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A Novel Consumer Preference Model Based on Blockchain and Topic Similarity Clustering in Cross-Border E-Commerce

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ABSTRACT

Nowadays, countries in the world have frequent economic exchanges, and the scale of cross-border E-Commerce (CBEC) is getting larger and larger. CBEC refers to trading, payment, logistics, customs clearance, and other transactions. It also refers to the services between countries or regions through Internet technology and e-commerce platforms. In this article, the authors proposed a consumer preference model by blockchain and topic similarity clustering to obtain more consumer preference information. First, this article builds a blockchain-based consumer information collection system for CBEC to extract various features of consumers in CBEC. Secondly, by improving the performance of multiple characteristics of consumers, the accuracy of consumer preference prediction is improved. Finally, a method of consumer preference prediction based on topic similarity clustering is proposed to obtain consumers' purchase preference types. Experimental results show that the method can reach 84.3% of the H-mean, getting the best predictive performance and assisting CBEC by predicting consumer preferences.

KEYWORDS

Blockchain, CBEC, Consumer preference, Topic Similarity Clustering

INTRODUCTION

Cross-border e-commerce (CBEC) is one of the crucial ways or platforms for modern consumers to shop (Zhu et al., 2019; Kawa & Zdrenka, 2016). Relying on the progress of blockchain, CBEC has established a substantial industrial chain and innovative sales methods, making it convenient for people in different countries or regions to get more goods. However, different consumers have different needs and purchasing goals, and mastering consumers' purchasing preferences as soon as possible can profoundly impact the strategic decisions and operations of CBEC.

The consumer preference model is a mathematical or statistical model that describes and predicts consumers' purchasing behaviors and choices (Chung & Rao, 2012). It can help e-commerce businesses

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better understand consumers' needs and preferences, optimizing product positioning, marketing, and service strategies. The consumer preference model also has its characteristics (Zhu & Li, 2018). First, consumer preferences are diverse, and each has unique preferences and needs. Considering consumers' differences, a comprehensive and accurate preference model may need to cover many factors and variables. Second, consumer preferences may change over time as the environment and other factors change. Therefore, the established model must be adaptable and able to capture the changes and trends in consumer behavior at any time (Al-Alawi & Bradley, 2013). Then, the construction of the consumer preference model requires too much data support, and these data may involve multiple dimensions, such as personal information, purchase history, and social media behavior. The collection, collation, and analysis of data is a complex process. In addition, various factors often affect consumers' decisions, and sometimes, consumers' decisions may be uncertain, leading to a certain degree of uncertainty in the predicted results of the model (Xie et al., 2021; Viciunaite & Alfnes, 2020).

According to the above characteristics, there are many difficulties in constructing the consumer preference model. First, the consumer preference model data cost is high, and many complex and valuable features must be extracted. Steps such as data preprocessing and feature engineering require careful processing to guarantee accuracy and reliability (Nguyen et al., 2019). When building a consumer preference model, appropriate mathematical or statistical models need to be selected to describe consumer behavior and choices. Second, consumers' decision-making may be influenced by multiple factors, such as personal characteristics, environment, and competitors. Finally, because many factors influence consumer behavior, sometimes consumers' decisions may be irrational (Yenipazarli, 2019). Therefore, the model's predictive accuracy may be limited to some extent. The consumer preference model has the characteristics of diversity and dynamics, while data acquisition, processing, model selection, and prediction accuracy are the main difficulties in constructing the consumer preference model. It is necessary to apply data science comprehensively, statistics, and industry experience to overcome these difficulties and better meet the market demand and the individual demand of consumers (Ma et al., 2019).

At present, the study of the preference model is an important content in the recommendation service. In preference models, many scholars have made great progress. Zheng et al. (2010) divided users' learning information needs into long- and short-term and added some psychological concepts such as situational interest and personal interest to build a user interest model through comprehensive research, which can better respond to the changes in users' interests at any time and be targeted. Al-samarraie et al. (2017) believe that consumers' learning behaviors in E-learning reflect the users' current psychological activities. Users' preferences were analyzed by extracting the trajectory of consumers' behaviors, and an interest model based on consumers' learning behaviors was built. To better provide personalized services for learning consumers. Amin et al. (2020) extracted consumers' interest information using interactive question-and-answer behavior, built a preference model based on consumers' reading behavior, and proposed a new algorithm for consumers' preferences, values, and interests. However, all these methods were based on predicting consumers' consumption preferences by studying their subjects. In CBEC, collecting information on consumer subjects is complex, and consumers' browsing and search records and personal information can only be indirectly obtained.

