Enabling Cost-Effective and Secure Minor Medical Teleconsultation Using Artificial Intelligence and Blockchain

Anubhav Elhence, Varun Kohli, Vinay Chamola, and Biplab Sikdar

Abstract

While the onset of the COVID–19 pandemic has increased the popularity of home-based consultations, worries over privacy, high consultations costs, slow response times, and the burden on doctors due to the overwhelming number of COVID–19 cases have made current in-person and online models ineffective. In this study, we present an advanced, privacy-protected, artificial intelligence and blockchain-based consultation framework for minor medical conditions. Patients can post their medical queries anonymously on the blockchain network, which may be answered by any available medical professionals. The queries are sorted into their respective domains using naive Bayes and logistic regression. The consultations provided by medical specialists are evaluated based on their reputation, expertise, detail orientation, and the use of supporting documents, and rewards are given in accordance with the evaluation scheme. This fair and incentivized system provides cheaper and more accessible healthcare to patients, which is the need of the hour.

Introduction

Rising awareness of health and wellness across the globe has led to the widespread development of the healthcare industry. A study conducted in the United Kingdom [1] found a 40 percent increase in the number of general medical consultations in the past three decades, of which 20 percent are for minor illnesses such as coughs, colds, fevers, and sore throats. This observation was supported by a study from Norway [2], which showed that nearly 30 percent of doctor appointments were for minor medical conditions which took up nearly 20 percent of the doctors' consultation time. Furthermore, a survey conducted in the United Kingdom [3] found that 7 percent of visits to general practitioners were avoidable and could be treated with telephonic consultation, self-medication, and community pharmacists.

The unprecedented outbreak of the COVID–19 pandemic has highlighted several faults in the current healthcare systems [4]. General consultation has become a burden on doctors, and while online and telephonic methods are gaining popularity, many doctors are unwilling to attend to patients due to the lack of time and incentive. In addition to this, it is also not physically and financially convenient for many patients to visit doctors for minor issues [1]. It is therefore important to make healthcare cheaper and more accessible. Focus on self-medication and consultations by medical specialists other than doctors can be a good starting point [5].

Keeping this in mind, researchers across the world are exploring applications of modern day technologies such as blockchain, machine learning, and the Internet of Things (IoT) [4]. Recent research on the applications of blockchain technology in healthcare include medical record management systems such as MedRec [6], online primary care provisioing systems such as HealthCombix [7], and optimized medical information exchange, as seen in ssHealth [8]. Various machine learning applications have also been developed, including actionable medical inference [9], medical imaging using computer vision, and predictive modeling of diseases such as COVID–19 [10] and their monitoring [11]. With the development of 5G, IoT has also found its application in efficient healthcare and telemedicine [11, 12].

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This study proposes a novel artificial intelligence (machine learning) and blockchain-based consultation system for minor illnesses. It focuses on user privacy, medical professional verification, centralized payment, and fair response evaluation. The proposed framework incentivizes medical professionals to provide quick and high-quality consultations at substantially lower costs than the current in-person and online healthcare systems, and therefore shows promise as a sustainable and low-cost healthcare system for minor consultations. The flow of this study is as follows. We provide a detailed description of the proposed system model. This is followed by an in-depth discussion on the individual evaluation parameters and the simulation environment. We then present the results of our proposed framework and analysis. Finally, we conclude our study.

System Framework

This section discusses the proposed framework and its components.

System Flow

Figure 1 shows the five overall steps in the proposed framework:

1. **Patient queries:** Patients anonymously post their queries on the public blockchain network.
2. **Medical professional responses:** Verified medical professionals provide their respective consultation within a time limit of 48 hours.
3. **Response evaluation:** Responses are then evaluated using four parameters: reputation, expertise, detail orientation, and supporting documents. Response-scores are generated as a summation of the scores obtained for each parameter.
4. **Payment management:** A notification is sent to the patients for their payment in accordance with a centralized payment scheme.
5. **Rewards:** The medical professionals are rewarded a share of the consultation fee, in the form of Ether, based on their response scores. Ether is the native cryptocurrency of the Ethereum blockchain network. Cryptocurrencies are decentralized financial tools that remove the requirement of intermediaries (e.g., banks) to manage transactions, hence increasing trust in the proposed reward system.

