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Research article

Decentralized recommender system for ambient intelligence of tourism destinations serious game using known and unknown rating approach

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A R T I C L E I N F O

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A B S T R A C T

Tourism destinations serious game (TDSG) requires the ability to respond to players through recommendations for selecting appropriate tourist destinations for them as potential tourists. This research utilizes ambient intelligence technology to regulate the response visualized through a choice of serious game scenarios. This research uses the Multi-Criteria Recommender System (MCRS) to produce recommendations for selecting tourist destinations as a reference for selecting scenario visualizations. Recommender systems require a decentralized, distributed, and secure data-sharing concept to distribute data and assignments between nodes. We propose using the Ethereum blockchain platform to handle data circulation between parts of the system and implement decentralized technology. We also use the known and unknown rating (KUR) approach to improve the system's ability to generate recommendations for players who can provide rating values or those who cannot. This study uses the tourism theme of Batu City, Indonesia, so we use personal characteristics (PC) and rating of destinations attribute (RDA) data for tourists in that city. The test results show that the blockchain can handle decentralized data-sharing well to ensure PC and RDA data circulation between nodes. MCRS has produced recommendations for players based on the KUR approach, indicating that the known rating has better accuracy than the unknown rating. Furthermore, the player can choose and run the tour visualization through game scenarios that appear based on the recommendation ranking results.

1. Introduction

1.1. Background

A serious game is one of the most interesting pedagogical media products to research and development. This type of game is an interactive technology development that includes education, simulation, visualization, analysis, and training [1,2]. International organizations have even used serious games to teach and train skilled content [3]. Serious games help players increase their knowledge and skills on content without neglecting the fun elements that characterize a game [4]. When playing a serious game, the player's

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concentration becomes active to enjoy the game scenario flow well. The following effect increases learning effectiveness through the game features [5]. Researchers and game developers use serious games in various fields, for example, health monitoring [6], consumer engagement [7], employment-oriented [8], transaction simulation [9], soil tillage [10], engineering education [11], and safety education [12].

Another area that still has the prospect of a broad implementation of the serious game is tourism. A serious game in the tourism sector is a promotional medium for developers to introduce their tourist destination brands [13] to increase tourist arrivals at tourist destinations [14]. Its implementation in the tourism sector can increase players' knowledge and travel experience as potential tourists [15,16]. Knowledge and information about tourist destinations for potential tourists are essential things they must have, especially in the initial phase of the trip, namely before the trip [17]. This knowledge becomes the basis for determining tourist destinations to visit before preparing and planning a trip. Recommendations as knowledge content in the game can be visualized through automatic scenario changes. In this study, a serious game is used to transfer knowledge about recommended tourist destination choices to players, called the Tourism Destination Serious Game (TDSG).

This research offers ambient intelligence as technical support integrated into it to increase players' comfort, connectedness, and interest with TDSG. Ambient intelligence is a virtual environment development technology that can respond adaptively to users. A virtual environment with intelligent ambient has several characteristics, including sensitive, responsive, adaptive, transparent, ubiquitous, and intelligent [18]. The presence of ambient intelligence in the game is expected to increase interest and understanding through the suitability of visualization of knowledge based on awareness of the present, needs, and characteristics or preferences of players [19]. Systems in an ambient intelligence environment can detect and interpret human activity and provide multimedia feedback to provide guidance, recommendations, and learning [20]. In TDSG, multimedia feedback can be visualized in the form of changes in the choice of travel scenarios set automatically in the game. The scenario represents the choice of recommended tourist destinations through serious games. Therefore, an integrated recommendation system is needed in the serious game to determine recommendations for selecting tourist destinations according to player preference data.

In this study, the recommender system is an essential part of producing recommendations for selecting tourist destinations to reference the ambient intelligence serious game system response to players. A game needs recommender system support to generate valuable knowledge about object or item selection [21]. Recommender System (RS) is an intelligent system that provides recommended item choices to the user [22]. RS generally has three models: Collaborative Filtering, Content-Based Filtering, and Hybrid System [23,24]. This system is used in various applications to recommend videos, music, news, tourism, and scientific papers [25]. Some large applications also use RS to provide recommendation options to their users such as Google, Youtube, Amazon, and Netflix [26,27]. Two approaches are commonly used to predict user-recommended item selection, including single criteria and multi-criteria [28]. Of the two approaches, the Multi-Criteria Recommender System (MCRS) has better capability and accuracy [29] which uses more criteria as a reference in the recommendation prediction computation process [30]. In this study, we used MCRS to generate recommendations for choosing tourist destinations using several reference criteria. The determination of these criteria is based on factors that influence tourists to determine tourism destination choices. These factors include personal characteristic factors: gender, age, job, hobby, motivation, marital status, origin, people in a group, education, dan repetition, and factor destinations attribute: attractions, accessibility, amenities, available packages, activities, and ancillary services [31].

In terms of the recommendation system for selecting tourist destinations, there is a possibility that players as tourists cannot provide an assessment of tourist destination items because they have never been there. This condition results in sparsity in MCRS based on collaborative filtering, where the system has difficulty generating recommendations because there are many empty rating references [32]. The rating recommendation system is prone to cold start problems when no rating record is found [33]. Cold start is a common problem in recommendation systems where the system has difficulty providing recommendations because the user does not know the ratings of the item. Therefore, this study proposes a combination of two approaches used in the recommendation system: the known and unknown ranking approach (KUR). In the known rating approach, the system works based on the similarity of player ratings with rating data from previous travelers. Meanwhile, when using the unknown rating approach, the system works based on the similarity of player preferences with previous tourist preference data, which is processed using Artificial Neural Networks (ANN).

Besides using more criteria, MCRS requires machine learning support to produce more accurate recommendations [22]. The complexity of the relationship between the parts in MCRS requires a capable data-sharing system to handle data distribution. Two types of data-sharing architectures commonly used in research are centralized and decentralized [34]. The centralized architecture emphasizes centralized network management, where communication between nodes always requires the central node's approval. The weakness is that a system failure at the central node can cause data transmission failure. Meanwhile, a decentralized architecture has the advantage that each node can send data directly to the destination node without going through the central node approval [35]. The decentralized MCRS (DMCRS) increases communication effectiveness between nodes without depending on one node.

Blockchain is one of the latest data-sharing technology developments that use a decentralized architecture [36,37]. This technology has the characteristics of distributed data sharing and better security, allowing data to be stored at each node securely. Currently, blockchain handles cryptocurrencies like Bitcoin [38], but it has also been implemented in various fields. Example transaction simulation on games [9], decentralized storage on an industrial network [39], medical data sharing [40], and distributed network on the internet of the vehicle [41]. Besides these fields, blockchain still has broad development and implementation prospects in tourism destinations [42].

In this study, we try to use blockchain technology to implement the decentralized concept in supporting the rating data sharing required by the recommender system. Several studies have stated that blockchain has the characteristics of being decentralized, distributed, immutability, increased capacity, and better data security [35]. This technology follows the characteristics of the proposed tourism recommender system that requires decentralized and distributed data circulation handling and support for tourist rating and preference data security. Although not all variables from the data are classified as critical data, the secure data-sharing capabilities of the blockchain can undoubtedly make users feel more comfortable using their data in this proposed system. Of the various blockchain platforms currently developing, Ethereum is one platform that has the advantage of being easy to implement in a game-based system. This platform helps developers quickly implement blockchain technology into the Unity game engine [43]. In this research, blockchain supports data circulation and the delegation of tasks for all parts of the DMCRS on TDSG in a decentralized, distributed, and secure manner. Using blockchain is expected to improve the capability, data availability, and security of DMCRS.

1.2. Motivating Example, Contribution, and organization of paper

An essential motivation of this research is to design a recommendation system for players in choosing a suitable tourism destination as an ambient intelligence serious game response that is visualized with the scenarios offered. Ambient intelligence in TDSG in this study is designed to provide a visualization response to travel scenarios for players as tourists who have not or have come. The visualization of the travel scenario is selected based on the recommender system's recommendations for the choice of tourist destinations. For example, a tourist who want to travel to a destination city can play a travel scenario in a virtual environment of tourist destinations recommended by the system before they depart. The goal is for tourists to know the characteristics and environment of the selected tourist destination so that they can use it as a reference in designing a travel agenda.

Therefore, this study introduces a recommender system based on the known and unknown rating approach. The known rating approach is an approach for new tourists, and an unknown rating approach is for tourists who want to return. The known rating approach produces recommendations based on the similarity rating calculation known to the player and calculated using the MCRS method. The unknown rating approach generates recommendations based on PC player data using the ANN algorithm. Furthermore, this study uses blockchain-based decentralized data-sharing technology to support the circulation of data between players required by the recommender system in TDSG. With this capability, prospective tourists who have come to a tourist destination city can get recommendations based on the item criteria rating of tourist destinations they know. Moreover, tourists who have never come also can still get recommendations based on their preference data fields.

Furthermore, some of the main contributions of this research include the following:

1. The multi-criteria recommender system produces recommendations for selecting tourism destinations using the KUR approach. This approach can generate recommendations based on two input options: tourist destination ratings or player preferences. The goal is to ensure the availability of recommendations for players who have or have never visited a tourist destination.
2. This study offers several criteria for ranking tourist destinations as a reference for generating recommendations through MCRS: attractions, accessibility, amenities, available packages, activities, and ancillary services. In addition, we also define several player preferences variables as a reference in classifying the order of choice of tourism destinations.
3. -The recommender system utilizes decentralized datasharing to support the circulation of rating and user preference data. Furthermore, as a form of implementing the decentralized concept in the Unity game engine, this research uses the Ethereum blockchain platform with all its advantages.