Therefore, we propose a consumer preference model by the blockchain and topic similarity clustering to predict consumers' intention in CBEC, improve the service efficiency of CBEC, and create a good communication environment for CBEC and consumers.

The main contributions are as follows:

1. We collect blockchain-based consumer information systems to feed the data to the subsequent consumer preference model.
2. We improve the performance of various features of consumers and propose a consumer preference model by topic similarity clustering to obtain consumers' purchase preference types.
3. Our model achieves excellent performance while comparing other competitive methods.

RELATED WORKS

Application of Blockchain in CBEC

Core technologies such as point-to-point networking, time stamps, and smart contracts in blockchain provide features such as traceability, decentralization, and immutable information for blockchain technology. CBEC can realize the transformation operation through the application of blockchain technology, rebuild the current ecological mechanism of CBEC, establish a low-cost and high-efficiency CBEC trading system, and help the rapid development of CBEC.

Blockchain technology has the characteristics of decentralization and traceability. A real-time monitoring system can be established for CBEC logistics and transportation using these two characteristics of blockchain technology so that information can be shared among all links in logistics and transportation to solve the logistics problems CBEC faces. Wang et al. (2021) believe that since the data in the blockchain system is traceable and all the data are time-stamped, a real-time monitor can be established based on the blockchain technology. Xie et al. (2021) believe that blockchain has decentralization, which can integrate cross-border trade participants, such as logistics, supervision, trade, and finance equally, complete the interconnection of information and data in the trade ecology. Zheng et al. (2022) demonstrated that blockchain technology can reduce operating costs, build a credit system, avoid risks encountered in the operation of CBEC, and create a more efficient, fair, and transparent business environment.

The characteristics of traceability and high trust in blockchain can support CBEC in constructing a traceability system, which can ensure product quality and control the product quality. Lai et al. (2019) integrated the suppliers, consumers and other nodes involved in CBEC to establish a trade chain, effectively improving the security and effectiveness. Liao et al. (2021) believe that the time-stamp technology can provide the information in blockchain with time dimension, and the commodity information cannot be changed at will. By querying the blockchain system, consumers can obtain information about the source, agent, logistics, and other commodity characteristics to improve consumers' trust in the authenticity of CBEC.

Preference Model

Preferences can be understood as how much a person likes something. Understanding users' preferences can help information providers provide personalized services to users. Personalized recommendations based on user preference discovery also has been applied in real life. These applications will find users' interest in a certain product according to their historical choices and push relevant content to users. Wang et al. (2015) proposed a corresponding three-layer Bayesian graph model based on the collected personalized data, used an iterative expectation maximization algorithm, and used the Monte Carlo method to simplify expectation calculation. This method extracts user preferences by introducing hidden layer information. Liu et al. (2015) extracted the context information and then divided the context information into three classes: user, project, and interaction. The user preference information is mined by integrating the context information through the extended matrix decomposition model. This method solves the cold start problem of sparse user history score matrix and lack of user history information. Tondello et al. (2017) analyzed user diversity preference tendency based on user history data, introduced a time decay function to adjust user rating dynamically, and adjusted the proportion of the two by combining matrix decomposition technology and fatigue function. This method effectively alleviates the cold start problem of the recommendation system and retains the diversity of users' interests. Haboucha et al. (2017) convert users' preferences for specific objects into users' preferences for interest points contained in the object and then automatically aggregate users with the same preferences into a common preference group (CPG) for media information recommendation and sharing. Maiya et al. (2014) studied methods for improving the interpretability of visualized LDA topic models by outputting them. Terragni et al. (2021) compared the most advanced topic similarity measures and proposed a new measure based on word embedding. Peinelt et al. (2020)

suggested an innovative architecture leveraging BERT and topic information for detecting pairwise semantic similarity.