Blockchain Accounts

Each individual participating in the medical consultation network must have a blockchain account. The participants may belong to any of the following three categories: patients, doc-

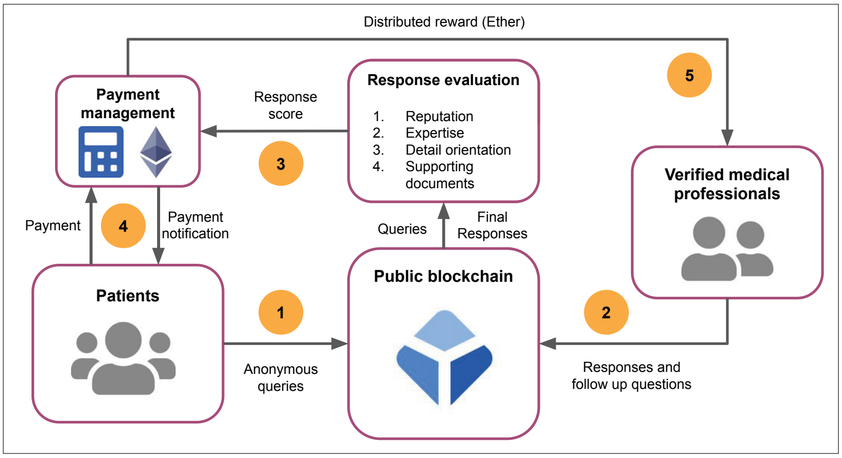

FIGURE 1. Flow of the proposed framework.

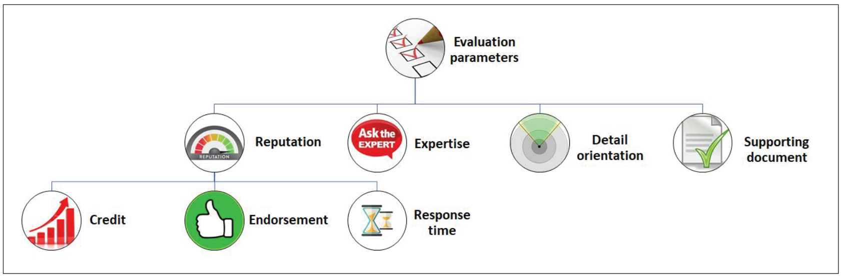

FIGURE 2. Parameters used to evaluate consultations.

tors, and medical experts (chemists, pharmacists, nurses, etc.). Doctors may hold degrees including a Bachelor of Medicine and Bachelor of Surgery (MBBS), and Doctor of Medicine (MD), while medical experts may hold a Bachelor of Science (B.Sc.), Master of Science (M.Sc.), or other degrees as required by their profession. Doctors and other medical experts are hereafter collectively referred to as medical professionals (MPs). Each person must provide their details as follows:

1. **Patients:** Patients must provide their name, age, and information pertaining to their medical history for better diagnoses.
2. **Doctors:** Doctors must provide their name, degrees, fields of specialization, post-graduate university names, and years of experience. They may also provide a link to their profile for the reference of patients and peers.
3. **Other medical experts:** Other medical experts must provide their name, degrees, university names, areas of expertise, and proof of experience, which may be in the form of published research, articles, or other appropriate documents.

Medical Professional Verification

Once the blockchain accounts for MPs are created with the aforementioned details, a verification check is conducted using the public-key of their Elliptic Curve Digital Signature Algorithm (ECDSA) signature. ECDSA is a highly secure and efficient public key cryptographic algorithm for the authentication of digital signatures. Since the public key of a signature cannot be used to tamper with the secured data, MPs must furnish the same to verify their legitimacy.

Queries and Responses

Once all participating MPs are verified by ECDSA, patients can post their medical queries anonymously on the public blockchain network. IoT devices may also be used to provide real-time telemetry data of temperature, blood pressure, and other information. Available MPs may also ask patients for details about specific symptoms and telemetry data for better diagnoses, or provide their final consultations. A sample query-response dataset is discussed later.

Response Evaluation, Payment, and Reward Calculation

Let the consultation fee paid by a patient be X. In order to incentivize MPs to provide high-quality consultations, the two highest rated responses share 60 percent of the consultation fee ($0.6X$) proportional to their response scores. The remaining 40 percent ($0.4X$) is divided among the other responses. The response scores are calculated as the sum of individual scores of four parameters, as shown in Fig. 2 (and discussed in more detail next):

1. **Reputation:** The reputation of the respondent is calculated on the basis of their degree credit ranking, peer endorsements, and response times.
2. **Domain expertise:** The expertise of a respondent is evaluated based on their area of specialization.
3. **Supporting documents:** Bonus points are awarded if a response cites trustworthy supporting documents.
4. **Detail orientation:** Additional points are awarded to relevant and detailed responses.

