Leveraging Blockchain to Improve Clinical Decision Support Systems

Vidya Soundararajan MD, FACOG, MSHMI [1] Bonnie McDaniel [1] Jiyo Shin MD, FAAFP, MSHMI [1] Sweta Sneha, PhD [2] Vijayaraghavan Soundararajan, PhD [3]

[1] WellStar Health System, Marietta. GA 30062
[2] Kennesaw State University, Kennesaw, GA 30144
[3] Vmware, Palo Alto, CA 94304
Soundararajan917@gmail.com

Abstract: Clinical decision support systems (CDSS) fail to reduce medical errors because they are unable to interact actively with various sections of the electronic health records (EHR) and provide context-appropriate alerts. The shortcomings of the CDSS increase the cognitive burden to clinicians, worsen alert fatigue, and increases the duplication of tests and health care costs without improving patient outcomes. An architectural framework that leverages together CDSS with a blockchain platform and smart contracts can provide a convenient abstraction that has the potential to solve this problem. We performed a literature search using the keywords CDSS, EHRs, blockchain technology. We manually and electronically looked at papers that were published from 2000-2018. We used CDSS, blockchain, EHR as keywords using the PubMed and Medline databases. The search returned 2338 articles which we narrowed down to 73 manuscripts that were relevant to our research identifying the gaps in the current EHR and CDSS environment. This paper identifies the shortcomings of the current CDSS and propose an architectural framework of a CDSS that utilize blockchain technology with smart contracts that interacts well with clinical workflow, reduces the cognitive burden to the clinician, eliminates irrelevant alerts, duplicate tests, and improves patient outcomes. The proposed architectural framework is designed with the goal of provisioning holistic information at the point of care thereby empowering the physicians with an integrated CDSS which holds the potential to reduce physician burnout, reduce healthcare costs, and improve patient outcomes. We use the STARR format for this research study.

Keywords: Clinical decision support system (CDSS), Electronic health records (EHR), Architectural, Framework, Blockchain.

1 Introduction

Clinical decision support systems (CDSS) are defined as knowledge systems integrated with EHRs that use two or more items of patient data in conjunction with evidence based clinical guidelines to generate case-specific advice[1]. CDSS also alert providers to potential problems such as medication interactions and can provide streamlined follow up instructions for patient care. The goal of a CDSS is to deliver the right information to the care team in a timely manner through a channel that conforms with clinical workflows and in a format that assists the provider with reaching the proper diagnosis.[2] In their current state, clinical decision support systems exist in a closed loop system and rely on historical events rather than evidence-based data[3]. The output from these systems follow an IF-THEN framework for triggering alerts and in creating the diagnostic report for the provider. The programs perform their function in an ordered, systemic manner of collecting inputs, analyzing the data and creating outputs [4].

The current design of clinical decision support systems has fallen short of the intended goals of improved medical outcomes due to a lack of efficacy [5]. Although integrated with the EHR, CDSS systems are not patient or context specific which leads to the increased firing of irrelevant and inappropriate alerts [6]. The CDSS can only use the structured patient data that is siloed in the individual providers' EHR that may not interact with other EHRs. The patient medical record is incomplete; therefore, the CDSS cannot take advantage of large data sets to provide physicians with the probability of an adverse condition or medication reaction [7]. Providers independently must search various areas of a patient chart to obtain the information they need and to assimilate the information: a time-consuming task. Current CDSS inundate the physician with big data without context specific filters. Physicians must expend cognitive energy to review and decipher unnecessary information which leads to an increase in cognitive burden [5]. This overload leads to inefficiencies and gaps in clinical workflows and increases the rate of provider burnout [8]. An interface between a CDSS and a patient medical record that includes a patient-specific and diagnosis-specific history would allow the CDSS to provide appropriate diagnostic recommendations that are specific to the patient's medical history [9]. Furthermore, the transaction of information is instantaneous and provides real time guidance for the clinician in a nonobtrusive fashion. This real time, instantaneous information that is context relevant and patient specific, allows the physician to evaluate a patient, and make appropriate decisions in a quick and efficient manner [10].