We divide this paper into several sections to explain each part of the system design, test results, and analysis. After the introduction, the second section is the preliminaries that explain the influence criteria for choosing tourism destinations, the multi-criteria recommender system, and blockchain-based decentralized data sharing. The third section describes the system design and method, containing a decentralized multi-criteria recommender system, data sharing system, and recommendations for visualization in serious games. Furthermore, the fourth section is the results and discussion, which explains the results of testing and analysis of decentralized data sharing, MCRS using the known approach, and the unknown rating approach. Finally, we write the conclusion of this paper in the fifth section.

Table 1
Related work for recommender systems in games and other applications.

References	System/Method	Object	Application
[21]	Logistic regression-based system	In-game item selection	Online game
[44]	The intelligent exergame-based rehabilitation system	Patient rehabilitation	Serious games
[45]	Recurrent neural networks	Game item	MOBA game
[46]	Feedforward neural network	Game item and product	Video games
[47]	Neural network	In-game item selection	Video games
[48]	ELECTRE	Traveler itinerary	Web-based
[49]	K-means + GA	Tourism destinations	Mobile
[50]	Opinion-mining technology	Tourism destinations	Web-based
[51]	Topic modeling + emotional analysis + haversine	Tesser-known tourism place	Not mentioned
[52]	MCRS using a fuzzy approach	Tourism service	Web-based
[53]	Destinations ratings-based MCRS	Halal tourism destinations	Desktop game
[54]	Weighted sum model-based MCRS	Tourism destinations	Web-based
[55]	Decentralized collaborative filtering	Movies	Not mentioned
[56]	Decentralized hybrid systems	Advertising	Mobile
[57]	MobRec	Movies, music, restaurants, etc	Mobile

2. Related work

2.1. Recommender system

The recommendation system is an essential part of the game system, especially to provide players insight and advice about item selection when they play the game. Table 1 shows several studies discussing recommender systems' use in games and other applications. One of them is the research conducted by Looi et al., in 2019. They proposed a recommender system in online games to advise players on selecting and purchasing the necessary items. This research with Dota 2 objects utilizes the concept of a rule-based system that is based on clustering for the system with logistic regression that was developed [21]. Furthermore, Gonzales et al. propose a recommendation system for learning about patient health rehabilitation in the serious game genre. This research, published in 2018, aims to produce a serious game that can motivate patient adherence while undergoing treatment. The recommendation system can intelligently analyze patient interactions and history and recommend appropriate training options. In addition, the proposed recommendation system can also provide suggestions according to the difficulty level of the game and the abilities of the players [44].

Several studies use different methods to support recommender systems in their game proposals. For example, in 2018, Yao et al. proposed an item selection recommendation system in multiplayer online battle arena (MOBA) genre games. The research using the King of Glory data set uses the Recurrent Neural Networks (RNNs) method based on hierarchical attention. The results show that the proposed method has an accuracy of 2% higher than non-sequence models [45]. In addition, Simone et al. introduced a recommender system design for an item and product selection in a game. The authors use the concept of a recommender system based on in-game profiling to generate recommendations for players. They use a feedforward neural network method with a single hidden layer to perform the classification process based on the data-inferred profile and preferences [46]. In another study, Bertens et al. propose machine learning in a recommendation system in video games. The system in the game provides recommendations for selecting interesting items for players. Players automatically get recommendations according to their wishes or personalization while playing through the recommender system. The 2018 study used an ensemble-based model and a deep neural network algorithm in a game recommender system [47]. Several previous studies are references to support the proposed system discussed in this study, especially for planning the concept and implementation of a serious game's tourism destination recommender system.

On the other hand, several studies have specifically proposed various methods for selecting tourist destinations to build a recommendation system. In his paper, Kzaz describes an approach to supporting the tourism recommender system divided into the classical and non-classical approaches. Some of the methods included in the classical approach are Collaborative Filtering and Content-Based Filtering. In contrast, Personalized Approaches, Context-aware, and Ontology-Based Approaches are included in the non-classical approach [58]. Moussa et al. in a study, discuss a personal-based system to provide travel plan selection knowledge to tourists. They use the ELECTRE method in developing web-based applications [48]. Furthermore, Tenemaza et al. publish a paper that discusses a mobile application-based tourism destination recommendation system. The system is built based on the design of tourist trips to produce recommendations according to environmental changes and tourist interests [49].

Furthermore, Zheng et al. propose a recommender system for tourism destinations based on user sentiment, user preferences, and destination popularity. The results show that the proposed system can improve the quality and accuracy of recommendations [50]. While in another study, Buranasing et al. propose a recommender system to provide knowledge about lesser-known places for potential tourists. They used topic modeling concepts to find related subjects, dynamic analysis to measure visitor attitudes, and haversine techniques to find lesser-known sites. In the implementation phase, they use web technology and social media to get data reviews, locations, and ratings [51]. The concept of single criteria from several previous studies needs to be increased to multi-criteria because many factors influence the context of selecting tourism destinations. In addition, in developing a tourism recommendation system based on a rating assessment, it is necessary to consider the possibility that users who have never been to a tourist destination cannot provide an assessment rating of at least one of the items offered. Therefore, in this study, we propose the concept of a KUR-based MCRS. When the rating is not known, the system can still generate recommendations based on the preferences of users who are game players.

In one study, Colale et al. introduced a context-aware-based recommendation system for promoting tourism events. They designed the system to provide dynamic support to tourists by developing a mobile-based system. The results of their research show that the system can generate recommendations for finding cities and events based on the position and global profile of tourists [59]. Furthermore, research on recommender systems with a context-aware approach was also carried out by Casillo et al., in 2021. The authors discuss the prospects for developing the recommendation system to be implemented in the Cultural Heritage field. A recommendation system that can provide recommendations for exemplary service to tourists based on their current situation is an exciting research challenge, and context awareness plays an essential role in it [60]. Research on a context-aware recommendation system is exciting. It has challenges, but in this study, we focus more on rating item destinations and tourist preferences as a reference for generating recommendations.

In 2016 Farokhi et al. introduced the MCRS implementation in the tourism sector. The authors used a dataset from TripAdvisor in the experiment and supported it with a fuzzy C-means algorithm [52]. Arif et al. in a study, also proposed destinations ratings-based MCRS as a method for providing recommendations for choosing halal tourism based on desktop games [53]. On the other hand, Santosa et al. also proposed using MCRS in the tourism destinations recommender system based on the weighted sum model (WSM), one of the multi-criteria decision-making techniques (MCDM). They use a web browser-based user interface and a centralized data-sharing architecture where every data is stored on a database server [54]. The centralized architecture in several previous studies raises the challenge of limited system capabilities that depend on the server. So it is necessary to increase the ability of data sharing that does not depend on one node to get support for the circulation of new reference data that is not easy and safe. Therefore, this study proposes using a recommender system with decentralized data sharing to guarantee data existence because it is stored in every node connected to the network.

Along with developing data-sharing communication technology, several studies have discussed decentralized architecture concepts to support performance between sections in the recommender system. In 2020, Ai et al. proposed a decentralized concept for a recommender system based on a collaborative filtering approach. The system's accuracy is also affected by differences in the popularity of items shown through the centrality model in the network [55]. Furthermore, a study discusses the concept of a decentralized recommender system to overcome privacy problems in collecting user preferences centrally. The decentralized concept is implemented in a mobile-based recommendation system to display advertisements that match the interests and preferences of users online [56]. In another study, Beierle and Egger discussed the decentralized mobile recommender system. They introduced a mobile-based platform in a decentralized concept for the recommendation system computing process and data collection and storage called MobRec. The MobRec architecture consists of data collection through a data-sharing system between devices and a recommender system that works locally on each device, where recommendations are generated based on user interests and preferences. [57]. Several previous studies have succeeded in developing the decentralized concept in a recommender system, but a secure data-sharing system should certainly support the concept. In the context of the tourism destinations recommender system, we propose the concept that requires the distribution of user preference data to be secured. Therefore, this study chose a blockchain because it has advantages in securing data through hashing techniques, proof of work, and smart contracts.

2.2. Influence criteria for choosing tourism destinations

Tour trips are divided into three main phases: before, during, and after the trip [61]. Before the trip is the phase where tourists start looking for information and planning their trip. In this initial phase, tourists start planning a trip by determining which tourism destinations they want to visit according to their characteristics, goals, and expectations [17]. The study explains two main factors that influence tourists in determining their choice of tourism destinations. The first is tourists' characteristics (PC), including gender, age, job, hobby, motivations, marital status, origin, people in a group, education, and dan repetition. The second factor is the destinations attribute (DA) which represents the preference for tourism destinations. The DA factor consists of several criteria, including the number of attractions, ticket prices, surface area, attributes of nature, facility, infrastructure, access, and distance to the destinations [31].

In another study, the rating of DA (RDA) was carried out using the 6As Tourism Destinations (6AsTD) framework [62]. The framework assessment is divided into six criteria: attractions, accessibility, amenities, available packages, activities, and ancillary services [63,64]. Attractions are interesting spots or rides in a tourist destination that can stimulate the desire of tourists to visit. The attractions criteria include natural landscapes, artificial tourism, cultural tourism, and special events. While accessibility is a criterion that represents transportation facilities and access to and from tourism destinations. The criteria include transportation routes, terminals, and public transportation. Furthermore, amenities are criteria from the 6AsTD framework representing the supporting facilities available in tourism destinations. Some of the facilities included in the amenities criteria include lodging and hotels, restaurants, public facilities, and shopping centers.