Evaluation Parameters

This section provides insights into the response evaluation scheme and its related concepts.

Reputation

Reputation can be defined as the amount of faith people have in an individual. In the context of our study, the reputation of MPs is a measure of their trustworthiness among patients and peers on the network to provide timely and valid medical consultations. It is calculated as the summation of three individual scores:

1. **Credit:** The qualifications of the participating MPs are provided a score based on the general credit ranking system of medical qualifications (e.g., +5 for MD, +4 for MBBS, +3 for M.Sc., +2 for B.Sc., +1 for medical engineering, +0 for any other, as used in this study). This score acts as the minimum reputation points for an MP. Great care should be taken to correctly represent each qualification. Nevertheless, while qualifications may have different credit values based on general consensus, the proposed model provides MPs with the opportunity to increase their reputation points by working on other contributing parameters such as peer endorsement and response time.
2. **Endorsement:** Peer endorsements are recommendations provided by peers to an MP's response, to increase their credibility and hence their reputation. Reputation points are awarded on the basis of the endorser's reputation score, as shown in Table 1. For example, if an MP is endorsed by a peer with a reputation of 155, they are given +10 points, as compared to when they are endorsed by an MP with 95 reputation points, in which case they are given +7 points. Endorser reputation starts with a base value of 50, and further increases based on the number of endorsements received by the endorser for their own consultations.
3. **Response time:** It is also necessary to reward MPs based on their response times. But doing so may lead to a decrease in the quality of their responses. Therefore, to maintain a healthy balance between speed and quality, response times should be weighted lower than peer endorsements. For example, responses within 30 minutes of a query may be awarded 5 points, which decreases as time passes (+4 within 60 minutes, +3 within 2 hours, +2 within 6 hours, +1 within 24 hours, +0 within 48 hours).

Serial number	Endorser reputation	Points awarded
1	150	10
2	130–149	9
3	110–129	8
4	90– 109	7
5	90	5

TABLE 1. Points awarded for different ranges of endorser reputation.

Feature extraction	Naive Bayes			Logistic regression		
	P	R	F1	P	R	F1
CV	0.74	0.62	0.68	0.81	0.75	0.78
TF-IDF	0.77	0.75	0.76	0.86	0.83	0.85

TABLE 2. Query classification results of naive Bayes and logistic regression for CV and TF-IDF.

Domain Expertise

The domain expertise of an MP is defined by their field of specialization. Queries are classified into their respective domains using machine learning, and MPs with a specialization in the same domain as the query are awarded +10 bonus points for their consultation. Bonus points are not awarded in the absence of such a specialization.

1. **Dataset and pre-processing:** We use the Healthtap dataset [13] for question-answer models in our study. It contains 1,048,575 question-answer pairs across 226 domains. We convert sentences to lower case, and remove categories with less than 1000 question-answer pairs.
2. **Feature extraction:** Feature extraction is the process of transforming a dataset into its relevant aspects. In the case of language models such as this, these features may be the frequency of a word, or its semantic and grammatical similarity with other words.

We use two common frequency-based feature extraction methods for our study, namely count vectorization (CV) and term frequency-inverse document frequency (TF-IDF). Both of these methods are available in the sklearn python toolkit. CV converts language data into matrix notation. The rows and columns comprise the corpus documents (pre-processed queries) and corpus terms (individual words), respectively, while the values in the matrix represent the frequency of each corpus term in a document. Considering equal weight assigned to both relevant terms and stop words in CV, it is important to filter out stop words. In contrast, TF-IDF does not require stop words to be filtered due to the IDF assigned to them, thereby lowering their influence on the extracted features. The TF of relevant terms is weighted proportionally. In general, terms with greater significance in a document have higher TF-IDF scores. TF-IDF provides the frequency of a term relative to both the document and the entire corpus.

3. **Machine-learning-based classification:** The features extracted from CV and TF-IDF are provided as inputs to two common machine learning classification algorithms: naive Bayes and logistic regression. As discussed earlier, +10 points are awarded to responding MPs whose area of expertise corresponds to the predicted domain of the query.

Naive Bayes is a probabilistic, supervised machine learning algorithm based on the Bayes theorem. In the context of this study, the naive Bayes model provides the likelihood of each set of input features of a query document from the Healthtap dataset to belong to a particular domain. The domain corresponding to the highest probability is selected as the predicted category.