For example, a provider prescribes a blood pressure medication for a 90-year-old woman with diabetes and a serum creatinine level of .8 and the CDSS generates an alert stating the medication is contraindicated during pregnancy. Clearly the individual is not pregnant; thus, the alert is irrelevant and considered a nuisance by the physician and is ignored. However, along with an alert regarding pregnancy, there may be an alert that emerges that suggests that the medication is contraindicated in a patient with renal disease. This alert may be relevant and critical, however, because a nuisance alert had popped up at the same time, both alerts may be ignored, and patient harm can occur [11]. Some CDSS software allow adjustments to reduce some of the nuisance alerts; however, the fundamental problem is the alert is triggered by the medication. The CDSS scans its information on the medication and lists the various interactions (which are not context based) for the medication alerts [12]. This routine leads to alert fatigue which leads to clinical error. Ideally, the clinical decision support system should be able to extract not only the name of the medication prescribed, but relevant information about the patient (labs, gender, age and medical problems/surgeries) and refine the number of alerts generated [13]. In the example stated, the CDSS should be able to extract the patient age, 90, her medical problems (hypertension and diabetes), important labs (creatinine .8), to use this clinical context to scan its database of interactions and conclude that no alerts should be triggered. A context-based CDSS reduces alert fatigue and also reduces the cognitive burden to the physician by only producing appropriate alerts.

Currently, EHRs are not designed to store the patient information and allow the CDSS to utilize it actively and simultaneously. Rather, both systems function in a dyssynchronous fashion and create delays in patient care [14]. Additionally, because of the lack of interoperability, the partial patient information is siloed in a provider's EHR and the provider cannot access critical information from other hospital systems. This lack of interoperability leads to the duplication of tests and efforts and places additional cognitive burden on the physicians to assimilate information from various sources [10].

Various departments (pharmacies, nurses, providers) and clinical settings utilize the CDSS simultaneously; it is imperative that the source of the clinical information from which the CDSS pulls its information is immutable, portable, and irreversible in order to provide clinical consistency and prevent errors [16]. However, for the CDSS to function in this manner, it needs to be interoperable with multiple EHR systems, laboratory systems and pharmacy systems. When the CDSS is embedded separately in each of these entities, multiple interfaces are needed to be maintained or the CDSS can malfunction [15,16].

Therefore, if a platform existed that could store the patient's clinical information as a base layer coupled with an interface between this base layer and a nonintegrated clinical decision support software system, EHRs and outside sources would only need one interface to the CDSS.

Blockchain technology together with smart contracts hold the promise of providing a secure platform where once validated, irreversible patient data can be shared and aggregated amongst providers [17]. Blockchain allows for secure and scalable data sharing to enhance clinical decision making [18].

A CDSS linked to a medical record blockchain could alleviate cognitive burden for the physicians by utilizing patient specific information, prevent the duplication of diagnostic studies, and eliminate inappropriate alerts. By alleviating these problems, we would reduce patient errors and consequently improve patient outcomes. If the complete patient record were stored on a blockchain and an interface existed between the blockchain and the CDSS, the CDSS could use the data in its algorithms. The algorithm results would be sent real-time to the provider via an interface between the CDSS and the EHR. Any alerts or suggestions triggered by this workflow would be context-driven and clinically accurate.

The research question that we address is: How can relevant holistic patient information be made available to the healthcare providers at the point of care with the goal to enable well informed clinical decision making thereby improving patient outcomes and reducing inefficiencies in healthcare delivery and practice. Our research objective is to provide an architectural framework of a CDSS that interacts with EHRs by leveraging a blockchain platform where patient data is stored as connected blocks. The proposed CDSS has the potential to provide an integrated holistic view of all patient information at the point of care thereby enabling the provider team to make well informed clinical decision in a patient centered environment while addressing current issues of inefficiency and interoperability. We utilize the STARR format in our research as described below:

Situation: Clinical decision support systems (CDSS) fail to reduce medical errors because they have been passively embedded into Electronic Health Records (EHRs). Furthermore, each entity that interacts with EHRs (pharmacies, labs, radiology) have their own embedded CDSS. Each CDSS utilizes the siloed information to trigger alerts. This passive incorporation leads to the massive triggering of inappropriate alerts that increase the cognitive burden to clinicians and leads to provider burnout, alert fatigue, duplication of tests, and rising health care costs without improving patient outcomes.

Task: To keep the CDSS independent of the EHRs and to create a digital platform that can contain a complete set of patient records with which the EHRs and the CDSS can interact. With access to the complete patient records, the CDSS can create context-driven appropriate alerts and that actively assist health care providers with timely clinical decisions. More appropriate alerts that are context-driven can reduce alert fatigue, reduce provider burnout, reduce health care costs and improve patient outcomes. Blockchain technology provides a potential solution as a digital platform that contains a complete set of patient records.