The quality and reviews of CBEC websites will affect consumers' preferences, and consumers' differences will also affect their purchase preferences. Susana et al. (2020) studied the influence of cause-related marketing on consumers' purchase preferences and believed that cause-related marketing suitable for a brand positively influences consumers' intentions. Liu et al. (2020) studied the influence of different online comment language styles on consumers' purchase preferences. They found that when purchasing experiential products, figurative comments have a more significant impact on consumers, thus enhancing consumers' purchase intention. Zhao et al. (2020) studied how sellers' responses to negative online comments affect consumers' purchase preferences and found that apologizing and reclaiming negative comments can better restore consumers' purchase preferences. Viciunaite and Alfnes (2020) studied consumer preferences for these sustainable business model elements. They believed that the sustainability of business model elements can often become a preferred product for consumers. Liao et al. (2019) evaluated and quantified consumer preferences for business models in the context of electric vehicles and explored the impact of consumer attitudes on business model preferences and choices. Saeed et al. (2020) studied the effects of family characteristics, sociodemographic characteristics, understanding of AV technology and new travel choices, psychological factors, and architectural environmental characteristics on consumer preferences.

CONSUMER PREFERENCE MODEL BASED ON BLOCKCHAIN AND TOPIC SIMILARITY CLUSTERING

A Blockchain-Based Consumer Information Collection System in CBEC

We built a blockchain-based consumer information collection system for CBEC to analyze consumer preferences. The method primarily collects key consumer information to provide input for the subsequent consumer preference model.

Consumers tend to have certain purchasing habits when they consume. Therefore, we can collect their past consumption, recent searches, and others to provide a data basis for the preference model. However, considering the characteristics of CBEC, blockchain becomes the best choice for information collection and storage. At present, there are many blockchain technology platforms on the market; due to the lack of unified technical standards, the design goals of each blockchain technology platform are different, and the characteristics, performance, and application fields of the forum are also very different. Therefore, not all blockchain platforms are suitable for CBEC. Considering the immaturity of blockchain technology, this article has preliminarily screened the scope of blockchain technology. Considering that mainstream blockchain technology is more mature, the risk, when applied, is relatively small, and the blockchain platform designed with the issue of digital currency is excluded.

This paper selects Hyperledger Fabric (HF) as the baseline in our consumer information collection system in CBEC. This is an open-source, enterprise-grade, permission-requiring blockchain technology. It does not have a cryptocurrency built in but focuses more on the distributed information aspect of blockchain technology. The technology supports pluggable consensus protocols; users can choose from various consensus mechanisms based on their needs. Hyperledger has better privacy and confidentiality, provides the functions of private chain and alliance chain, and can carry out identity management, which only authorized users can access. The parallelism of HF improves the system. The HF-based consumer information storage mode in CBEC uses the decentralized storage and tamper-proof blockchain, which can be a multi-source collaborative platform. The community composed of various roles and functions located on the blockchain platform can participate in identifying consumer data in CBEC and realize the sharing of underlying data, and there is multi-stakeholder collaboration.

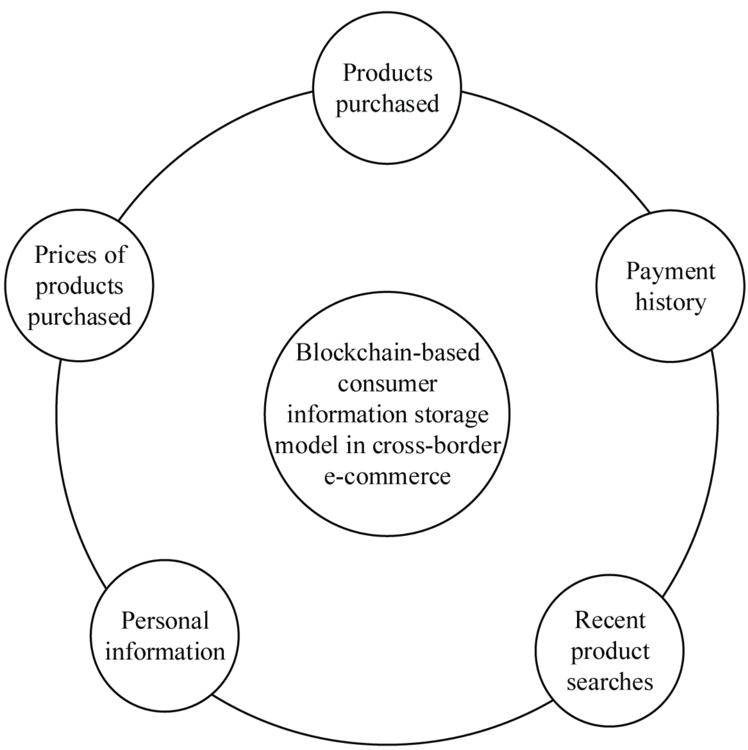
As shown in Figure 1, HF is used in this paper to establish a consumer information collection system based on blockchain. This system collects information, such as product purchased A1, personal information A2, price of product purchased A3, recent product search record A4, and payment record A5, to provide data support for the subsequent prediction of consumers' purchase preferences. Figure 1 shows the types of features involved in our information collection system. The system has completed consumers' purchase preferences by collecting features in the figure.

