Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Improving the performance of recommender systems based on blockchain technology

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| ABSTRACT

Blockchain technology has received the focus of many scientists as a promising technology in distributed systems. It was made possible by blockchain aspects such as visibility and Permanence. The newness of blockchain technology causes many challenges in this field. One of these challenges is managing data in the blockchain and presenting data suitable to the user's interests. In current centralized systems, recommender systems have solved this challenge. Implementing recommender systems in blockchain intelligent contracts and raising the transaction cost make the recommendations inaccurate due to the lack of complex calculation facilities of machine learning algorithms in innovative contract programming languages. They were introducing a novel method for enhancing recommender systems using blockchain technology. This method involves storing data in the blockchain according to a structure stipulated within the smart contract. The data is then provided to the off-chain recommender system through the public key of the smart contract, enabling the necessary processing for providing the appropriate recommendation to the user. The results are then stored in the blockchain and presented to the user during a transaction. The results of this method, as compared to previous research and works, demonstrate that performing complex calculations outside the chain not only reduces the transaction cost of establishing a contract but also decreases the transaction cost related to the recommender in the proposal system in terms of gas consumption, leading to increased scalability.

| KEYWORDS

Business, Process, Management, Blockchain, Smart Contracts, Recommender Systems

| ARTICLE INFORMATION

ACCEPTED: 12 June 2025 **PUBLISHED:** 08 July 2025 **DOI:** 10.32996/jcsts.2025.7.7.48

1- Introduction

In recent years, blockchain applied science has become a major development in today's digital world. A blockchain has a complete list of completed transactions in its body. Some of these transactions are financial, and others are only data recordings. Each block in the blockchain Features a header along with a body, and the previous block's hash (block wall) is stored (Ghobaei-Arani et al., 2020). The first block in the chain of blocks is called the generator block, which has no parent. Another potential benefit of the Chinese blockchain is the implementation of smart contracts (Abduljabbar et al., 2021). Digital contracts are programmed codes that facilitate the automatic implementation and enforcement of real-world agreements within the digital landscape. A digital contract is a digital form of a traditional legal understanding that includes a set of publicly available protocols using a public key (Zutshiet al., 2021). The participants in the blockchain can use these contracts. Before implementing the smart contract, its participants must agree on the protocol used because, after implementation, they can no longer change the defined rules. The availability of automated contract code using the public key in the blockchain leads to immutability and, as a result, creates trust in the participants, and the automatic execution of this contract eliminates the need for a third party

(Alsharari., 2021). For example, suppose several organizations cooperate to buy and sell a product. The existing agreements and laws between these organizations entered the blockchain through smart contract codes, and all data and transactions (Yeh & Kashef., 2020) related to the product are made available to all related organizations lucid and immutable (Leeuwen et al., 2020). Therefore, it is impossible to manipulate the data, and if there is a problem between the organizations, it could Identified by checking the list of transactions (Agarwal et al., 2024). There are many challenges in blockchain. One of these challenges is data management and recovery after implementing the smart contract. They store all data related to contracts and transactions in the blockchain (Gul et al., 2021). In the meantime, finding suitable information, such as buying a product according to the user's interest, will be difficult. In today's embedded systems, recommender systems (Bahrampour et al., 2021) are often centralized so that the user can find the information he is interested in (Frey et al., 2016), there is a central reference that has all the information and data of the users and advises the users using different artificial intelligence algorithms. For example, collaborative filter recommender systems based on user similarity find similar users and recommend their interests to each other through similarity measurement between user records(Zkik et al., 2024). Various methods, such as Pearson's correlation coefficient, have calculated this similarity (between one and a negative one) and the correlation of users stored in a similarity matrix, and the greater the similarity among users, the closer their affinity component is to one (Zutshi et al., 2021). In centralized recommender systems, the user only receives the result and is unaware of the data and functions used to provide these suggestions. Therefore, user trust is low in different organizations' offers (Kummer et al., 2020). In this regard, developing recommender systems using blockchain data restores integrity in the data that matches users' tastes when receiving recommendations (Aitkenhead et al., 2003). This research aims to provide an efficient solution using smart contracts in apps used for businesses (Zheng et al., 2018). This method proposes a distributed recommender system based on data obtained from transactions between organizations under a smart contract on the blockchain platform so that users can offered products that suit their interests (Kuo et al., 2018). In this system, because all the functions and data used by the user are available, it is transparent and provides accurate recommendations to the user (Fahmideh et al., 2024). In addition, users can trust it because they know these suggestions based on the data and functions presented to them (Solanki et al., 2022). Also, the data and rating functions are unmanageable and not controlled by a specific institution (De Abreu Ferreira., 2022). The smart contract is made available to the user interface and recommender system after being established in the blockchain network to achieve this goal (Abduljabbar et al., 2022). By connecting to the smart contract, the user interface stores users' data who enter the structures defined by the contract on the blockchain during transactions (Gómez-Goiri et al., 2024). Further, the recommender system extracts the data stored in the blockchain (Ke., 2024). After the necessary processing, the results are stored in the blockchain during a transaction and displayed in the user interface. The implementation results have been compared and evaluated with similar methods. The article's structure is as follows: their second part reviewed the literature of the done works. Their third section describes the proposed method (Lan et al., 2024). The fourth part is implementing the proposed method, evaluating its results, and comparing them with previous works. In the fifth section, they discussed conclusions and future works.