Approach: We design an architectural framework that leverages blockchain technology to improve existing Clinical Decision Support Systems (CDSS).

Result: We design an architectural framework that leverages blockchain with CDSS to produces context-driven alerts which results in fewer inappropriate alerts, reduces physician burnout, reduces duplicate test ordering, decreases health care costs and improves health care outcomes. The design is not yet implemented at a healthcare facility. We provide details of a case scenario to test the validity of the proposed architecture.

Reflection: In this paper, we provide an architectural framework that leverages blockchain technology with CDSS. Future research will focus on implementation and validation of the proof of concept. The current limitations of the architectural framework include but are not limited to the following: the scalability of the CDSS; the security of the patient data once it is in the blockchain format; the last mile issues of converting the off chain patient data to on chain structured patient data.

2 Background CDSS, Blockchain and MedRec

A CDSS links patient data with a knowledge base to generate information and suggestions that help providers improve the health care they deliver [3]. At a high level, blockchain technology is a platform for directly and securely sharing audited, permanent data based on permissions granted by the owner of the data [17].

2.1 CDSS

Clinical decision support systems (CDSS) are defined as knowledge systems integrated with EHRs that use two or more items of patient data in conjunction with evidence based clinical guidelines to generate case-specific advice [1]. According to Berner et al., CDSS software incorporates the generic steps in input, processing and output: (i.) The patient-specific data is entered by health professionals involved in the care, (ii.) processed and linked to knowledge stored in a database, and (iii.) notifications are communicated back to clinicians [19]. According to this concept, if the patient knowledge is stored in the same database, the CDSS can be effective in reducing clinical errors. However, when patient knowledge database is heterogenous and siloed in various databases, the CDSS becomes ineffective in reducing clinical errors and increases the cognitive burden for clinicians and increases the number of inappropriate alerts and does not reduce the duplications of tests [15]. Huang et al describe a CDSS based on heterogenous data sources that can assist inexperienced physicians with the diagnoses of complex illnesses [20]; however, without the interoperability of databases, it is difficult to create a common consistent patient knowledge base from which a CDSS can receive its input and provide accurate clinical outputs [21]. Goldberg et al describe an enterprise clinical rules service that utilize a single, logical service that can replace innumerable discrete decision support modules that uses API to connect to the EHRs [22]. The system utilizes numerous patient databases with a single CDSS. One of the limitations of the ECRS is the caching of patient data is not available beyond the boundary of a single decision support transaction [21]. The diagram and summary table below show the current state of information flows in an EHR based clinical decision support system When all of the patient data is in a single database or a single prevention is evaluated, this model works well [15].

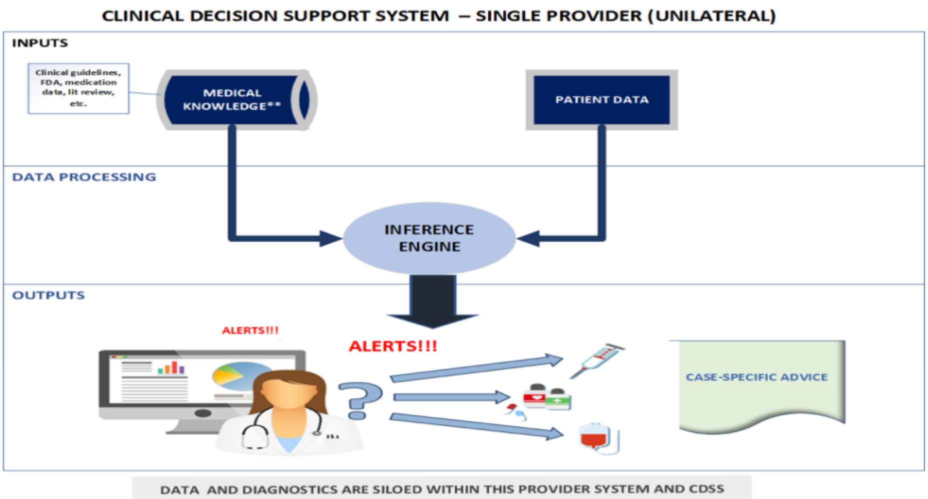

Fig. 1. An illustration of the current state of data flow in a clinical decision support system.