Processing Methods of Consumers' Purchase Preference Characteristics

We assume that consumers with similar purchase intentions have similar purchase choices in the future because of consumers' purchase preferences. In this paper, consumers' purchase preference is expressed as the probability distribution of consumers on each purchase intention. Considering that the five characteristics of a consumer's purchased products, personal information, purchased product price, recent product search record, and payment record can completely represent any consumer, this paper defines the similarity of consumers as the similarity of their purchase preferences. By calculating the distribution vector of many consumer purchase records, the probability matrix of the current consumer purchase preference similarity is obtained, and the purchase preference prediction matrix incorporating the consumer feature similarity is obtained to predict the consumer's future purchase preference.

The cosine similarity (CS) is commonly adopted to calculate the vector similarity. The enhanced CS calculation method can compute the similarity between consumers, and the penalty coefficient is introduced to reasonably measure the difference in the probability value of the corresponding position of the consumer vector. The equation of the penalty coefficient is as follows:

Figure 1. Blockchain-based consumer information collection system



$$sim\left(u,v\right)=\frac{\sum\xi\left(\frac{1}{e^{\theta\left|u-v\right|}}\right)u\cdot v}{\left|u\right|\cdot\left|v\right|} \tag{1}$$

where sim(u, v) denotes the similarity between consumer u and consumer v, u refers to the A2 and A5 features of consumer u, v represents the A5 and A2 features of consumer v, ξ represents the penalty coefficient, which is used to punish the dissimilar consumer feature distribution vector, that is, the more significant the difference in the corresponding position probability value of the distribution vector, the greater the penalty coefficient value, the stronger the penalty.

The purchasing preference of consumers is not only affected by similar consumers but also by similar purchasing habits. Assuming that the user will prefer similar items, the target user is recommended to the items with high similarity to his favorite things. When assessing the similarity of purchased information, the most important consideration is whether there is a fungible relationship between the information, mainly represented by the gap between the objects of purchase and the record of consumers' recent search for products. Therefore, the following formula is used in this paper to define the similarity of personal purchase information:

$$dis\left(r_p,r_c\right)=\frac{\left|r_p-r_c\right|}{\left|r_p\right|\cdot\left|r_c\right|} \tag{2}$$

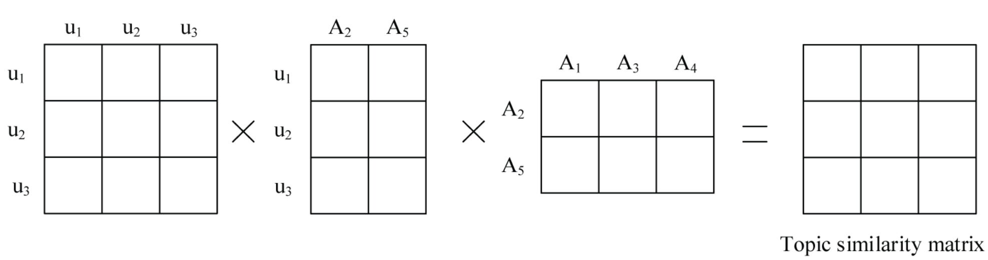
where rp and rc represent the information on goods purchased in the past and the information on goods searched by the same consumer, according to the formula, the similarity of consumers' purchase preferences in different periods can be calculated. It should be noted that feature r contains A1, A2, and A4 information. Therefore, the consumer's current purchase preference feature can be represented by A = {r, v, u}, the consumer's purchase preference feature, as shown in Figure 2.

Consumer Preference Prediction Method Based on Topic Similarity Clustering

The consumer's consumption preference feature A can be obtained through the above method. Considering the large number of commodities in CBEC, we divide the different commodity quantities into a series of topics B. By calculating the similarity between A and B, the final consumer preference is obtained. Therefore, we propose a consumer preference prediction model based on topic similarity clustering.

