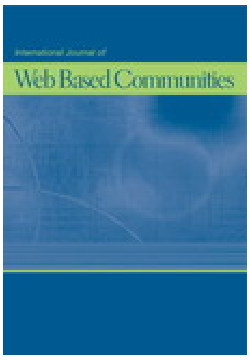

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HaoJie Zi

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Predictive model of consumer online purchase behaviour based on data mining

HaoJie Zi

Department of Economics and Management,
Huanghe Jiaotong University,
Wuzhi, Henan Province, 454950, China
Email: haojiez@mls.sinanet.com

Abstract: The existing consumer online purchase behaviour prediction model does not reduce the noise of purchase behaviour data, which leads to poor prediction effect. Therefore, a consumer online purchase behaviour prediction model based on data mining is proposed in this paper. The behaviour data are divided into different datasets by K-means clustering. The neighbourhood rule is used to update the centre of clustering sample data and collect behaviour characteristic data. Empirical mode decomposition (EMD) method is used to obtain the instantaneous frequency of purchasing behaviour and denoise the characteristic data of consumers' online purchasing behaviour. With the data mining method, the system of consumer online purchasing behaviour characteristics is established, and a consumer online purchasing behaviour prediction model is built according to the behaviour characteristics fusion selection means to realise behaviour prediction. The results show that the accuracy of this model to predict consumers' online purchasing behaviour is more than 93%.

Keywords: data mining; consumer behaviour; purchasing behaviour; behaviour prediction; online shopping.

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Biographical notes: HaoJie Zi received her Master's in Business Administration from Zhengzhou University of Light Industry in 2014. Currently, she is an Associate Professor and the Director of the Teaching and Research Section of Huanghe Jiaotong University. Her research interests include marketing and agricultural economy.

1 Introduction

With the rapid development of computer and network technology, the internet has become an indispensable part of people's study, work and life, and online shopping has become the main way of people's shopping (Greene et al., 2017). The complexity and variability of consumer purchase behaviour has come to the focus in many e-commerce related industries (Forbes-Bell et al., 2019). The rapid development of e-commerce industry has formed a relatively perfect ecological chain in China (Kim et al., 2020), which makes consumers' online shopping more characteristic than the offline shopping business model, such as consumer market segmentation, personalised consumer services, expanded range of commodity choices, and biased shopping behaviour (Sobhanifard and Sadatfarizani, 2018), bringing certain challenges and opportunities to consumers' online shopping behaviour prediction. Especially in the background of the new type of coronary pneumonia virus, 'no contact' has become a popular word of living habits, which needs to be mined and analysed by consumers' online purchase behaviour data (Waheed and Yang, 2018). The prediction model of consumers' online purchasing behaviour refers to mining the potential consumption behaviour of online consumers by obtaining the data of consumers' online purchasing behaviour. It is crucial to judge the trend of consumers' purchasing behaviour to help e-commerce enterprises obtain effective information about consumers' purchasing behaviour. It can promote consumers to quickly find suitable products from a large number of products, improve the service quality of related industries and increase sales profits. Accordingly, it has certain research significance to design and study the prediction model of consumers' online purchasing behaviour (Butu et al., 2020).

Among the related research results, Shin et al. (2018) proposed a predictive model of consumer online purchase behaviour based on the theory of planned behaviour. The model uses planned behaviour theory and normative activation model for development and design. It judges consumers' behaviour trends based on their online purchase intentions, and uses structural equation models to judge consumer attitudes, subjective norms, perceived norms of behaviour, and personal norms. Eventually, the behaviour prediction of consumers' intention to visit or purchase is achieved. According to experimental research, this model can improve the accuracy of consumer online buying behaviour prediction, but because it does not mine consumer buying behaviour characteristics and reduce noise, its recall rate is low, which compromises behaviour prediction effect. Setia et al. (2020) proposed a consumer online purchase behaviour prediction model based on n-gram analysis and access logs. The model integrates usage mining and content mining technology, uses Web mining technology to accurately predict consumers' online purchase search behaviour, and uses n-gram analysis and product query clicks to obtain more contextual information, which improves the browsing prediction of consumers' online purchase of webpages. The model was evaluated using search logs. The results showed that the model can improve the prediction accuracy. However, under the massive growth of internet data, the model has the problem of long behaviour prediction time. Rodgers et al. (2021) proposed an artificial intelligence-driven consumer online buying behaviour prediction model. The facial and biometric recognition technology of artificial intelligence is used to digitally convert consumers' cognitive and emotional states, and to predict the behaviour of value creation in these digital signals. For consumers who are highly involved in purchasing conditions, music biometric identification methods can help establish emotion-guided cognition and behavioural intentions, which is conducive to constructing the transfer relationship between consumer behaviour, cognition and emotion, and the combination of music's melodiousness and rhythm has a positive impact on consumers' online buying behaviour According to the research results, the model can effectively identify consumers' online purchase behaviour and has certain controllability for consumers' online purchase behaviour. However, the model has the problem of low accuracy of behaviour prediction.

Although the above methods have achieved certain research results, there are still problems of low accuracy of behaviour prediction, long behaviour prediction time, and low model recall rate. In order to solve these problems, this paper designs and proposes a data mining-based consumer online predictive model of buying behaviour. The overall design of the model is as follows:

1 The K-means clustering algorithm is used to divide the data of consumers' online purchase behaviour into different datasets, including the data of consumers' purchase potential, purchase intention, online browsing commodity characteristics, purchase decision-making ability, etc. The centre of clustering sample data is updated using proximity rule to collect the characteristic data of consumers' online purchasing behaviour.