2- Literature review

Today, blockchain is used in several fields such as emerging technologies (Himeur et al., 2021), supply chain (Himeur et al., 2022), business process management (Agbo et al., 2019), cloud computing (Khan et al., 2020), etc. With the expansion of blockchain innovation and smart contracts, many researchers' studies have presented in the field of existing concepts and challenges (Abduljabbar et al., 2021). One of the most essential research studies in this field is the article by Zheng and his colleagues (Zheng et al., 2020). Their research carefully examined blockchain concepts and discussed the existing challenges in this field. Leeuwen and his colleagues (Leeuwen et al., 2020) systematically reviewed blockchain security issues and privacy protection. In another research, Zheng and his colleagues examined intelligent contracts, their platforms, and their challenges (Zheng et al., 2018).

The combination of recommender systems and blockchain is a novel topic that has attracted the attention of researchers in recent years (Agbo et al., 2019). In 2019, Gururaj and his colleagues (Gururaj et al., 2023) presented a method for creating a blockchain-based recommendation system that offers users transparency and dispersed scoring strategy. In their system, there is no central authority for monitoring (Yu and Buyya., 2005). They proposed a framework in this context that the recommender system inherits attributes of blockchain, public, anti-tampering, and durability (Zhang & Guin., 2019). They implemented several Smart Contracts in Solidity to create their system and deployed it under the product ranking Uzkiss on Ethereum's Ropsten test network. In this framework, basic mathematical functions within the smart contract, specifically weighted average and simple average methods, are utilized to determine the recommended ranking for an item, which can result in inaccurate suggestions (Potashnikov et al., 2021). Inaccurate recommendations occur when the recommender system consistently suggests the same item to all users (Mantey et al., 2023). Additionally, these scores may be misleading due to numerous negative reviews and targeted marketing from rival companies (Wang et al., 2019), with the system's capacity limited to only 4,000 rating records due to gas constraints. Yeh and his team proposed a collaborative recommender algorithm leveraging blockchain technology to address these challenges (Yeh and Kashef, 2020). They utilized a similarity matrix within the smart contract to compute the recommended scores for items. This matrix illustrates the similarity in relationships among users, where greater similarity significantly influences the recommendation scores (Meena & Sahu, 2021). Their proposed rating system aims to provide the most appropriate suggestions to users based on their preferences regarding the items (Yildizbasi, 2021). Each user evaluated their recommended approach along with the best offers made available to them. This system generates new blockchain addresses, notifies the company, automatically applies collaborative filtering to process data for recommendations, and ultimately enhances the visualization of suggestions for both users and the organization (Lu., 2020).

Also, this method makes the whole aspect of the customer's profile more secure. It will enable consumers to operate anonymously, which is guaranteed by blockchain (Sreenu et al., 2024). Yeh and his colleagues presented their evaluation results on the Movielens and Netflix datasets, and it noted that they filtered the datasets for ten users and only 200 movies due to the limitations of smart contracts in the Solidity language on the Ethereum blockchain (Yeh and Kashef., 2020). By examining their results, they found that the cost of implementing and executing their contract is high due to using the similarity matrix inside the contract (Fahmideh et al., 2024). Although they have also used calculations outside the blockchain chain, the result obtained in their evaluation is still higher than that of the work of Lisi and his colleagues (Lisi et al., 2019). This increase in cost led to their system being unable to have good scalability (Rehman Khan et al., 2022).

The two previous methods are ineffective due to their inaccuracy, high cost, and low acceptance scale. This article presents a technique that increases the system's scalability by reducing the cost of transactions and providing appropriate advice to the user. Table (1) compares the proposed approach with two similar approaches.