First, before topic clustering, we abstractly represent a product as a title and description text and use vector space to denote the features of the text. These texts are primarily derived from consumers' previous consumption records and some consumers' attributes, including all types in Figure 1. In this

Figure 2. Topic similarity calculation method



way, the topic features of each commodity in CBEC are obtained. When the news text is represented as a spatial vector, the similarity between the news content can be represented by calculating the distance between the vectors. The formula for measuring similarity is as follows:

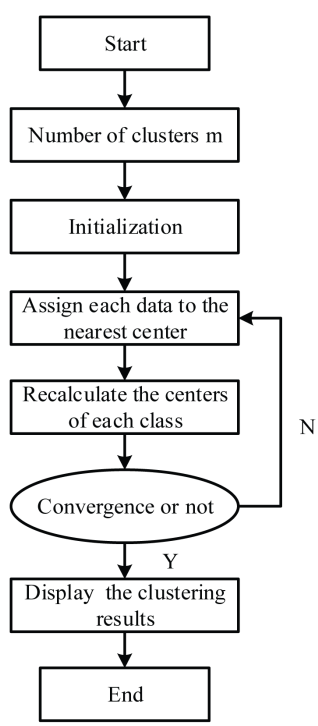
$$sim\left(d_i, d_j\right) = \sqrt{\sum_{k=1}^{n}\left(w_{ki} - w_{kj}\right)^2} \tag{3}$$

where di and dj denote the topic characteristics of item i and item j, the more similar the content of item i and item j is, the more the value of sim(di, dj) approaches 1.

Then, this paper employs the K-means algorithm as a clustering model to predict consumers' preferences. The initial clustering center selection algorithm preprocesses m topic clusters of CBEC goods. In general, m is far smaller than the total number of goods M on the platform. For the set of commodities to be processed, we also get the possible commodities contained in each topic cluster when selecting the initial clustering center. The number of product features contained in each initial topic cluster is not very different from that after many iterations, and we can roughly use this statistic to automatically determine the value of the topic group m.

Finally, we compute the distance between each seed and center, which can be assigned to the nearest center. For the distance calculation between each seed and each cluster center, Euclidean distance or other distance measures are usually used to measure the similarity between them. Euclidean distance is one of the most commonly used distance measures, which calculates the straight-line distance between two seeds, which can be presented as equation (3). Then, we present this process in Figure 3, which will be repeated continuously until the termination. Therefore, the most real purchase preference of the consumer can be obtained.

Figure 3. K-means clustering



EXPERIMENT AND ANALYSIS

Dataset and Implementation

We used the CBEC dataset (https://www.zenodo.org/record/4675227, doi: 10.5281/zenodo.4675227) to test a consumer preference model based on blockchain and topic similarity clustering in cross-border e-commerce. The experiment parameters are in Table 1. We set the weight decay term of the model to 0.004 and adopted SGD as the optimizer.

Considering consumer preference, Precision, Recall and H-measures are adopted as evaluation criteria for the method. Among them, the formula for calculating the positive and negative samples of regression prediction is as follows:

$$Precision = \frac{V\left(gt \cdot pr\right)}{V\left(pr\right)} \tag{4}$$

$$Recall = \frac{V\left(gt \cdot pr\right)}{V\left(gt\right)} \tag{5}$$

$$H - mean = \frac{V_P \times V_R}{V_R + V_R} \tag{6}$$

where pr represents the consumer preference result predicted by the model, and gt represents the true value of the data set annotation. The H-measure is a commonly used evaluation metric for clustering. It is the harmonic mean of precision and recall, where precision is the ratio of correctly predicted positive observations to the total predicted positives and recall is the ratio of correctly predicted positive observations to all observations in the actual class.

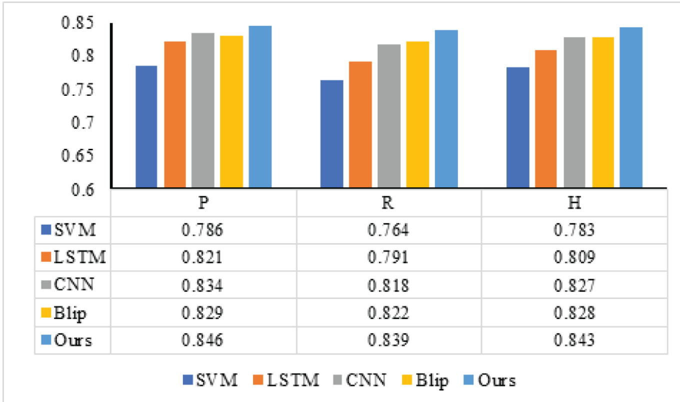
Comparison of Our Method and Other Methods