Figure 1 is an illustration of the current state of data flow in a clinical decision support system. The inference engine, which is embedded in the EHR utilizes structured patient data entered by the provider with evidenced based guidelines and triggers alerts when key words are identified. The CDSS is passive, can only act upon a single decision support transaction, and does not actively interact with the patient data source. Ideally, the alerts are context based. However, the inference engine is limited by the data entered by the provider and cannot abstract patient information from sources outside the EHR unless an interface exists with the outside source. Figure 1 shows the current workflow of a CDSS. The data inputs interface into the CDSS in a unilateral direction. The unidirectional flow of data creates a passive rather than active CDSS [17].

Table 1. Current state of CDSS.

Properties	Purpose	Problem
Software Embedded in HER	CDSS is integrated with EHR system to assist with decision making	CDSS assessment guidelines provide generic and unnecessary information that inundates providers with too much unfiltered data and increases physician burnout.
Dataset siloed in EHR	Provides triggers for CDS	•CDS can only recognize structured data entered by providers and cannot assimilate unstructured data from outside sources. This leads to incomplete patient records which limits the efficacy of the CDS. Providers need to manually assimilate the information. The process disrupts the provider workflow and increases cognitive burden for the provider. •Critical time is wasted with manual transfer of records. •Patient is required to sign multiple forms to authorize the release of records. •Lack of access to outside records leads to duplicate testing and inefficient utilization of resources.
Alerts	Warns providers of possible interactions	Alerts not context based. Alerts tend to be intrusive. Noncritical alerts fire frequently and create alert fatigue.
Passive		Cannot pull relevant information from EHR. Results in duplicate testing.

CDSS software is embedded in the EHR systems and uses the passive steps of input, processing and output to provide alerts and recommendations. It uses the patient data knowledge source stored in a structured format to generate alerts when triggered. Since the data source is restricted to the database in the EHR, the CDSS's ability to provide appropriate recommendations is limited (please see table 1).

Current clinical decision support systems are vendor specific. The inputs are controlled by the vendor and the patient data is local to the specific provider's EHR [23]. It cannot interface with labs, pharmacies or data obtained from other medical providers who utilize a different EHR. The inference engine which utilizes the medical knowledge and the patient data for recommendations is limited by the inputs it receives [15]. It is also programmed to fire specific alerts based on criteria programmed in the EHR [19]. Therefore, alerts are not context aware and may not be clinically relevant. While the end result is case-specific, the report is not complete. Figure 1 shows the current workflow of a CDSS. The data flows in one direction from the information sources into the CDSS. The unidirectional flow of data creates a passive rather than active CDSS [17].

Ekblaw introduces a novel concept of a single patient database that is portable in the form of the blockchain platform [24]. There is now the potential to combine a portable complete patient data knowledge source with an interactive CDSS and produce numerous decision support transactions.

2.2 Blockchain and Medrec

In a blockchain network the chain of transactions is decentralized and shared amongst all members based on their granted level of permission. Transactions submitted to the chain must be validated as authentic by a consensus of experts who are compensated for validation [25]. Once consensus is reached, the new transaction in the chain is linked to previous transactions by a cryptographic hashtag and cannot be reversed except through a new transaction [26]. Information added is available immediately and becomes a single source of truth for the information being recorded [26]. Permissions to and use of data are executed through code stored on the blockchain platform knows as smart contracts [16].

Briefly, smart contracts can be thought of as code that is executed in response to accesses to the blockchain. It is called a smart contract because the action can be automated and it can access data on the blockchain and can therefore enforce the terms of the contract in an automated way [31,32].

For example, suppose a piece of data is stored on the permissioned blockchain. If the physician tries to access the blockchain via an app, the smart contract looks at the access and the physician access rights and determines if the physician is capable to access code. The smart contract either allows access or denies access as a result. The same process can be held for the CDSS and other third parties participating in the patient care.