Table 1: Comparing the two proposed approaches of the recommender system in blockchain with the proposed method

Researcher	Lisi et al	Yeh et al	Suggested method
Recommended method	Using average ratings and weighted average ratings	Using collaborative refinement and creating a similarity matrix in intelligent contract	Using an off-chain collaborative recommender and using blockchain data
Yuzkis used	Scoring products	Movie rating	Selling movies
dataset	Not mentioned	MovieLen and Netflix	MovieLen
Scalability	Maximum 4000 records	Ten users, 200 movies	200 users, 1000 movies, 9102 rating records
Smart contract	Solidity	Solidity	Solidity
Blockchain	Ethereum	Ethereum	Ethereum
Benefits	All processes are implemented in the contract	More detailed recommendations for the user than the previous method	Reducing cost and increasing scalability compared to previous methods
Disadvantages	Incorrect recommendations due to the use of simple calculation functions	High cost due to the use of a similarity matrix within the chain	Display only one top record in the user interface

3- Suggested method

This section outlines the structure of the proposed system. As illustrated in Figure (1), the system comprises the following componentsBlockchain: the blockchain deployed the smart contracts defined in this section.

1- User interface: By connecting to the smart contract, the user can send and receive data with blockchain. These data are stored in the blockchain and made available to the public under the structures defined in the smart contract.
2- Recommender systems analyze the information stored in the smart contract for appropriate recommendations outside the blockchain and store the results during a transaction in a defined blockchain structure to display to the user.

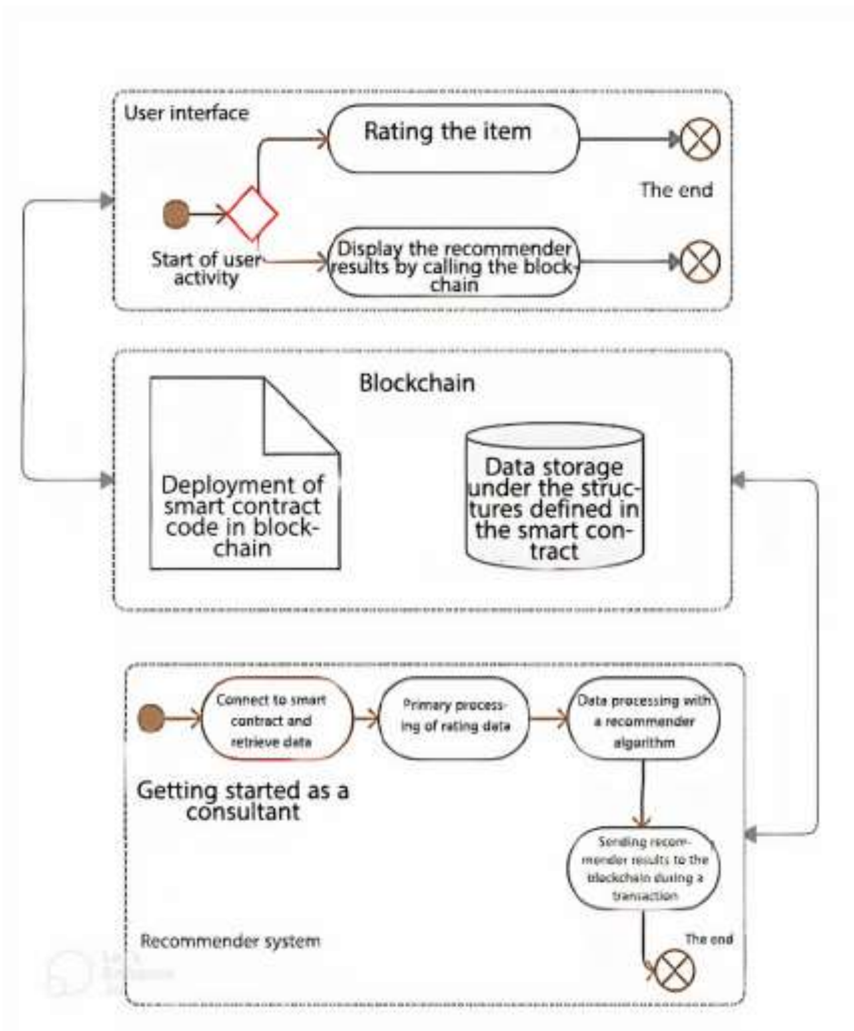

Figure 1: Architecture of the proposed system

The proposed method uses a collaborative recommender system based on the blockchain model and data. This method creates the ranking system based on the smart contract, and the ranking data is outside the chain (Fang, 2024).

