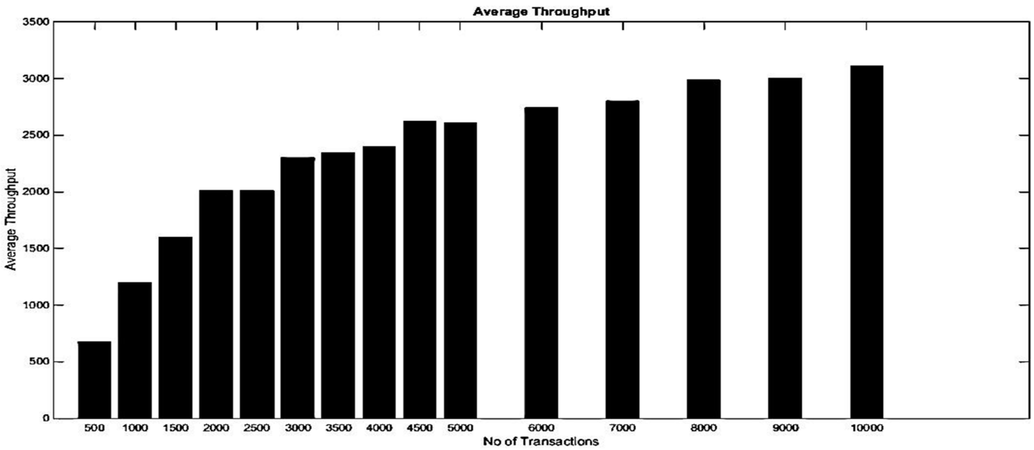

FIGURE 13. Average throughput.

consumption and improves throughput. Fig.13. shows the average throughput with an increase in number of transactions across the system. The proposed model uses smart contracts-based transaction validations (instead of consensus mechanisms) and hence the transaction rates are higher. Processing rates and latency also influence the throughput. A comparative analysis between the proposed model and the existing works is presented in Table 6. It is evident from Table 6 that the proposed model provides enhanced features o improve the overall efficiency of the smart healthcare systems.

B. DISCUSSION

Healthcare is always a challenging domain and the need for quality treatments and services at reduced costs is ever growing. With the conventional approaches failing to meet the rising demands, digital technologies can transform the healthcare sector by building trust amongst the stakeholders and providing mutual benefits. Use of blockchain provides a secured platform for data sharing and storage and immutable record keeping allows faster claim process. Overall, the developed system is transparent, autonomous, and scalable. The proposed model is suitable in environments where interdependencies among the entities in a system plays vital role. Further, this method outlines the qualitative approach that can be used by the entities of the system to derive optimal policies.

There is a vast scope for improvement in this area of research in future. With the advent of quantum computing, there is a need to shift from conventional hashing and other encryption schemes used in the blockchain and develop quantum-proof algorithms. Device authentication is another area of concern. This is essential to ensure only authorized devices are getting access to the system resources. PUF-based device authorization and mutual authentication schemes can be employed to prevent fake devices and provide secured communication among different entities. In the present work, authors implemented the prototype on a permissioned Ethereum blockchain. This system can be further extended to operate in multichain interoperable networks.

V. CONCLUSION

A novel model using non-cooperative game strategy and emerging technologies like cognitive IoT and blockchain is proposed in this model. This strategic game satisfies Nash equilibrium conditions and provides stable operational conditions. The three players in the game, doctor, hospital and insurer abide to the game rules and strategies and each user will try to get benefitted from the actions of other players. The strategy incorporates ranking to hospitals, insurers and provide best possible coverage for the patients with low premium. Blockchain platform provides an immutable and secured medical record keeping. Ethereum-based permissioned blockchain allows only authenticated users into the healthcare network. IoT devices at the patient end can perceive changes at the patient's end, such as oxygen-supply, pulse rate variations etc., and each of these events are recorded in the blockchain. The doctor prescriptions and other medical records are stored electronically in the off-chain database. To provide data privacy, the sensitive data is stored in the off-chain database, and only transaction related data is stored in the blockchain. Smart contracts are used to provide access to the off-chain data. The simulation results show that the system provides a stable operational environment in terms of latency, throughput and scales with the increased transactions. The proposed model provides a flexible operating environment wherein the interdependent communicating entities can follows diversified strategies to yield optimal results that provide mutual benefits to all the players in the system.

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