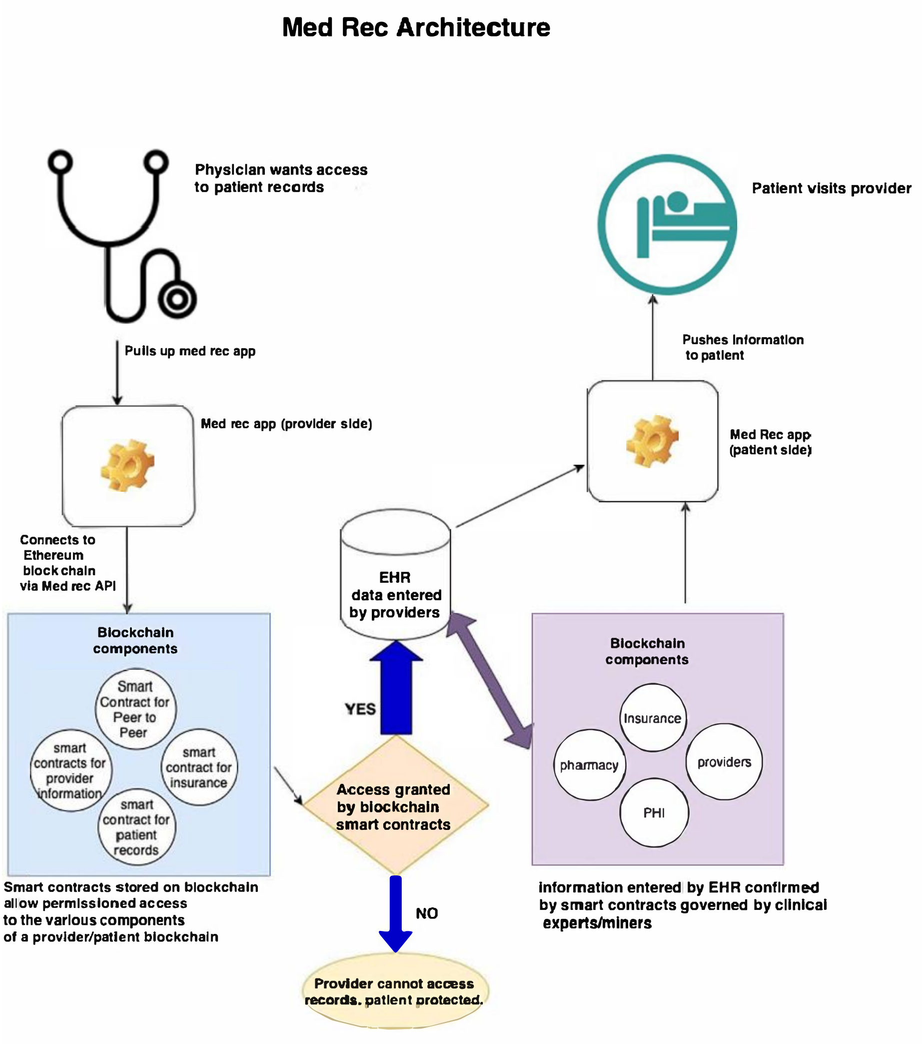

Fig. 2. MedRec system architecture [30]

Figure 2 describes the MedRec architecture. MedRec is a decentralized medical record management system designed using blockchain technology [26]. MedRec uses smart contracts built on an Ethereum blockchain and a backend API library to manage the EHR interface. The APIs illustrated above in MedRec is manage access and permissions to data recorded on the blockchain [3]. The physician registers with the MedRec App. When a provider needs access to a patient's records, they request access to the records. The Gatekeeper runs a server listening to query requests from clients. The request is cryptographically signed by the patient and allows the gatekeeper to confirm if the provider is allowed access to the query.

It is this interface that allows for the interoperability of diverse EHR systems and which would provide the data for the CDSS in a standardized format across systems. MedRec does not store the records on the blockchain, but instead points to where the record is located at the various points of service, also known as nodes [24,30]. These nodes agree to run the smart contracts as requested by the MedRec blockchain. With patient permission, the physician can access medical information across all records linked to the MedRec ledger. By utilizing an API and storing the data off chain, MedRec can simultaneously address the interoperability issue of EHRs and the scalability issue of blockchain technology [18,26,29].

The MedRec blockchain has built in capabilities for a public blockchain. The validation necessary to make the records immutable is a consortium of miners with medical backgrounds who receive incentives for agreeing that the records to be added to the blockchain are authentic [27]. On a MedRec blockchain network, the miners are incentivized by gaining access to anonymized healthcare data. This same anonymized data that is granted to the miners could also be accessed by the CDSS through additional code in the smart contract [30].

These features provide an ideal vehicle to provide accurate information that a clinical decision support system can use to assist providers and improve the delivery of health care [30].