Available packages are assessment criteria for tour packages offered to tourists at a tourism destination. The following criteria are activities, namely the criteria used to assess all activities in tourist destinations. Every enjoyable activity tourist can do in tourist destinations can trigger them to come and visit [65]. The sixth criterion, namely ancillary service, represents assessing the supporting facilities inside and outside the tourist destination required by tourists. These facilities may not directly support tourist activities, but actually, they need them. Some assessment components in this criterion include communication channels, internet services, ATMs or banks, postal services, and medical services.

We utilize the combination of RDA and PC in the MCRS proposal to provide recommendations for choosing suitable tourist destinations for tourists. The system uses DA based on the 6AsTD framework as the rating criteria for tourists' assessment of tourism destinations. In contrast, the PC is a reference criterion in the training data for the classification process of the similarity of tourist preferences to the choice of tourist destinations.

2.3. Blockchain-based decentralized data sharing

The data-sharing rating section is one of the essential factors supporting data availability in this proposed system. This section is responsible for circulating data between sections on the recommender system. Therefore, the system requires a data-sharing network architecture to ensure ease of communication, data availability, and data security. Two commonly used data-sharing network architecture concepts are centralized and decentralized [34]. Between the two architectures, decentralized has more capabilities to overcome the limitations of centralized capabilities, namely dependence on the central node. In a decentralized network, each node can communicate directly without getting approval from any of the nodes. This concept makes data circulation between nodes easier and more distributed [66].

Ethereum is a blockchain platform with smart contract-based data-sharing technology. In its implementation, a smart contract is a collection of program code containing functions and statuses deployed in the blockchain network. All nodes executing a smart contract must get the same result stored on the blockchain. Smart contracts execute methods according to the data provided by the user to perform services in the network. The blockchain platform can calculate, store information, and expose properties as a mirror of an open public state using smart contract [34]. In this study, smart contracts are essential in ensuring the automatic agreement function of user rating and preference data transactions between nodes in the blockchain network.

3. System design and methods

One of the objectives of this research is to build a recommender system that can produce recommendations for selecting tourist destinations as a response from the ambient intelligence system to players according to their preferences. We divide TDSG into three main parts to achieve this goal: tourism destination recommender system (TDRS), data sharing system, and game visualization. The TDRS section and the data-sharing system are essential in generating recommendations based on the preference data and other user ratings obtained through blockchain-based decentralized data sharing. At the same time, the game visualization section is in charge of visualizing the results of the recommended tourism destinations into a game scenario for players.

In TDSG, every player can run the game and get recommendations based on preference and rating data from other players. Therefore, every player running a device with TDSG must connect with other devices via the Ethereum blockchain network. Fig. 1 shows the relationship between devices in the TDSG framework with its three main parts. Every player connected to the network must have a device with the TDSG system installed. At the same time, the server in this study is a backup of data preferences and ratings from players.

Referring to the three main sections of TDSG, we explain them in detail in several sections with their respective workflows in Fig. 2. In the TDRS section, we use the MCRS method to provide recommendations for players regarding the selection of tourist destinations that they play through game scenarios. The recommendation generator section produces a Top-N recommendation, a recommendation ranking of tourism destinations. MCRS generates recommendations based on computing preference and player rating data compared to other player preference and rating data stored in the database. The data is from other players obtained through the Ethereum platform in the blockchain network. Each player can submit their preference and rating data for tourism destinations through the game menu, also available in the game visualization section. This activity is one of the essential jobs for players because the system has the task of distributing every data from them to every player node and server in the blockchain network to add variations to the database for other nodes. Furthermore, in in-game visualization, a section of tourism destinations scenario selection selects game scenarios for players based on the Top-N recommendation rating from MCRS. The selected scenario is one from the Tourism Destinations Scenario Collection designed using the Finite State Machine.

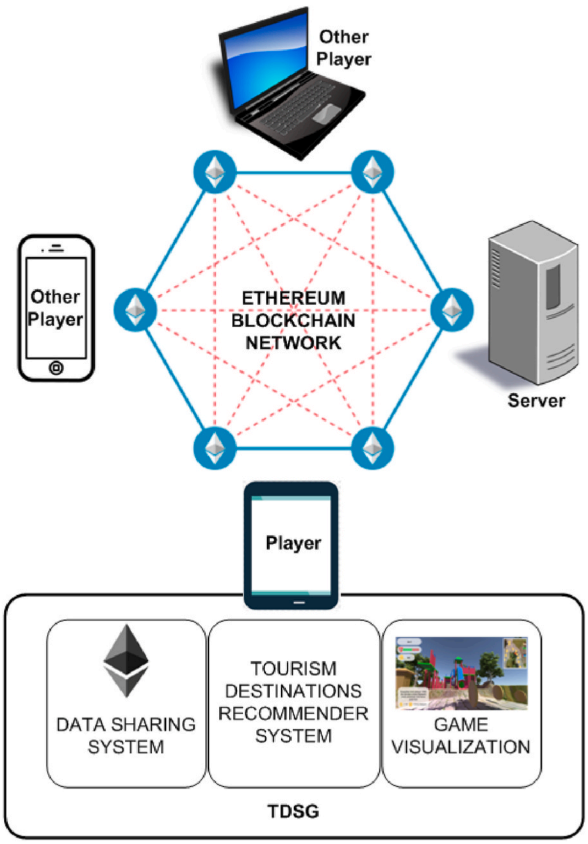

Fig. 1. TDSG in the ethereum blockchain network.

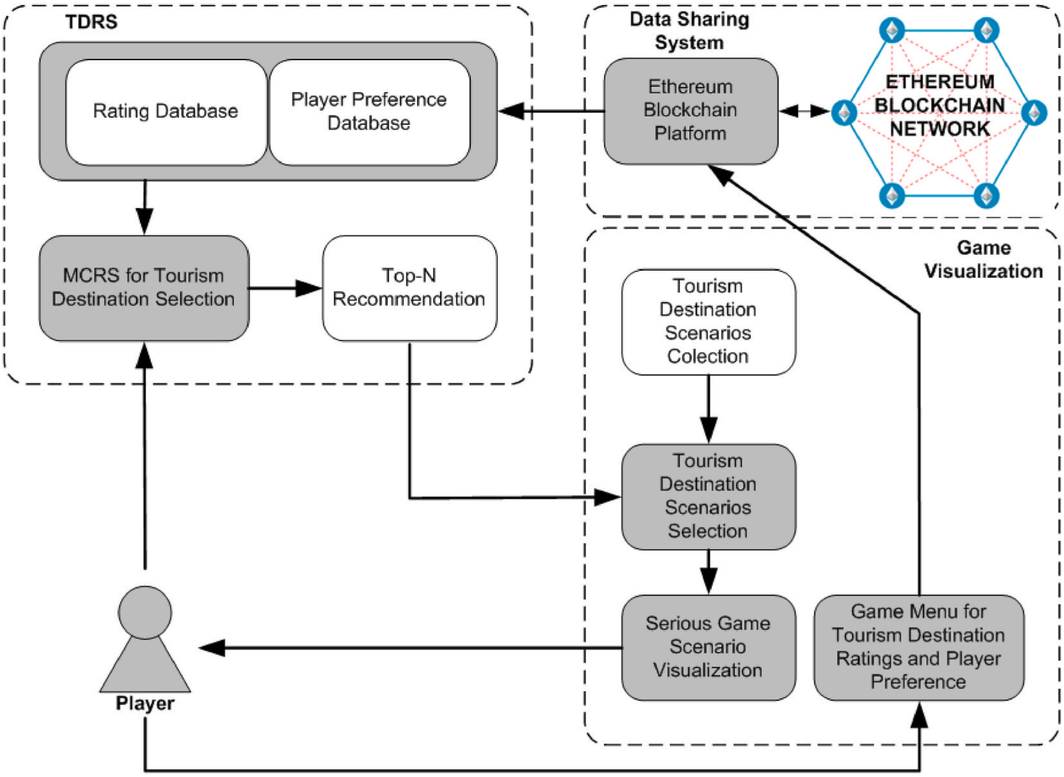

Fig. 2. Proposed Ambient Intelligence TDSG system.

3.1. Blockchain-based Player's preference and rating data sharing

This study offers a TDRS for supporting ambient intelligence TDSG, which can generate recommendations based on rating criteria data for tourism destinations and player preference data. In other words, each TDRS can generate recommendations in two ways. The first, recommendations are generated based on the similarity of player ratings to other player ranking data sets, and the second is based on the suitability of a player's preference against the classification results of another player's preference data set. Table 2 shows the notation of each rating and player preferences used in TDRS.

Every data in the rating and preference database is from previous players and can continue to grow with the assessment response from players who have used TDSG. Therefore, the system should ensure that players' rating and preference data exchange goes well and safely. Furthermore, we offer a data sharing system that uses blockchain technology to support data exchange activities between TDSG players. In this study, we try to take advantage of the advantages of the Ethereum platform to handle data transmission transactions to every node in the blockchain network.

The step of data transactions in the Ethereum blockchain network begins with an agreement between all nodes connected in the network. What is meant by agreement is the program code containing the algorithm in the data transaction agreement, which is a smart contract. When the player finishes filling in the preference and rating data, the conditions that are prerequisites in the smart contract are met, triggering a data transaction. After the smart contract runs, the system forms a block consisting of several parts: index, hash, previous hash, transaction root hash, receipt root hash, timestamp, difficulty level, nonce, gas limit, and the gas used. Each

Table 2
Tourism destination rating and player preference data.