The blockchain was changed to facilitate the intricate computations necessary for the recommender system. Finally, after the recommender's processing, the recommendation results are a transaction in the blockchain. This transaction executes a function in the smart contract. Finally, the results are demonstrated in the user interface (Javed et al., 2023)..

In the recommender systems section, the model-based collaborative refinement method and SVD algorithm have been used to predict products of interest to the active user. The collaborative filtering method uses a ranking matrix as a recommender input. This matrix is a numerical matrix containing the scores of each user for each item. The number zero in this matrix indicates that the user has not viewed the item. This matrix is thin because the user has not seen many items. In the recommender system, the user predicts the rating of unseen items using various machine learning algorithms such as SVD. From the mathematical point of view, SVD is a method that decomposes a matrix into three matrices, the product of which will be the original matrix. For example, matrix A could be posed by formula (1):

formula (1) : SVD (A) = USV^T

Let A be an m × n matrix, and let S be a diagonal matrix containing only r non-zero entries. This results in the dimensions of the matrices U, S, and V being m × r, r × r, and r × n, respectively. Both U and V are orthogonal matrices, while S is referred to as the singular value matrix, as expressed in formula (2).

formula (2):

$$\begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix}_{m\times n} = \begin{bmatrix} \mathrm{u}_{11} & \cdots & \mathrm{u}_{1r} \\ \vdots & \ddots & \vdots \\ \mathrm{u}_{m1} & \cdots & \mathrm{u}_{mr} \end{bmatrix}_{m\times r} \times \begin{bmatrix} s_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & s_{rr} \end{bmatrix}_{r\times r} \times \begin{bmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{r1} & \cdots & v_{rn} \end{bmatrix}_{r\times n}$$

The entries of the diagonal matrix... S (S_1, S_2, ...S_r) that are in the form si > 0 and $S_1 \geq ... \geq$ Sr. The first columns of U and V correspond to the orthogonal eigenvectors associated with the r non-zero values of AA^T and A^TA. In other words, the left and right singular vectors represent the r columns of the non-zero values in the column space and row space of matrix A, respectively. This forms the best linear approximation of the original matrix A at a lower rank.

This property is made possible by keeping the unique k and r and removing other values. This new matrix, whose low values are called Sk. Here, r is the initial number of non-zero elements, and the dimensions of S and k are the dimension reduction factor (Li et al., 2024). The entries of S are stored in the form $S_1 \geq S_2 ... \geq S_k$; the diminution process is carried out by keeping the first k values . Decrease the values and converting into U_k and V_k matrices, respectively. Therefore, to produce a forecast using SVD, first, the rank matrix A with dimensions m × n is decomposed into three component matrices of SVD, U_k, S_k, and V_k, with k features, which is its product A secondary estimate of the ranking matrix A is Then the prediction made by calculating the similarity of different methods such as cosine (point multiplication) between m, U_k customer. $\sqrt{S_k}T$ and n quasi-products. In general, The score prediction Pi,j for the customer i and the product j produced by adding the average ratings made by the user (rl) I and similarity, and its formula will be formula (3):

(1)

$$P_{i,j} = r_i + U_k.\sqrt{S_k}^T(i).\sqrt{S_k V_k^T}\,(j)$$

The value investigated for SVD analysis, and the prediction generation process only involves a point multiplication calculation, the time complexity of this operation is O (1) since k is a constant. Finally, among the predicted ranks, the items that have a high rank are recommended to the user (Bokde et al., 2015).

4- Evaluation and results

The Ethereum public test network (Buterin, 2014) named Rinkeby and the private test network Ganache to implement and evaluate the suggested method. Due to the limited count of users, the Ganache network of initial tests and the Rinkeby network are used for larger-scale tests(Xiang et al ., 2024). Also, I will use blockchain programming language, use the Truffle tool to compile smart contracts in a Windows environment (Gan et al., 2024), remix IDE to deploy contracts on the Rinkeby network and use MetaMask wallet to manage accounts. In this research, the MovieLen dataset was used to test the structure's presentation, and entered far, the rating data of 200 users for 1000 movies. As a result, 1000 records for film and about 9102 records for rating and recommender results have been saved for 200 users. However, the innovative, intelligent contract has not reached its gas limit, and users can still transact. The system preserved the users' privacy because the data was stored only in the blockchain platform with the users' hash code (Karpagam et al., 2020). In addition, the recommender can update the information on the blockchain platform and make better recommendations by increasing the data over time. In this system, although the recommender system can predict top items, the user interface displays only the first option to the user to reduce the cost. Here, the cost is the cost of each transaction according to the consumed ether and Gas mentioned in the following concepts.