3 Methods

A review of the literature on clinical decision support systems in Medline and Pub Med was performed utilizing the search terms "clinical decision support", "alert fatigue", "EHR and clinical decision support", "physician burnout", and "interoperability". The purpose of these search terms was to get a consensus on current issues in clinical decision support and why these issues occur. The searched revealed over 2,338 articles. We refined the search to "EHR and physician burnout" which isolated 16 articles. We discovered that many of the burnout issues were related to functionality and disrupted workflows programmed into the EHR. A literature review was also performed on "blockchain technology and healthcare" which produced 57 articles. The initial search was for terms related to blockchain in order to obtain an understanding of the functionality and current developments. We used the search terms, "blockchain", "ethereum", "smart contract", and "Hyperledger" "blockchain miners", and "nodes". After gaining an understanding of blockchain technology we focused our search on blockchain opportunities in healthcare.

4 Architectural Framework

We combined the concepts of a MedRec blockchain, which is a portable and complete patient record, with an independent, non-integrated clinical decision support system. The purpose is to provide clinically consistent output along with context specific alerts that fire appropriately. The goal of this combination is to reduce cognitive burden to physicians, provide clinical consistency with the independent CDSS thereby reducing duplicity in tests, healthcare costs and improving patient outcomes. The architectural framework is illustrated in figure 3 and the high level conceptual workflow is provided below:

1. The Medrec blockchain is accessed through the APIs built into the MedRec platform.
2. Data needed for the current clinical diagnosis follows the code built into the smart contract that retrieves the data stored "off chain" in the databases of the providers who have treated the patient.
3. The CDSS is able to assess actively this data by using the CDSS knowledgebase, algorithms and data mining techniques and to create context-based and patient specific alerts, diagnostic tests, and clinical recommendations.
4. The diagnosis, orders and tests from this encounter are then routed back to the provider database where they will feed back into the blockchain.

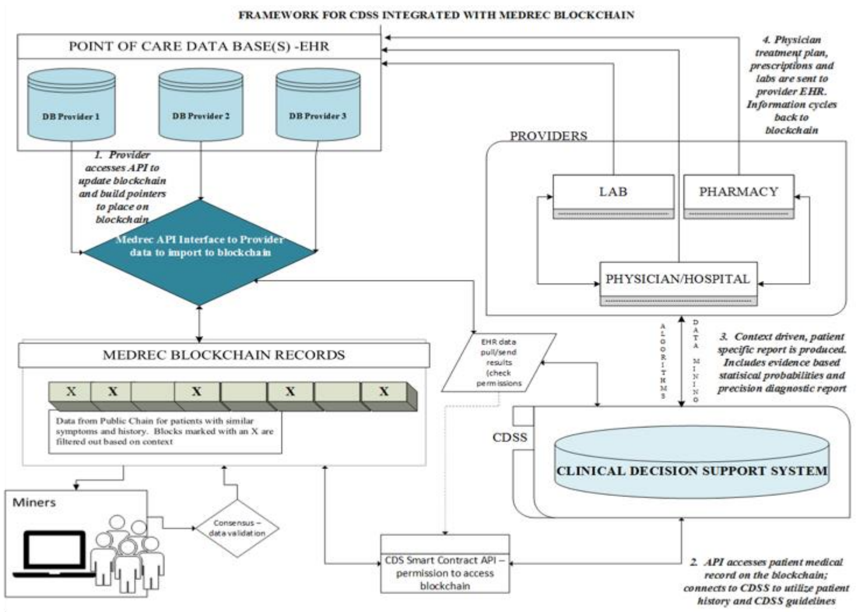

Fig. 3. An illustration of the architecture of our proposed blockchain solution to improve the CDSS.

Table 2. –Proposed Changes to CDSS

Properties	Purpose	Advantages
CDSS software is separate from the EHR. The CDSS interfaces with the blockchain platform	CDSS interacts with a consistent source of patient specific information.	CDSS able to retrieve relevant patient information to reduce duplicate tests.
Patient medical record is accessible via a blockchain interface.	Immutable portable source of patient records that is independent of the EHR system used.	•Patient records are portable. Reduced time wasted trying to collate patient records. •Patient authorization is stored electronically.
Alerts context based	CDSS retrieves relevant information from the medical records and fires alerts.	•Alerts are context based. •Fewer alerts fired. •Reduces alert fatigue.
CDSS actively interacts with the EHR	CDSS retrieves relevant information from the entered information to assist provider with decision making.	•Improved clinical care through the development of algorithms in a neural network that can assimilate data within seconds. •improved clinical workflow. •Reduces medical errors. •Facilitates precision medicine.