RDA			PC		
Symbol	Criteria	Value	Symbol	Criteria	Value
R0	Overall rating	1–10	P1	Motivations	1–4
R1	Attractions	1–10	P2	Age	1–4
R2	Accessibility	1–10	P3	Employment	1–4
R3	Amenities	1–10	P4	Marital status	1–2
R4	Available packages	1–10	P5	Hobby	1–5
R5	Activities	1–10	P6	Gender	1–2
R6	Ancillary services	1–10	P7	Hometown	1–2
			P8	Group	1–5

block in the blockchain network is interconnected based on the similarity of the previous block hash in the current block with the block hash in the previous block [43].

This research utilizes Photon 2 as a network provider platform. This platform has many product lines that can be used on various devices. One of the popular Photon products is PUN (Photon Unity Networking) which uses a central Photon network server to manage data flows. We use PUN in the data-sharing experiment in this study. Furthermore, we also use a blockchain network based on the Ethereum platform. The advantage of the Ethereum network is that it is public and peer-to-peer so that all connected nodes in the network can have the right to access data shared by other nodes. The function of PUN and the Ethereum blockchain in this study is to handle PC and RDA data-sharing systems between nodes in the network.

The Ethereum blockchain platform does its job by storing and processing every PC and RDA data. The platform is also transparent and can serve as a long-term data storage medium on the network. This capability makes each shared data accessible to every node connected to the network. Another advantage of this platform is its better data security with encryption. Furthermore, the steps for applying blockchain technology in handling data sharing in this study are as follows.

- The first step is the block-chaining process. This process occurs after all connected nodes in the network have made a transaction agreement. The agreement is in a smart contract with program code representing the terms of the transaction agreement between nodes. When these conditions are met, then the first transaction occurs.
- The conditions referred to are fulfilled when the game player has finished inputting data, so data-sharing transactions are processed.
- After the transaction runs, the following process is making the next block.
- The first task of the blockchain system when data transactions occur is securing data using a hashing algorithm called SHA-256. The algorithm processes input data into 256-bit messages [9,67].
- When data transactions occur in a blockchain network, the initial block is a repository for when no new transactions are made. However, if a new transaction exists, the system will repeat the hashing process to form a new block.
- The data transacted to the blockchain network in this study is PC and RDA data.
- When the data transaction has been verified, the transaction has been successfully executed on the blockchain network.

In this decentralized recommender system study for a tourism serious game, the system automatically shares data through the blockchain network when a serious game node receives new data. Furthermore, to verify the transaction terms, the system utilizes the smart contract function. However, the system sends an error message if the verification fails. Conversely, when verifying that the conditions in the smart contract are fulfilled, the system shares data with the Ethereum network. The following process forms the data block structure, followed by the hashing process to generate new transactions. The process is continued by being validated using Proof of Work (PoW), and when the validation is successful, the data is broadcast on the Ethereum network. Every player node connected to the network gets PC and RDA data through the blockchain.

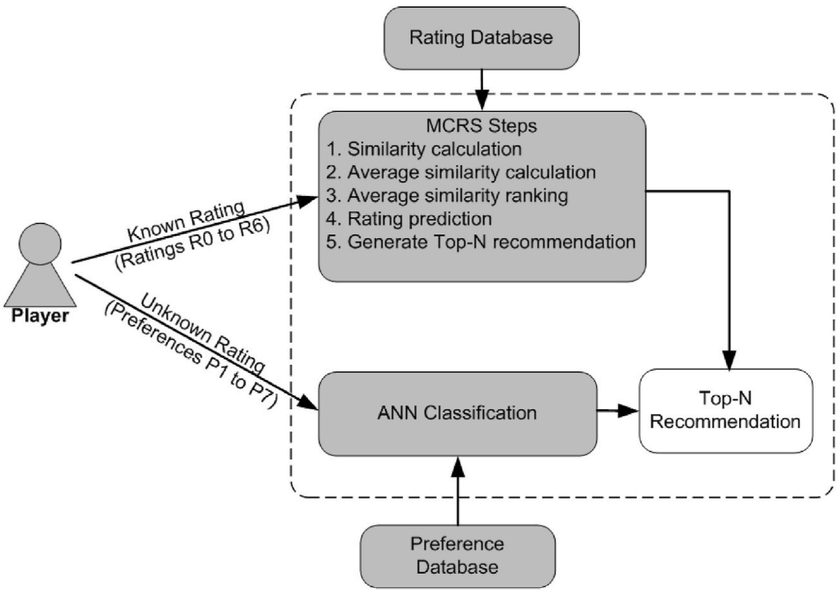

Fig. 3. Generate Top-N recommendations using the KUR approach.

3.2. Known and unknown rating-based recommender system

This study proposes a concept of a multi-criteria-based recommendation system to generate recommendations through two approaches, namely the known and unknown rating (KUR) approach. We describe known rating as an approach carried out when the player already has an assessment of all criteria, at least in two of the tourism destinations. In the known rating approach, the system generates recommendations through the calculation step of the MCRS method based on the similarity of player ratings with other player reference data stored in the database. In the unknown ranking approach, the system uses the similarity preference classification between players and other travel reference data sets to derive recommendations for selecting tourist destinations. The classification method used in the unknown rating approach is an Artificial Neural Network. Fig. 3 shows the relationship between known and unknown rating approaches in the form of a block diagram.

Equation (1) is the basic formula of MCRS, that the R function is the result of the $User's$ rating on all *Items* criteria. In the multi-criteria concept, recommenders generate recommendations based on more than one rating criteria *Items* $R_0, R_1, \dots, R_n$. In this study, R_0 is the user's overall rating for an item tourism destination. While $R_1, \dots, R_n$ is the rating of each tourism destination C criteria C ($C =$ 1, …, n).

$$R : Users \times Items \rightarrow R_0 \times R_1 \times \dots \times R_n \tag{1}$$

According to Gediminas Adomavicius and Young Ok Kwon, the recommender system works through two main stages: prediction ratings and item recommendation. The system calculates the R function for the $Users \times Items$ area at the prediction rating stage based on the known item rating ratings. At this stage, the recommender system predicts the rating of the unknown item based on its similarity to the previous user rating data. Two approaches that can be used to generate rating predictions are Heuristic-based approaches and Model-based approaches [68]. In this MCRS system, we use heuristic-based approaches to generate the rating predictions. This approach can produce accurate, efficient recommendations and a faster calculation process [69]. By utilizing the capabilities of the heuristic approach, it is hoped that it can improve the suitability of the recommendations produced and support the game to make it more real-time.

The first step in implementing heuristic-based approaches in the MCRS system is calculating user similarity. Eqs. (2) and (3) show the similarity calculation formula to get the value of $sim(u, u')$ using the cosine-based similarity technique and Pearson correlation. Cosine-based similarity uses a more detailed calculation pattern based on the similarity of every two samples. In comparison, the Pearson correlation produces a similarity value based on the calculation of the correlation between two random variables [28]. These two formulas are used to compare new user data with each data from the data set in more detail, to obtain a similarity value. Furthermore, we also compared the two formulas to see which technique is more accurate to apply in this study. The formula is used to calculate the similarity of rating on each criterion of user u and user u' as a game player. Meanwhile, $R(u, i)$ is the user's rating as player u on the item tourism destinations u. On the other hand, $I(u, u')$ represents the common items that have been averaged by user u and user u'.

$$sim(u, u') = \frac{\sum_{i \in I(u,u')} R(u,i) R(u',i)}{\sqrt{\sum_{i \in I(u,u')} R(u,i)^2} \sqrt{\sum_{i \in I(u,u')} R(u',i)^2}} \tag{2}$$

$$sim(u, u') = \frac{\sum_{i \in I(u,u')} \left(R(u,i) - \overline{R(u)}\right)\left(R(u',i) - \overline{R(u')}\right)}{\sqrt{\sum_{i \in I(u,u')} R(u,i) - \overline{R(u)}^2} \sqrt{\sum_{i \in I(u,u')} R(u',i) - \overline{R(u')}^2}} \tag{3}$$

The second step is finding a similarity ranking. Several methods that can be used to find similarity rankings include average similarity $sim_{avg}(u, u')$, worst-case (smallest) similarity $sim_{min}(u, u')$ and aggregate similarity $sim_{agregate}(u, u')$ [70]. Where $sim_c(u, u')$ is the similarity criteria between user u and user u' and c is the criteria for item tourism destination. In the calculation of the average similarity shown in equation (4), the number of criteria that have a rating value from the user is represented by k. Furthermore, equation (5) shows the calculation of worst-case (smallest) similarity. While equation (6) shows the calculation of aggregate similarity where w_c is the weight of the criteria c owned by each tourism destination item. In this study, we tried to analyze the three similar formulas to find the one that has the highest level of accuracy for the problem of recommending tourism destinations.

$$sim_{avg}(u, u') = \frac{1}{k+1} \sum_{c=0}^{k} sim_c(u, u') \tag{4}$$

$$sim_{min}(u, u') = \min_{c = 0, \dots, n} sim_c(u, u') \tag{5}$$

$$sim_{agregate}(u, u') = \sum_{c=0}^{n} w_c sim_c(u, u') \tag{6}$$

The third step is to predict the rating of each unknown user criterion u based on user rating criteria with the highest similarity average. After getting all the rating criteria values for all tourist destination items, the following system ranks tourism destination items based on the overall rating value of R_0. This step is the last in implementing the known rating approach to get a Top-N tourism destination ranking.