Logistic regression is another supervised machine learning model for classification problems. It predicts one-hot encoded vectors with values between 0–1. Each output vector value is obtained from a sigmoid function. The category with the highest predicted value is taken as the predicted category. The logistic regression model is trained using a loss function (in our case logarithmic loss), which evaluates the closeness of a prediction to the actual category. A more accurate prediction has a lower loss value, while a less accurate one has a higher loss value. An optimization algorithm (popularly Adam or stochastic gradient descent) uses the loss value as well as the defined learning rate of the algorithm to adjust the model's parameters for better future predictions. In this study, the inputs given to the logistic regression model are the query feature vectors, and the outputs are vectorized domains. The performance of the two classifiers is evaluated based on the three common evaluation metrics: precision (*P*), recall (*R*), and F1-score (*F1*), as discussed later.

Supporting Documents

Bonus points are awarded to MPs based on the types of supporting documents used. Peer-reviewed publications are given +5 points, while blog posts and articles are awarded +2 points. Any other document is given +0. In addition, MPs with expertise matching with a question's domain need not provide a supporting document, and are by default given +3 points. If such an MP provides a document, they are awarded +2, making their total score for this parameter +5 points.

Detail Orientation

Responding MPs are also awarded points on the basis of the detail orientation and relevance of their responses. This is achieved by creating a list of all the words from every response document to form a bag of words. Stop words are removed using the Natural Language Tool-Kit (NLTK) library in python. Based on the list of keywords obtained, a cosine similarity score (CSS) is evaluated as a measure of the alignment of the response to the domain. For example, the responses to a query on dialysis can be expected to contain terms such as potassium, kidney, and banana. Therefore, such responses would have a higher CSS as compared to those lacking these keywords.

Once the CSS of each response is evaluated, every response above a 0.30 threshold is awarded bonus points. The highest ranked response is awarded +10 points. The next three responses are each given +7 points, and all remaining answers above the similarity threshold are given +4 points each.

Simulation Environment

This section discusses the dependencies used to create the proposed medical consultation model. The blockchain framework is made using Node.js. The Node Package Manager (NPM) contains dependencies such as Ganache, which is our local blockchain. We also use the Google Chrome extension Metamask to bind the Metamask Ethereum Wallet with the Ganache blockchain. In addition, we use Truffle Suite for tools such as Mocha and Chai, which are used for testing and assertion, respectively, in the Ethereum smart contract.

Several python libraries are also used. NLTK is used for pre-processing (cleaning, sentence casing, stop word removal, and bag of words). Sklearn is used for feature extraction methods (CV and TF-IDF) and machine learning algorithms (naive Bayes and logistic regression). Lastly, Pandas is used for data management, while matplotlib and seaborn are used for data and result visualization.

Results and Discussion

Table 2 shows the overall results for the classification of queries into respective domains by naive Bayes and logistic regression classifiers on the Healthtap dataset. It can be seen that TF-IDF has higher *P*, *R*, and *F1* values as compared to CV for both naive Bayes and logistic regression classifiers. The proposed logistic regression model performs substantially better, with *P*, *R*, and *F1* of 0.86, 0.83, and 0.85, respectively as compared to 0.77, 0.75, and 0.76 for the naive Bayes classifier.

Question	Response number	Response	Reputation			Expertise	Detail orientation (CSS)	Supporting document	Reward ($)
			Respondent	Response time	Endorser reputation				
Can a dialysis patient eat a banana?	R1	Should be avoided generally but occasionally half banana can be eaten 6 hours before dialysis.	Pharmacist Master of Science (M.Sc.)	10	115	Pharmacy	0.36	Published research	3.1
	Score	**28**	3	5	8	0	7	5	
	R2	Depends on the potassium level. If the potassium is below 5, occasionally eating a banana a few hours before dialysis is not risky.	Technician	10	96,105,155	Medical appliances	0.55	Blog	7.1
	Score	**42**	0	5	25	0	10	2	
	R3	No as it has high potassium, and that is not easily released during dialysis.	Nephrologist MD, MBBS	15	105,138	Nephrology	0.47	(NA)	**7.9**
	Score	**47**	5	5	17	10	7	3	
	R4	No. Refer to attached document.	Doctor MBBS	70	98	MBBS	0.00	Published research	3.3
	Score	**29**	4	3	7	10	0	5	
	R5	No high potassium diet is recommended such as bananas, coconuts,s, mangos, and so on.	Dietitian Master of Science (M.Sc.)	120	98	Dietology	0.41	(NA)	3.6
	Score	**32**	3	2	7	10	7	3	
								Total consultation fee:	**25**

TABLE 3. Response scores and $ equivalent rewards for a sample question-answer dataset on dialysis.