Figure 3 provides an illustration of the architecture of our proposed blockchain solution to improve the CDSS. Rather than the single transaction of input, process, output, the CDSS/blockchain framework will allow for multiple transactions operate on a continuous loop system that follows the steps of input, process, output, input to blockchain and store in the patient database. Information flows in a bidirectional fashion from the clinician and the patient datasource to the CDSS. This framework allows for an actively interactive CDSS that can then create context specific alerts and clinical recommendations.

4.1 Scenario for conceptual Validation of the Proposed Framework

With the proposed architectural framework, a clinical encounter would proceed as follows. A 90-year-old women with a medical history significant for hypertension and diabetes, who has been on numerous medications in the past, and a serum creatinine of 2.0 presents to the primary care provider for blood pressure management. The patient signs a consent which allows the provider to engage in the permissioned blockchain that stores her records. The physician orders an ace inhibitor for the patient. The CDSS would receive the input from the clinician and scan the blockchain datasource, recognize that the patient is 90 (not of reproductive age), identify the medical problems of diabetes and hypertension, review previous prescriptions for the patient, and recognize the serum creatinine of 2.0. A context specific alert would arise regarding the elevated creatinine and a potential contraindication for this medication with possible alternative medications. After the clinician acknowledges the alert, the information will be validated and added to the blockchain. In this situation the alert is context specific and the CDSS actively interacts with the patient knowledge source to assist the physician.

5 Barriers and conclusion

5.1 Barriers

There are potential barriers to creating this architectural framework: the scalability of the CDSS, the security of the patient data once it is in blockchain format, the last mile issues of conversion of off chain patient data to on chain structured patient data.

The MedRec blockchain points to the data in the provider EHR rather than trying to store the data in the blockchain. By pointing to the location, the speed of CDSS transactions increases and allows for scalability [28,29]. The blockchain would have to have permissioned access via the API's [26]. The potential vulnerabilities in the API's need to be tested and validated. The last mile issues of the conversion of unstructured patient data in various media formats into structured data would require further development of natural language processing (NLP). With each of these barriers comes the potential for the advancement of complimentary technological advances.

5.2 Conclusion

The current state of CDSS is ineffective as it produces irrelevant alerts that are not context based and consequently increase the cognitive burden to physicians while increasing health care costs and not improving patient outcomes. We suggest an architectural framework that leverages blockchain technology with a CDSS that is not embedded in the EHRs. This framework provides a CDSS that actively interacts with EHRs and a complete patient knowledge database and is able to produce context relevant, patient specific alerts. This architectural framework reduces the cognitive burden to the clinician, provides context relevant alerts and eliminates the duplication of tests. These attributes can reduce physician burnout, reduce healthcare costs and improve patient outcomes.

Competing Interests

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest, or nonfinancial interest in the subject matter or materials discussed in this manuscript.