(2)

$$1 \text{ Ether} = 10^{18} \text{ Wei}$$

The minimum amount considered for the Gas in formula (5):

(3)

$$1 \text{ GAS} \geq 1\text{GWei} = 10^9\text{Wei} = 10^{-9} \text{ Ether}$$

The sender must determine the maximum gas consumption in each transaction, and the program will stop automatically. In some cases, return transactions also consume Gas, which depends on the method of programming the contract for that transaction (Herzegovina et al., 2018). The cost of each transaction is a cost that changes according to the price and gas limit set by the sender for the smart contract. (Vujičić et al., 2018). For a precise comparison, first, the transaction cost of establishing a smart contract with different gas prices and restrictions is given in Table (2) the process of increasing the establishment transaction cost with two parameters of restrictions Gas and cost of Gas is shown.

The cost of the establishment transaction according to the price and Gas limit of the previous works compared to the proposed method is given in Table (3). According to the results, the proposed method has lower transactional methods than previous ones and can support more data with the same gas limitation. With more data (Yeh & Kashef., 2020) and its extraction by the recommender (Lisi et al., 2019), more accurate results for the recommendation could reached. In addition, with the increase in data, the cost of contract transactions does not change and remains constant. As a result, it does not reach the gas limit. In this sense, the system's scalability is higher than that of the previous systems that get the gas limit with increased data.

The goal of the proposed plan is to reduce the cost of transactions. In the previous methods, due to performing calculations inside the chain in rounds and when executing the intelligent contract every time, the contract reached the defined gas limit very soon and could no longer be executed. In previous works, they raised the gas limit for more execution times, which increased the

cost of establishing a smart contract in the blockchain. In this research, to solve this problem and improve the scalability of the contract of all complex calculations, considering
Detailed Python functions and libraries moved off-chain. This method reduced the costs of establishing the contract, implementing it, and providing recommendations to the user. Therefore, the proposed method allows the smart contract to be executed more times with fewer gas restrictions. Table (4) shows the average costs of implementing the considerable functions of the draft smart contract.
In addition to all these cases, using Solidity to write the recommender does not provide accurate results due to the lack of proper libraries and support for floating data. This research used to provide a recommender system that provides appropriate advice to the user for the surprise library and the SVD function in Python.

Table 2: The transaction cost of establishing the proposed smart contract in the blockchain with different restrictions and gas prices

Costs	Gas limit	Gas cost to GWEI	Cost per transaction in Ether or ETH
Deployment transaction fee	2764262	1	0.002764
	2764262	15	0.041464
	2764262	20	0.055285
	4700000	1	0.0047
	4700000	5	0.0235
	4700000	15	0.0705
	4700000	20	0.094
	8900000	20	0.0089
	8900000	1	0.1335
	8900000	15	0.178

Table 3: Comparison of contract establishment costs of the proposed method with the previous two methods

Methods	Gas cost to GWei	Gas limit	The cost of each transaction in Ether
Lacy et al	15	4700000	0.0708
Suggested method	15	4700000	0.0705
Yeh et al	20	8900000	1.20
Suggested method	20	8900000	0.175

Table 4: Average costs of implementing the main functions of the smart contract

Function name	GWEI gas cost	Gas limit	The cost of each transaction in Ether
Add Movie	20	139131	0.002800
Add Rate	20	338280	0.006800
Recommendation	20	109619	0.002200

5-Conclusion

This article aimed to increase the possibilities of using blockchain and smart contracts. For this purpose, I evaluated the available methods in this field. This review observes that implementing algorithms with non-linear time complexity causes an increase in the cost of implementation and earlier termination of the intelligent contract due to the gas limitation. For this purpose, a method for each user to predict a suitable recommendation by transferring the contract information outside the chain is delivered, performing the SVD algorithm, and transferring this recommendation to the contract as a transaction. With the evaluations, it concluded that the proposed method reduces the transaction costs of Ether and Gas for the execution of smart contract functions, makes the contract executed more times, and has greater scalability. In addition, take advantage of the existing recommender systems and provide a more accurate recommendation to the user. Today, various fields, like the Internet of Things, have used blockchain.
In future works, it will be investigated, considering that the records of each user with the hash code of the user are available in the blockchain, whether it is possible to implement a design recommendation that can make a more accurate recommendation by extracting the entire user transaction records from the blockchain under similar intelligent contracts. It is up to the user. Can this method be effective for the cold start problem of collaborative refinement recommenders, and to what extent can this method be scalable? In addition, the proposed system should analyzed for existing vulnerabilities.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

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