Unknown rating is an approach in our proposed system that uses machine learning support to generate recommended ranking predictions for users. The system uses one of the methods in machine learning, namely Artificial Neural Network (ANN), to classify the recommended choices of previous user data sets according to their PC data. ANN is a classification method that can overcome cold-start problems in the recommendation system [71]. In this study, ANN performs the classification process offline to get the weight value of each preference for each ranking of TOP-N tourism destinations. With the recommendation system using tourist PC data, it is hoped that it can produce recommendation predictions in the early stages of using the system before the user assessment data is known against the DA criteria. The ten PC criteria used as initial data in this study were gender (X1), age (X2), job (X3), hobby (X4), motivations (X5), marital status (X6), origin (X7), people in a group (X8), educations (X9), and repetition (X10). The data set for each criterion is training data obtained from previous tourists. After training and obtaining a classification model of tourist destination choice (DW) based on X1 to X10 as PC1 to PC10 data, the PC User data input is matched with the classification results to get an estimate of DW choice recommendations according to the User PC. The design of an ANN-based recommendation system using PC data is shown in Fig. 4.

3.3. *Recommendations visualization in serious game*

The previous section explained that the DMCRS only limited the five highest-ranking recommendations for tourism destinations for players. However, the serious game in this study still had to provide all travel scenarios for each destination that became TDSG content. When the game system displays scenarios based on the results of the DMCRS recommendations, players can choose one for them to play. Fig. 5 shows the sequence of player activities in playing TDSG. Starting from entering a rating or preference, choosing one of the five recommended travel scenarios, running the selected game scenario, searching for each icon in the selected tourist destination, and getting score information from the icon search results before the game is over.

Fig. 6 is a travel scenario design described using a finite state machine. The initial part of the TDSG scenario design is the Display the Ever Came form. The system provides a choice of approaches for players to obtain recommendations, namely through known rating = yes or known rating = no. Furthermore, the system runs the state MCRS calculation when the player enters the rating data value. Meanwhile, when the player enters the preferences data, the system runs the Player weight calculation state. The game system provides five scenario options based on the highest recommendations generated from the two states' results. Next, the system runs one of the scenarios chosen by the player. The story idea of each scenario in TDSG describes the tourists' journey through each attraction in the tourist destination. Each tourist destination has a different virtual environment visualization in the game, including icons and supporting objects. Players must find and get icons in each featured attraction to increase the score acquisition as a challenge in playing the game.

4. Result and discussion

4.1. *Collection and preparation of data*

This section describes the results of experiments and testing of several system parts, including blockchain-based data sharing, KUR-based recommendation systems, and in-game systems. implementation. This subsection discusses the collection and preparation of datasets before they are used as a reference in generating recommendations. This study uses tourist destinations around Batu City, East Java, Indonesia. This city is one of the tourist development areas with various exciting tourist destinations. Table 3 shows 14 popular tourist destinations of various types in the Batu City area and its surroundings as objects in this study. This study uses rating and preference data from 227 respondents as a dataset for calculating recommendations to support system development and testing. We distributed questionnaires to each respondent, who were tourists who had visited each tourist destination in Batu city. The dataset includes a collection of tourists' RDA and PC data, complete with their choice of tourist destinations. Table 4 shows the demographics

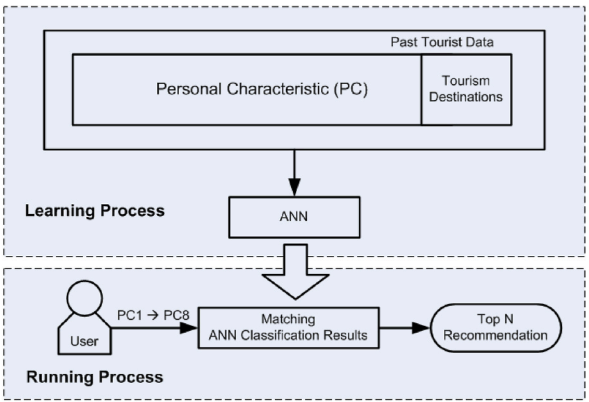

Fig. 4. An ANN-based recommender system using PC data.

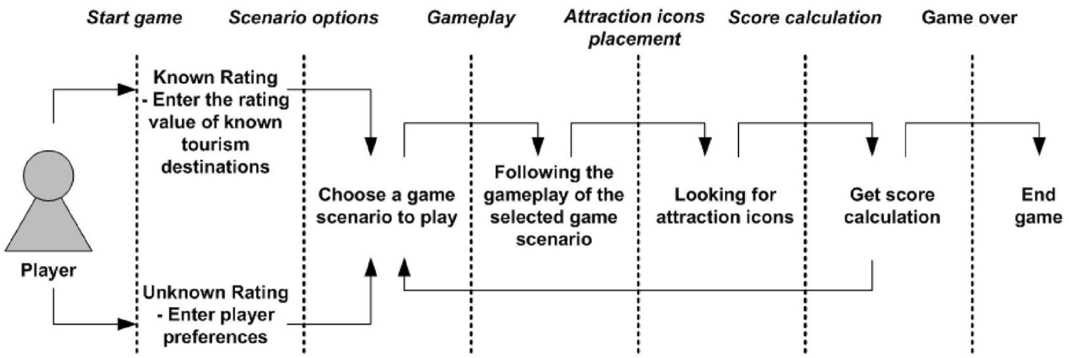

Fig. 5. Player activities in TDSG.

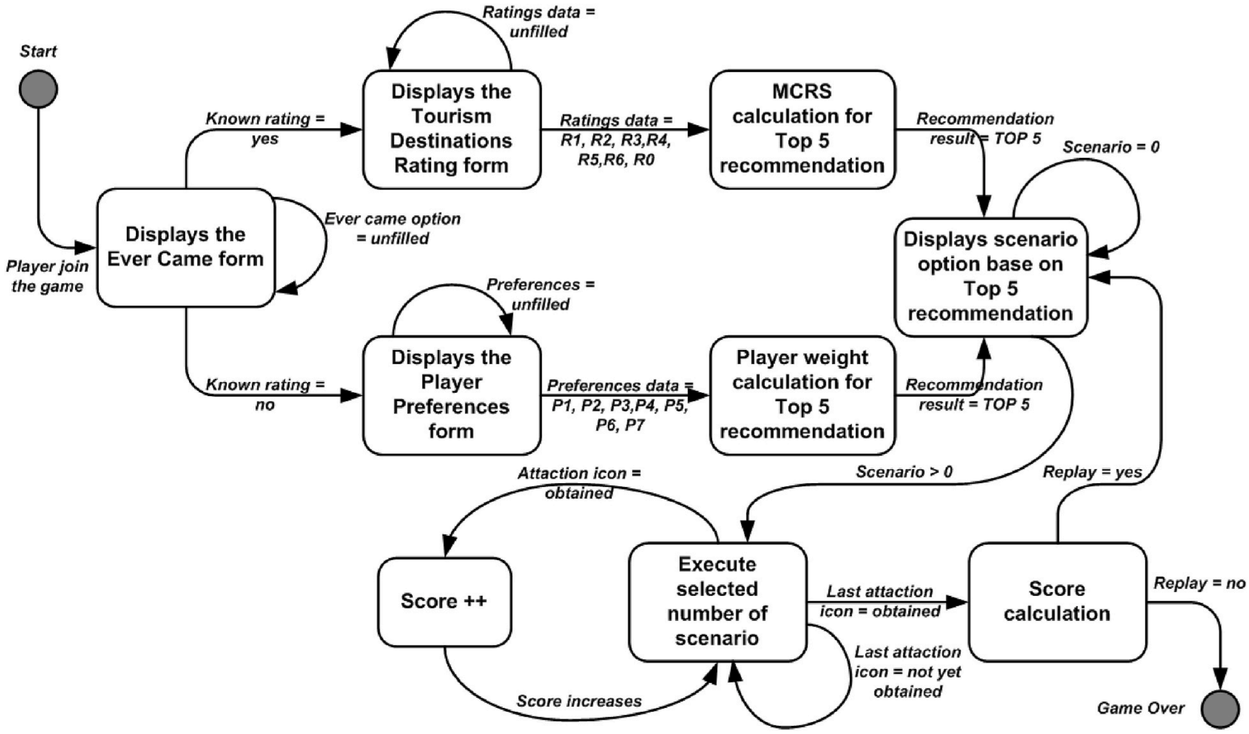

Fig. 6. TDSG scenario using FSM.

of the respondents that support data collection in this study.

We perform a feature selection process of the ten proposed PC criteria to determine the most influential criteria among all existing PC criteria. In this study, to perform feature selection with chi-square, the results are shown in Fig. 7. The results of the chi-square calculation on all of the respondent data taken in the Batu City tourist area show that the five highest criteria that affect the selection of tourist destination items are X3, X4, X7, X8, X10 are the criteria for job, hobby, origin, people in a group and repetition. These five criteria are then used in the learning and running process to produce recommendations based on the ANN classification.

4.2. Blockchain-based data sharing for TDSG

This research uses the Ethereum blockchain as a platform to implement decentralized data sharing in developing TDSG through the Unity game engine. The first process in the Ethereum blockchain setup is to create a wallet to accommodate the smart contract tokens needed to process data transactions on this TDSG. Smart contracts are one of the excellent features of the Ethereum framework, through which developers can program transaction rules for sharing ratings and player preferences. In this research, we program the Smart Contract algorithm in Solidity language, compiled at www.remix.org. Meanwhile, to manage the flow of data sharing in TDSG, this research uses PUN which utilizes a central server of Photon Network.

Table 3
Tourism destinations item for TDSG.

Item Code	Tourism Destinations	Type
i1	Jatim Park 1	Artificial
i2	Jatim Park 2	Artificial
i3	Jatim Park 3	Artificial
i4	Museum Angkut	Cultural Heritage
i5	Selecta	Natural Landscape
i6	Batu Night Spectacular (BNS)	Artificial
i7	Eco Green Park	Artificial
i8	Alun-Alun Batu	Artificial
i9	Kusuma Agro	Natural Landscape
i10	Cangar	Natural Landscape
i11	Coban Talun	Natural Landscape
i12	Songgoriti	Natural Landscape
i13	Coban Rais	Natural Landscape
i14	Predator Fun Park	Artificial

Table 4
The demographic of potential tourists as game players.