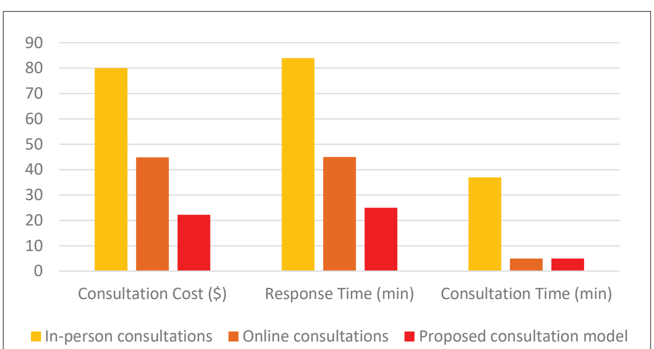

FIGURE 3. Comparison of consultation cost, response time and consultation time of in-person consultation, online models, and the proposed framework [15].

As discussed earlier, the final score of a response is calculated as the sum of its scores in the four discussed parameters. Table 3 provides results for a sample query-response dataset using the proposed evaluation scheme. The patient's query lies in the category of nephrology and dietology, wherein nephrologists, doctors, and dietitians are given bonus points (+10) for expertise, while the remaining MPs (technician and pharmacist) are given no bonus points. The table also shows the CSS for the five responses. R2 has the highest CSS of 0.55 and therefore gets +10 points, while R1 (0.36), R3 (0.47), and R5 (0.41) are given +7 points. Furthermore, R4 (0.00) is awarded 0 points since it is below the 0.3 threshold.

As seen in the table, the doctor (MD, Nephrology, R3) achieved the highest response-score of 47 among the five responses due to an overall high score across all parameters. The other doctor (MBBS, R4) could only gain a score of 29 despite their expertise bonus. In contrast, a technician (R2) with no expertise bonus attained a score of 42 due to their quick response time, good endorsements, the highest detail orientation (CSS), and the use of a blog. This result shows that the proposed framework provides higher incentive to the quality and speed of a response in comparison to the base qualification itself. In addition to this, out of the total consultation fee of $25 as taken in this example, R4 and R3 gained proportional rewards ($7.9 and $7.1, respectively) from 60 percent ($15) of the fee. The remaining responses received their proportional share of rewards from the remaining 40 percent ($10) of the consultation fee. These rewards are given as Ether equivalents. It is also worth noting that while the doctor (MBBS, R4) may have provided a short response (possibly due to a shortage of time), they provided a published research paper to support their response, and therefore rewarded for their effort.

Figure 3 shows a comparison of the expected consultation costs, response times, and consultation times of the proposed framework with the current systems. In comparison to a preliminary study by the Organization for Economic Cooperation and Development Statistics [14], the average consultation cost for patients in the proposed model is expected to be significantly lower than the current in-person ($80) and online ($44.8) consultation systems. In addition, due to the presence of a centralized, transparent reward system, all consultation rewards are fair. Additionally, we estimate the average response time for MPs in the proposed framework to be under 30 minutes due to the incentive for quick responses. This response time is lower than the current systems (84 minutes for in-person and 45 minutes for online [15]). Furthermore, the consulting time is expected to be on par with the current online/telephonic consultations [15].

Conclusions

In this article, we propose an incentivized machine learning and blockchain-based framework for minor medical consultations to tackle the flaws of current online and in-person medical consultation systems. The system incentivizes both quality as well as speed of responses, leading to patients getting the best consultation from the available medical professionals at rates lower than current systems. The medical professionals receive rewards in the form of Ether by providing medical consultation to queries on the blockchain consultation network. The rewards are calculated on the basis of a response score, which is evaluated by considering four parameters: reputation, expertise in the domain, supporting documents, and detail orientation. In addition, the proposed centralized reward system provides fair rewards to all participating MPs. As projected by the study, the proposed model has the lowest consultation charges and response times among current in-person and online consultation systems, and therefore can successfully provide cheaper and more accessible healthcare to all patients for minor illnesses.

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