We perform the performance experiment of our method on the cross-border e-commerce dataset. We selected some excellent feature models, such as SVM, LSTM, CNN, and Blip, and compared the performance, as shown in Figure 4. Compared with other futures price prediction algorithms, our

Table 1. Implementation parameters

Types	Parameters
CPU	R5-7600x
GPU	Rtx 3090Ti
Deep learning method	Pytorch
Epochs	30
Batch size	32
Initial learning rate	0.001
Momentum	0.88

Figure 4. Comparison with other methods



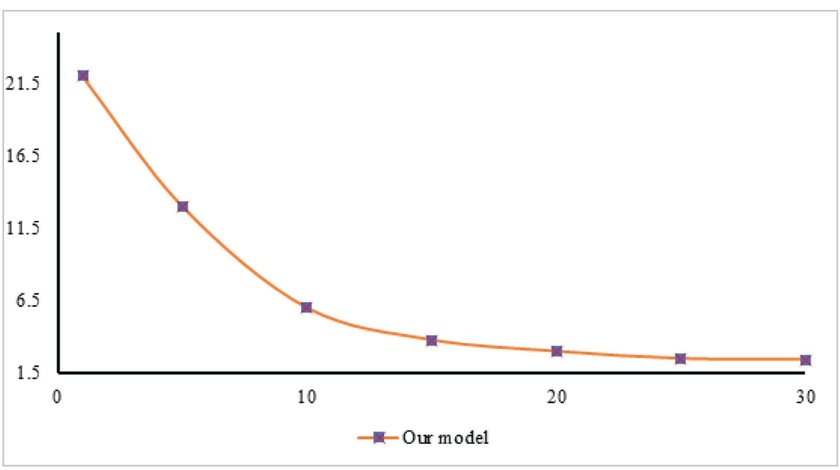
	P	R	H
SVM	0.786	0.764	0.783
LSTM	0.821	0.791	0.809
CNN	0.834	0.818	0.827
Blip	0.829	0.822	0.828
Ours	0.846	0.839	0.843

method can obtain the highest precision, recall, and H values, which are 0.846, 0.839, and 0.843, respectively. Compared with SVM, our consumer preference prediction method improves precision, recall, and H values by more than 0.06. The principal reason for this improvement is that our method does not use fixed categories for classification but adopts an adaptive method to establish a cluster core closer to consumers‘ personal habits. Compared with LSTM and CNN, our method is still in the leading position, with more than 0.01 improvement in each index. Our method has improved its H value by 0.015 compared to the latest Blip.

Although the Blip method still uses a fixed type of pattern, it still achieves excellent results due to deep networks. Our approach further improves the model’s performance by integrating the consumer’s five characteristics: product purchased A1, personal information A2, price of the product purchased A3, recent product search record A4, and payment record A5. In addition, the adaptive classification core adopted by our model can better match consumers with different preferences, and it is no longer hard classification simply and roughly. Hence, the effect is better than SVM, LSTM, CNN, and Blip.

In addition, by the structure of K-means, the training process of our model also needs to verify the performance. The model’s input is the consumer’s five characteristics for training. The loss function curve is in Figure 5. It can be found that the model reaches the fit at the 25th epoch, which

Figure 5. The loss of our model based on K-means



means that the model's training obtains the best model parameters at the 25th epoch. In addition, the K-means algorithm is a small-scale AI model. In this paper, five features are constructed to meet its training requirements, and the number of adaptive clustering cores is designed. These measures further shorten the problems, such as overfitting and gradient explosion of the model.

Feature Testing and Evaluation

To test the performance of the feature processing method proposed by us, we will conduct an ablation experiment on five features of consumers: product purchased A1, personal information A2, price of product purchased A3, recent product search record A4 and payment record A5.

In the algorithm, we adopt the consumer similarity feature {A2, A5} and the consumer purchasing habit similarity feature {A1, A3, A4}. First, we keep the similarity feature of purchasing habits unchanged and conduct an ablation experiment on the consumer similarity feature {A2, A5} in Table 2. We can conclude that the consumer similarity feature {A2, A5} has a good expression effect, and our topic similarity clustering prediction method has strong malleability. As more and more features are added to the model, the performance of the model gradually increases. The consumer similarity feature {A2, A5} can always improve the model2 index5 regardless of whether the model has a consumer buying habit similarity feature {A1, A3, A4}.