Variable	Category	Frequency	Percentage (%)
Gender	Male	81	35.7
	Female	146	64.3
Age	<11	1	0.6
	12–25	140	61.6
	26–45	66	29
	>45	20	8.8
Employment	Entrepreneur	78	34.3
	PNS/TNI/POLRI	9	3.9
	Student	91	40
	Other	49	21.8
Origin	In the city	115	50.6
	Out of town	112	49.4
Travel Motivation	Recreation/Holiday	215	94.7
	Educational Research	4	1.7
	Business	5	2.2
	Other	3	1.4
Marital status	Marry	85	37.4
	Not married yet	142	62.6
Hobby	Swim	32	14
	Travel	113	49.7
	Climb	10	4.4
	Sport	57	25.1
	Photography	15	6.8

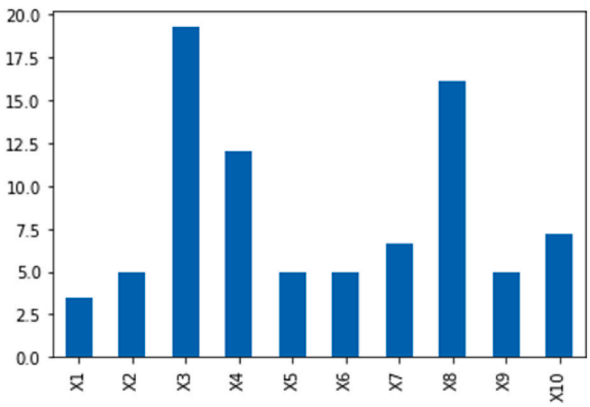

Fig. 7. Feature selection results using chi-square.

In this research, we use www.metamask.io as a wallet account provider to store the fees required for each data transaction. While in the experimental stage, we are utilizing Rinkeby Test Network as a blockchain network provider and erc20 as a dummy token provider. The first test is about the average time required to process data transactions. The test is carried out by carrying out the process of sending RDA data 25 times consisting of the names of tourist destinations, R1, R2, R3, R4, R5, R6, R0, and PC data consisting of P1, P2, P3, P4, P5, P6, P7, P8 and five choices of tourist destinations. Data transmission is done by configuring the int index, int address, string name, string RDA, and string PC. Fig. 8 shows the time it takes to process a transaction for 25 times of testing data transmission. Where the average transaction time required is 20.44 ms.

Furthermore, the second test is carried out to obtain a shorter average transaction processing time by setting the value for the gas price variable. Fig. 9 shows the time required for RDA and PC data transactions to the gas price value. The average transaction time for gas price = 10 gwei is 27 ms, gas price = 20 gwei is 20 ms, gas price = 30 gwei is 20 ms, gas price = 40 gwei is 17 ms, and gas price is = 50 gwei is 14 ms. So, it can be concluded that the greater the value of the gas price, the potential to shorten the processing time of data transactions on the Ethereum blockchain network.

4.3. Recommendation result in TDSG based on KUR

The primary purpose of developing KUR-based MCRS in this study is to recommend tourist destinations for players in conditions of known and unknown ratings as a response to ambient intelligence TDSG. There are two stages of testing the recommendation system in TDSG. The first is testing recommendations based on the known rating approach using RDA data, and the second is the unknown rating approach using PC data. In the MCRS test based on known ratings, we tested the results of the recommendations to 10 players as potential tourists. Then we compare the ranking of recommendations generated by the system with the choice of tourist destinations by tourists

We analyzed the experimental results using reference values for accuracy (*ac*), precision (*pr*), recall (*re*), and F1 score (*F1*). This study uses a confusion matrix approach by first defining TP, FP, TN, and FN values to produce these values. The TP variable is a representation of the number of recommendations produced by the system following the user's original recommendation data, while FP is the number of system recommendation results outside the TOP N user recommendations. On the other hand, *FN* is the number of user recommendations not recommended by the system. At the same time, *TN* is the number of samples that are not recommended by users and are not recommended by the system. Equations (7)–(10) are the formula for calculating *ac, pr, re,* and *F1*.

$$ac = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$pr = \frac{TP}{TP + FP} \tag{8}$$

$$re = \frac{TP}{TP + FN} \tag{9}$$

$$F1 = 2 \times \frac{pr \times re}{pr + re} \tag{10}$$

In the known rating approach testing stage, we compare several possible rating items for tourism destinations known to players from 2, 3, 4, to 5. Table 5 shows the value of the test results for the variables accuracy, precision, recall, and F1 scores based on aggregate, average and worst-case similarity for the Cosine-based Similarity and Pearson correlation-based Similarity methods. Tests were conducted on ten users, Un1 to Un10, based on all reference rating data from previous tourist respondents. The test results show that using the cosine-based similarity method with the worst-case ranking calculation produces the highest value of accuracy, precision, recall, and F1 score, especially for 2 and 4 input items. For the two input items, the accuracy value is 0.657, precision is 0.520, recall is 0.520, and F1 score is 0.520. As for the four input items, the accuracy value is 0.729, precision is 0.620, recall is 0.620, and F1 score is 0.620. Next, the Pearson correlation-based similarity method with the worst-case ranking calculation produces the highest accuracy, precision, recall, and F1 scores, especially for 3 and 5 input items. For the three input items, the accuracy value is 0.671, precision is 0.540, recall is 0.540, and F1 score is 0.540.

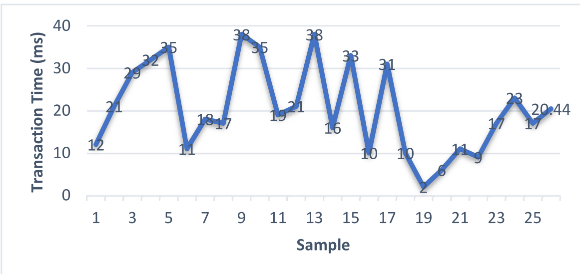

Fig. 8. Average time required for data transactions.

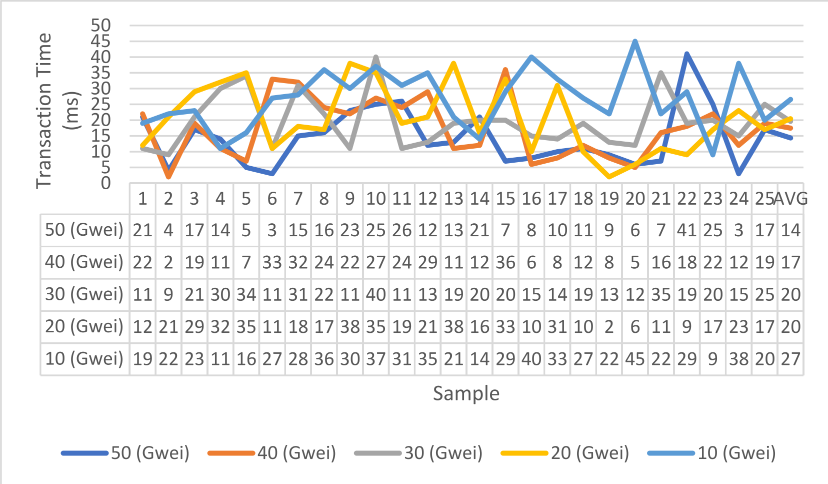

Fig. 9. Influence of gas price on transaction time.

Table 5
Comparison value of accuracy, precision, recall dan F1 score for Cosine-based Similarity and Pearson correlation-based Similarity method.

Number of Player Rating Items Input	Compared Variables	Cosine-based Similarity			Pearson correlation-based Similarity		
		Worst Case	Average	Aggregate	Worst Case	Average	Aggregate
2 (Jatim Park 1, Jatim Park 3)	*ac*	**0,657**	0,643	0,643	0,629	0,686	0,686
	pr	0,520	0,500	0,500	0,480	0,560	0,560
	re	0,520	0,500	0,500	0,480	0,560	0,560
	F1	0,520	0,500	0,500	0,480	0,560	0,560
3 (Jatim Park 1, Jatim Park 2, Jatim Park 3)	*ac*	0,643	0,657	0,657	**0,671**	0,586	0,586
	pr	0,500	0,520	0,520	0,540	0,420	0,420
	re	0,500	0,520	0,520	0,540	0,420	0,420
	F1	0,500	0,520	0,520	0,540	0,420	0,420
4 (Jatim Park 1, Jatim Park 2, Jatim Park 3, BNS)	*ac*	**0,729**	0,700	0,700	0,686	0,586	0,586
	pr	0,620	0,580	0,580	0,560	0,420	0,420
	re	0,620	0,580	0,580	0,560	0,420	0,420
	F1	0,620	0,580	0,580	0,560	0,420	0,420
5(Jatim Park 1, Jatim Park 2, Jatim Park 3, BNS, Selecta)	*ac*	0,714	0,729	0,729	**0,743**	0,743	0,743
	pr	0,600	0,620	0,620	0,640	0,640	0,640
	re	0,600	0,620	0,620	0,640	0,640	0,640
	F1	0,600	0,620	0,620	0,640	0,640	0,640

Obtained through a questionnaire.