References

1. Buchman, B.: Precision Diagnosis: a view of the clinical decision support systems (CDSS)landscape through the lens of critical care. Journal Of Clinical Monitoring And Computing 31(2), 261–271 (2017).
2. Khairat S.: Reasons For Physicians Not Adopting Clinical Decision Support Systems: Critical Analysis. JMIR Med Inform, 6(2), (2018).
3. Sim I.: Clinical decision support systems for the practice of evidence-based medicine. Journal of the American Medical Informatics Association: JAMIA8(6),527–34, (2001).
4. Sittig D.: Grand challenges in Clinical Decision Support. Journal of Biomedical Informatics, 41(2),387-392, (2008).
5. Miller K.: Interface, information interaction: a narrative review of design and functional requirements for clinical decision support. JAMIA, 25(5), 585-592, (2018).
6. Ancker J.: Effects of workload, work complexity, and repeated alerts on alert fatigue in a clinical decision support system. BMC Medical Informatics And Decision Making, 17(1), 36, (2017).
7. Shortliffe E.:Clinical Decision Support in the Era of Artificial Intelligence. JAMA. Published online November 05, 2018.
8. Procop, G.: Duplicate Laboratory Test Reduction Using a Clinical Decision Support Tool. American Journal Of Clinical Pathology, 141 (5), 718–23, (2014).
9. Engelhardt M.: Hitching healthcare to the chain: An introduction to blockchain technology in the healthcare sector. Technology Innovation Management Review, 7(10),22-34, (2017).
10. Kamel B.: Geospatial blockchain: promises, challenges, and scenarios in health and healthcare. International Journal Of Health Geographics. 17(1),25, (2018).
11. Phansalkar, S.: Drug—drug interactions that should be non-interruptive in order to reduce alert fatigue in electronic health records. Journal of the American Medical Informatics Association,20(3), 489-493, (2012).
12. Phansalkar S.: Criteria for assessing high-priority drug-drug interactions for clinical decision support in electronic health records. BMC Medical Informatics and Decision Making,13(1), (2013).
13. Duke J.: A Successful model and visual design for creating context-aware drug-drug interaction alerts. AMIA Annual Symposium Proceedings Archive, 2011:339–348, 2011. www.ncbi-nlm-nih-gov/pubmed/22195086 (accessed 4 Oct 2018).
14. Zikos D.: CDSS-RM: a Clinical Decision Support System Reference Model. BMC Medical Research Methodology, 18(1),2018.
15. Kawamoto K.: A. Key principles for a national clinical decision support knowledge sharing framework: Synthesis of insights from leading subject matter experts. Journal of the American Medical Informatics Association, *20*(1), 199-207, (2011).
16. Kassakian S.: Clinical decisions support malfunctions in a commercial electronic health record. Applied Clinical Informatics, 8(3), 910–923, (2017).

17. Gordon W.: Blockchain Technology for Healthcare: Facilitating the Transition to Patient-Driven Interoperability. Computational and Structural Biotechnology Journal**,** 16(6), 224-230, (2018).
18. Zhang P.: FHIRChain: Applying Blockchain to Securely and Scalably Share Clinical Data. Computational and Structural Biotechnology Journal, 7(4), 267-278, (2018).
19. Berner,E.:Clinical Decision Support Systems: State of the Art. www.healthit.ahrq.gov/sites/default/files/doc/page 09-0069-EF_1.pdf, last accessed 2018/10/4.
20. Huang M.: A Clinical Decision Support Framework for Heterogeneous Data Sources. IEEE Journal of Biomedical and Health Informatics.
21. Beeler, P.: Clinical decision support systems. Swiss Medical Weekly,144(10), 2014.
22. Goldberg, H.: A highly scalable, interoperable clinical decision support service. Journal of the American Medical Informatics Association, 21(E1), 2014.
23. Kuo T.: Blockchain distributed ledger technologies for biomedical and health care applications, Journal of the American Medical Informatics Association, 24(6), 1211–1220, (2017).
24. Ekblaw A.: "A Case Study for Blockchain in Healthcare:"MedRec" prototype for electronic health records and medical research data"., 2016. healthit.gov … of IEEE Open & Big Data, last accessed 2018/10/4.
25. Leventhal, R. Blockchain's promise has Healthcare Innovators Eager Healthcare Informatics*, 34*(2), 29-31, (2017).
26. Halamka J.: The Potential for Blockchain to Transform Electronic Health Records. Harvard Business Review Digital Articles. 2-5, last accessed 2018/9/27.
27. Pirtle, Claude.: "Blockchain for Healthcare: The Next Generation of Medical Records?" Journal of Medical Systems, 42(9), 171-173, (2018).
28. Cyran, M.: "Blockchain as a Foundation for Sharing Healthcare Data." Blockchain in Healthcare Today, www.doi.org/10.30953/bhty.v1.13, last accessed 2018/9/27.
29. Bell, L.: Applications of Blockchain within Healthcare. Blockchain In Healthcare Today. 1(8), (2018).
30. Ekblaw, A.: MedRec: Medical Data Management on the Blockchain. Viral Communications. www.viral.media.mit.edu/pub/medrec. last accessed 2018/10/4.
31. Idleberger, F: Evaluation of Logic-Based Smart Contracts for Blockchain Systems. Rule Technologies. Research, Tools, and Applications. RuleML 2016. LNCS, vol. 9718, 167-183, (2016).
32. Azaria,A: MedRec: Using Blockchain for Medical Data Access and Permission Management. 2nd International Conference on Open and Big Data (OBD), 25-30, (2016).