In addition, we maintained the consumer similarity features {A2, A5} without alterations and performed an ablation experiment specifically on the purchasing habit similarity features {A1, A3, A4}, summarized in Table 3. The findings from this experiment are quite notable. Regardless of {A2, A5} features, features A1, A3, and A4 consistently correlate positively with the model's performance.

Notably, as we progressively integrated A1, A3, and A4 features into the model, there was a discernible enhancement in the prediction accuracy of consumer preferences. This observation underscores the significance of incorporating A1, A3, and A4 features into our model, further substantiating their relevance in accurately predicting consumer preferences.

DISCUSSION

Through the above experiments, the consumer preference model based on blockchain and topic similarity clustering proposed in this paper can help cross-border e-commerce providers understand consumers' intentions and ideas more deeply. First, blockchain is a decentralized distributed technology where consumers can view goods' origin, quality, and history, enhancing trust. In addition, the blockchain's data is encrypted and not easily tampered with, which can prevent data fraud and information leakage. There is no intermediary, reducing costs and speeding up the speed of preference prediction. Then, topic similarity clustering is a technique that clusters text data by topic or topic, bringing together goods or information with similar topics to provide more precise recommendations and search results. Relevant products can be recommended for consumers based on their interests

Table 2. Ablation of different {A2, A5}

A_2	A_5	$\{A_1, A_3, A_4\}$	Precision	Recall	H-mean
√			0.798	0.746	0.767
	√		0786	0.754	0.771
√	√		0812	0.798	0.806
√		√	0.837	0.824	0.829
	√	√	0.834	0.831	0.832
√	√	√	0.846	0.839	0.843

Table 3. Ablation of different {A2, A5}

A_1	A_3	A_4	$\{A_2, A_5\}$	Precision	Recall	H-mean
√				0.743	0.721	0.733
	√			0.739	0.725	0.735
		√		0.743	0.731	0.736
√	√			0.784	0.774	0.778
√		√		0795	0.771	0.781
	√	√		0786	0.761	0.772
√	√	√		0809	0.797	0.800
√			√	0.818	0.805	0.811
	√		√	0.814	0.799	0.804
		√	√	0.811	0.802	0.806
√	√		√	0.822	0.810	0.816
√		√	√	0.826	0.809	0.819
	√	√	√	0.829	0.814	0.821
√	√	√	√	0.846	0.839	0.843

and preferences to improve the shopping experience. The system can monitor changes in topics and trends in real-time and adjust recommendation strategies to meet market demand. Finally, combining blockchain and topic similarity clustering technology, a robust consumer preference model can be built to bring advantages to cross-border e-commerce. A consumer preference model can recommend products or services that meet consumers' interests by analyzing their historical transactions and browsing behavior on the blockchain. The model can help consumers discover more cross-border goods that meet their preferences and increase their willingness to buy. Blockchain technology can ensure that information about the origin and quality of goods is authentic and trustworthy, and consumers can view the entire supply chain history of goods, removing factors of mistrust and improving the sense of security in purchasing. Blockchain is a decentralized distributed ledger technology that differs from deep learning. Blockchain aims to ensure the security and transparency of information, especially in fields such as finance, supply chain, and contract management. However, deep learning aims to achieve intelligent models through simulating human brain neural networks for data analysis, prediction, and pattern recognition. Deep learning is an implementation method of topic similarity clustering, which can classify products that consumers are interested in, present personalized pages and recommendation results, and improve user experience.

CONCLUSION

We propose a consumer preference model integrating blockchain and topic similarity clustering to facilitate the rapid advancement of Cross-Border E-Commerce (CBEC) and forecast consumers' purchasing objectives. We establish a consumer information collection system in CBEC utilizing blockchain technology, enabling the extraction of diverse consumer characteristics and enhancing the performance of consumer profiling through a fusion approach. Subsequently, we employ K-means-based similarity to anticipate consumer preference outcomes. Our experiments demonstrate that our approach attains an accuracy of 84.6%, a recall rate of 83.9%, and an H value of 84.3%. Compared to alternative methodologies, our model achieves superior performance and can furnish insights into consumer preferences crucial for cross-border e-commerce.

AUTHOR NOTES

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