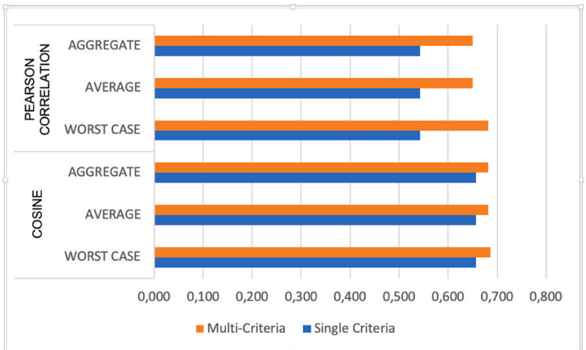

Fig. 10. Average accuracy comparison of the recommendations.

Meanwhile, for five items, the input value is accuracy is 0.743, precision is 0.640, recall is 0.640, and F1 score is 0.640. From the test results, it can be concluded that the more ratings the user knows, the higher the accuracy value generated by the system. The comparison of the accuracy values for each calculation of the similarity method can also be seen in Fig. 10, where the cosine-based similarity method with the worst-case ranking calculation produces the highest average accuracy value of 0.686. In addition, when compared to the single rating recommender system method, MCRS generally has a higher level of accuracy.

Furthermore, implementing the unknown rating approach into the game system, we tried several MLP ANN architectures to get the best architecture. Table 6 shows the results of a comparison of tests on several MLP architectures based on data from 5 input criteria: job, hobby, origin, people in a group, and repetition. Based on the table, the highest accuracy value of 0.660 is found in the MLP architecture 5-7-5-3-14, as shown in Fig. 11, where each hidden layer has a ReLU activation function, and the output layer uses a sigmoid activation function. In the data training process, the optimizer used is Stochastic Gradient Descent, with a learning rate of 0.1.

The following is an equation for calculating the feedforward output carried out in the data testing process as an implementation in the game using the weights, biases, and activation functions of the 5-7-5-3-14 MLP architecture. The feedforward calculation produces 14 prediction outputs, where if each of these outputs has a value of $Y_p \geq 0{,}5$, then it is equal to 1, whereas if $Y_p < 0{,}5$, then the output is equal to 0. Eq. (11) is the formula for calculating the output on hidden layer 1 Z_{in_j} while equation (12) is the calculation after applying the ReLU activation function on hidden layer 1 Z_j. Where x_i represents the input data in the input layer, w_{ij} represents the weight value from input layer (i) to hidden layer 1 (j), while w_{oj} represents the bias value in hidden layer 1 (j).

$$Z_{in_j} = \sum_{i=1}^{5} x_i w_{ij} + w_{oj} \tag{11}$$

$$Z_j = f\left(Z_{in_j}\right) = f\left(0, Z_{in_j}\right) \tag{12}$$

Furthermore, equation (13) shows the output calculation on hidden layer 2 T_{in_k}, and equation (14) is the formula after the ReLU T_k. Where v_{jk} is the weight value from hidden layer 1 (j) to hidden layer 2 (k), while v_{ok} is the bias value in the hidden layer (k).

$$T_{in_k} = \sum_{j=1}^{7} z_j v_{jk} + v_{ok} \tag{13}$$

$$T_k = f\left(t_{in_k}\right) = f\left(0, t_{in_k}\right) \tag{14}$$

Next, equation (15) is the formula for calculating the output on hidden layer 3 S_{in_m} while equation (16) is the output calculation after applying the ReLU S_m activation function. Where c_{km} is the weight value from hidden layer 2 (k) to hidden layer 3 (m) and c_{om} represents the bias value in hidden layer 3 (m).

$$S_{in_m} = \sum_{k=1}^{5} t_k c_{km} + c_{om} \tag{15}$$

$$S_m = f(s_{in_m}) = f(0, s_{in_m}) \tag{16}$$

Eq. (17) shows the calculation on the output layer Y_{in_p}, and equation (18) is the formula after the sigmoid Y_p. Where b_{mp} shows the weight value from hidden layer 3 (m) to the output layer (p) and b_{op} is the bias value at the output layer (p).

$$Y_{in_p} = \sum_{m=1}^{3} s_m b_{mp} + b_{op} \tag{17}$$

$$Y_p = f\left(y_{in_p}\right) = \frac{1}{1 + e^{-y_{inp}}} \tag{18}$$

4.4. Game implementation

In this research, we build TDSG using the Unity game engine, where every sub-system development is based on that platform. In Fig. 12, RDA Data Input shows the in-game user interface form to get RDA data from players: attractions, accessibility, amenities, available packages, activities, and ancillary services. At the same time, the Known Rating Result is an example of visualizing the recommendations based on the known rating approach for the top 5 tourist destinations. PC Data Input shows a visualization of the player's preference input form in the game, where they can enter their work preferences, hobbies, travel companions' area of origin, and repetition as input for an unknown rating-based recommendation system. Unknown Rating Result shows an example of the recommendation of 5 tourist destinations for players. Fig. 13 shows an example of the results of the development of TDSG, which includes the appearance of several virtual environments for tourist destinations.

4.5. Comparison method

In this section, we try to compare the results of this study with the results of several similar studies. The aim is to determine several

Table 6
MLP architecture test results.

MLP Architecture	5-7-5-14	5-5-3-1-14	5-7-5-3-14	5-7-5-3-14	5-10-7-14	5-10-7-14
Epoch	1000	1000	1000	1000	1000	1000
Learning rate	0,001	0,001	0,001	0,1	0,1	0,1
Optimizer	Adam	Adam	SGD	SGD	SGD	Adam
Loss	0,538	0,541	0,703	0,551	0,541	0,506
ac	0,431	0,556	0,625	0,660	0,529	0,451
pr	0,604	0,592	0,349	0,590	0,585	0,643
re	0,646	0,658	0,428	0,675	0,693	0,660
***F*1**	0.624	0.623	0.384	0.630	0.634	0.651

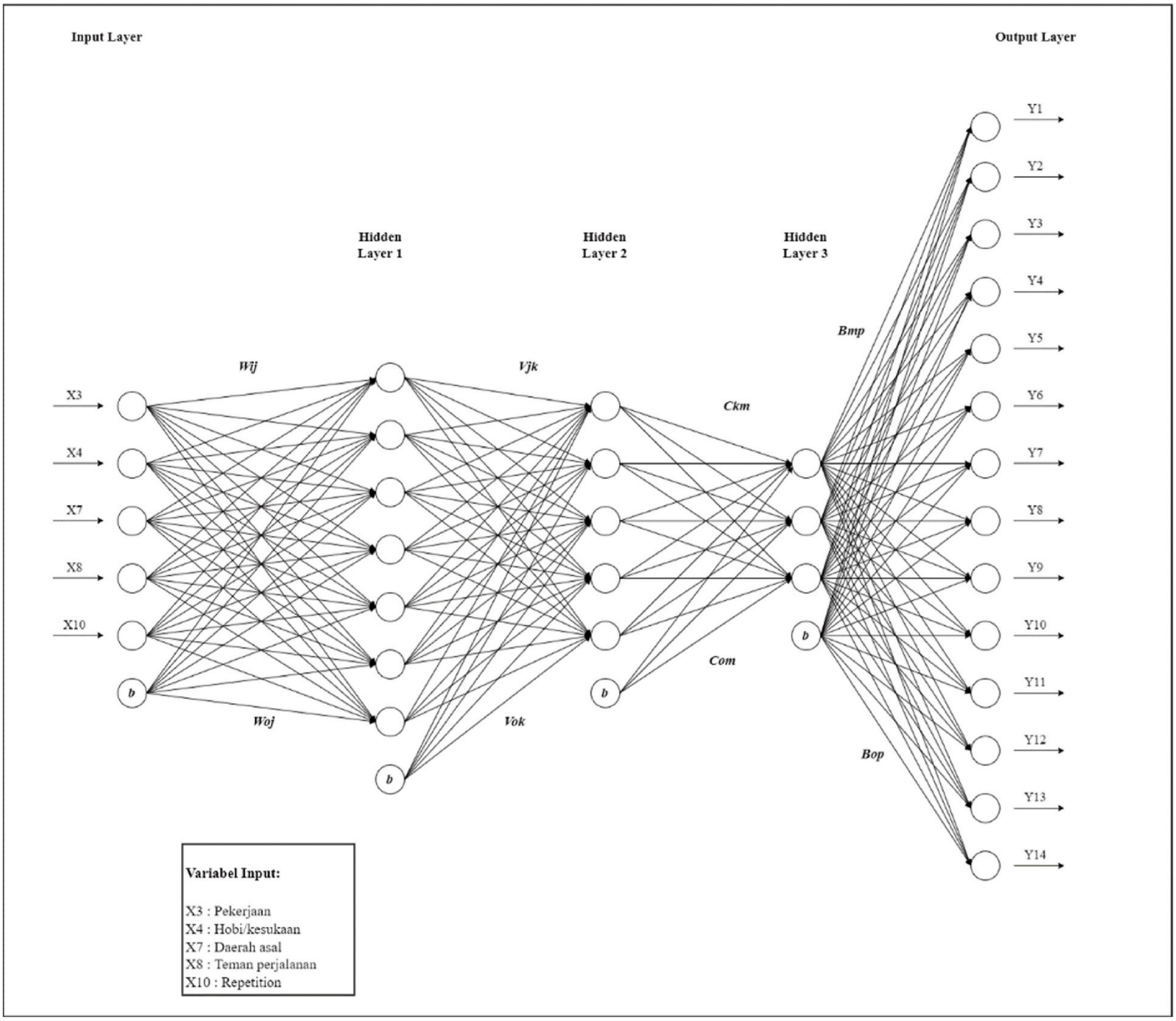

Fig. 11. MLP architecture 5-7-5-3-14.

compared studies' characteristics, advantages, and disadvantages. Table 7 compares methods, applications, items, and values of *ac, pr, re*, and *F*1. Meanwhile, Fig. 14 shows the comparison of *ac, pr, re*, and *F*1 values in the graph. Based on the comparison table, each reference uses a different recommendation method, starting from K-means and Genetic Algorithm and several MCRS variants. Each research is also built in various web-based, mobile, and game applications. The items that are the object of research include general tourist destinations in Refs. [49,54] and halal tourism in Ref. [53].

As shown in Table 7 and Fig. 14, Reference [49] does not mention the *ac* value of the resulting recommendations, nor does

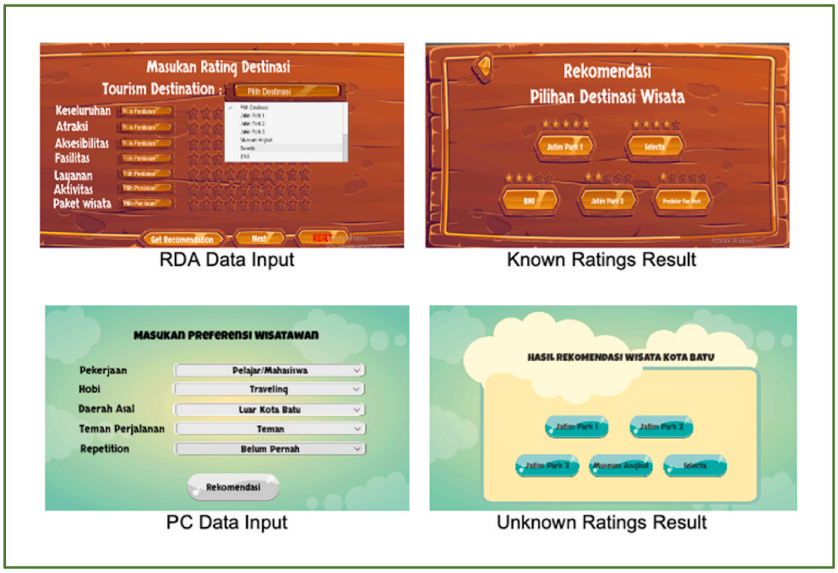

Fig. 12. Visualization examples of RDA and PC data input and recommendation results using known and unknown ratings.

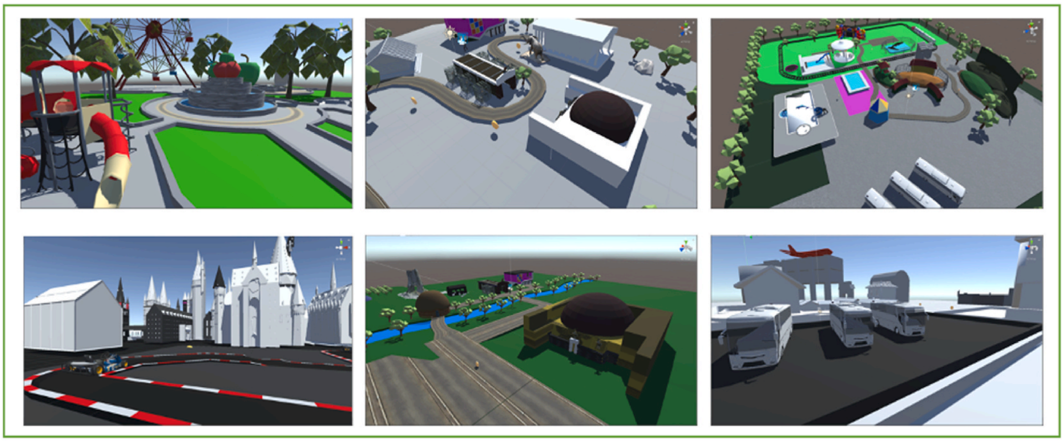

Fig. 13. Examples of tourism destination virtual environments in TDSG.

Table 7
Comparison of methods, applications, items, and values results for *ac*, *pr*, *re*, and *F*1.

Reference	Recommendation Method	Application	Item	Result			
				ac	***pr***	***re***	***F*1**
[49]	K-means + GA	Mobile Recommender System	General tourism destinations	Not mentioned	0.840	0.500	0.620
[53]	DR based MCRS	Desktop Game	Halal tourism destinations	0.600	0.670	0.640	0.650
[54]	WSM based MCRS	Web-based Recommendation	General tourism destinations	Not mentioned	Not mentioned	Not mentioned	Not mentioned
Ours	DMCRS - known rating DMCRS - unknown rating	Serious Game	General tourism destinations	0.743 0.660	0.640 0.590	0.640 0.675	0.640 0.630

reference [54] mention the value of *ac, pr, re*, and *F*1. Our proposed system yields a relatively higher ac accuracy rate of 0.743 for the known rating and 0.660 for the unknown rating approach. This value is higher than reference [53], which is stated to be 0.600. Meanwhile, the precision value of the pr system has not yet produced a high value, so further research is needed to improve it. This

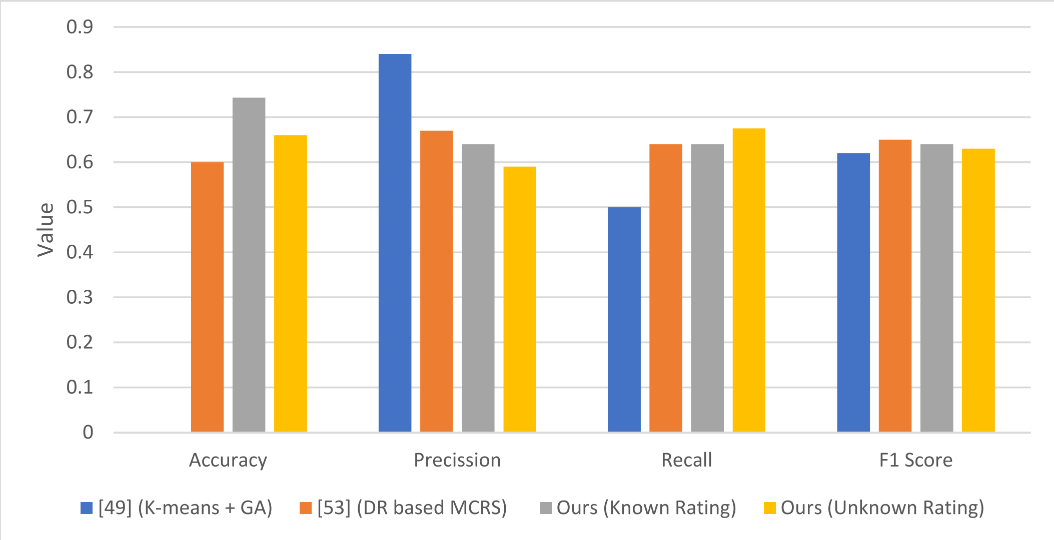

Fig. 14. Comparison for accuracy, precision, recall, and F1 score.

study has a precision value of 0.640, lower than reference [49,53]. However, this study has a relatively high score for the recall value of 0.640 for the known assessment and 0.675 for the unknown assessment approach. The recall value is still higher than the research results from reference [49]. Furthermore, for the F1 score, this study resulted in a value of 0.640 in the known rating approach and 0.630 in the unknown rating approach. The F1 score is still lower than the results of the reference study [53].

5. Conclusions

This study discusses the Multi-Criteria Recommender System for selecting tourism destinations as a reference for providing scenario choices in response to the ambient intelligence of TDSG. Recommendations for players are generated through the MCRS method supported by the Ethereum blockchain as a platform to handle data sharing of player ratings and preferences. We designed MCRS to produce recommendations if players have visited or have never visited, using the known and unknown rating approach. For the known rating-based recommendation system, we compare several methods to measure user similarity, namely cosine-based and Pearson correlation-based similarity, with ranking calculations using the worst-case, average, and aggregate. Meanwhile, based on the unknown rating approach, our recommendation system uses the ANN classification method with the MLP architecture to produce recommendations for the choice of tourist destinations. Furthermore, the system visualizes the recommendations for the choice of travel scenarios in the TDSG.

The results show that the Ethereum blockchain works well in supporting decentralized data sharing, rating tourism destinations, and player preferences. The average processing time for one transaction is 20.6 s, and the average cost per transaction of 0.000106944. Furthermore, there are differences in the recommendations generated by MCRS based on the known and unknown ratings. The MCRS test results based on the known rating approach have the highest scores for accuracy, 0.743, precision 0.640, recall = 0.640, and F1 score = 0.640, for the 5 rating items using the Pearson correlation-based similarity calculation. Meanwhile, the unknown rating system approach produces the highest value for accuracy is 0.660, precision is 0.590, recall is 0.675, and F1 score is 0.630 using the MLP 5-7-5-3-14 architecture. The test results show that the known rating-based recommender system has a better accuracy rate than the unknown rating in this study. However, although the unknown rating approach has a lower accuracy level, using this approach increases the recommender system's ability to overcome cold-start problems.

This research still needs to be developed further to produce a serious game system in the field of tourism. One part that needs attention in further research is data sharing systems. It is necessary to use other decentralized data-sharing systems that are simpler in securing data but still have decentralized and distributed capabilities required by the recommender system. In addition, the recommender system also needs to be developed using other methods. An example of a suggested method is based on a context-aware approach or another hybrid recommender system. The aim is to find the most suitable recommender system method to support ambient intelligence technology in tourism destinations' serious games.

Author contribution statement

Yunifa Miftachul Arif: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Duvan Deswantara Putra; Dyah Wardani: Performed the experiments; Analyzed and interpreted the data.

Supeno Mardi Susiki Nugroho; Mochamad Hariadi: Conceived and designed the experiments; Analyzed and interpreted the data;

Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no competing interests.

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