2 EMD method is used to obtain the instantaneous frequency of consumers' purchase behaviour, and soft and hard thresholds are used to construct the threshold function to denoise the characteristic data of consumers' online purchase behaviour, eliminate the interactive data and retain the effective characteristic data;

3 This paper uses data mining method to establish the system of consumers' online purchase behaviour characteristics, and uses data matrix to normalise the data of purchase behaviour characteristics. According to the behaviour characteristics fusion selection method, it constructs the prediction model of consumers' online purchase behaviour, and realises the prediction of consumers' online purchase behaviour.

2 Data collection and preprocessing of consumers' online purchase behaviour characteristics

In order to realise the effective prediction of consumers' online purchase behaviour, the proximity rule is used to update the centre of each clustering sample data to realise the extraction of the characteristics of consumers' online purchase behaviour, and perform noise reduction processing on the characteristic data signals so that interactive data can be eliminated while valid characteristic data can be kept.

2.1 Data collection of consumers' online purchase behaviour characteristics

In order to realise the effective prediction of consumers' online purchase behaviour, firstly, the characteristic data of consumers' online purchase behaviour is collected. Consumer's online purchasing behaviour includes: consumer's purchasing potential, purchasing intention, online browsing commodity characteristics, purchasing decision-making ability and other key data. The characteristics of these purchase behaviour data can reflect the probability of consumer purchase behaviour. Therefore, first of all, the data characteristics of consumers' online purchase behaviour are collected to lay the foundation for the subsequent prediction.

The K-means clustering algorithm is used to divide consumers' online purchase keywords into different datasets. The K-means clustering algorithm is an algorithm that can divide ideas (Maciaszczyk and Kocot, 2021), with the most significant features of simplicity and fast calculation speed. Applying this algorithm to the extraction of consumer online purchase behaviour characteristic data can improve data processing efficiency, divide all sample data, and calculate the centre point of the sample data according to different categories. Through multiple iterations to update the centre store, different types of central stores can be updated based on iterative changes of data samples.

It is assumed that the consumer online purchase behaviour data sample set that needs to be divided is represented by $P = \{P_1, P_2, P_3, \ldots, P_k\}$, where each sample data has certain dimensional attributes. When the number of delineated categories is m, the initial clustering of the K-means algorithm is $\{M_1, M_2, M_3, \ldots, M_m\}$, and the Euclidean distance is used to calculate the data sample partition from each data sample to each cluster centre (Tokar et al., 2020). The calculation formula is:

$$dis(X_m, C_n) = \sqrt{\sum_{j=1}^{m} (X_{mj} - C_{nj})^2} \tag{1}$$

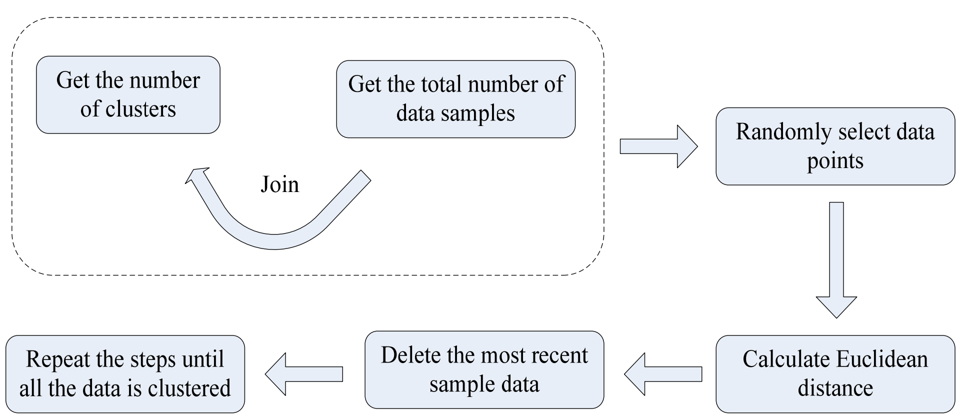
In the above equation, X_m represents the sample data of consumers' online purchasing behaviour; C_n represents the cluster centre set of the sample data; X_{mj} represents the attribute t of the sample data object; C_{nj} represents the attribute of the sample data cluster centre. After division of the sample data once, the dataset $\{S_1, S_2, S_3, \ldots, S_n\}$ is obtained. The K-means algorithm requires update of each cluster data centre after each sample data is divided. The update formula is:

$$C_j = \frac{\sum_{C_i \in S_n} C_i}{|S_n|} \tag{2}$$

In the above formula, C_j represents the centre of the j^{th} cluster set; $|S_n|$ represents the number of sample data at the centre of the cluster set; C_i represents the sample dataset at the centre of the cluster set.

Because the distance between the centre samples during initialisation of the cluster centres is too close, it is difficult for the K-means algorithm to achieve convergence. Therefore, the process of traditional clustering algorithms is improved, and the cluster centres of the sample data are dispersed as much as possible (Kaur et al., 2020). The process of improving the initialisation of cluster centres is shown in Figure 1.

Figure 1 Process diagram of improved initialisation of cluster centres (see online version for colours)



According to the improvement process of initialising the cluster centre shown in Figure 1, the centre of each clustering sample data is updated using the proximity rule to improve the recognition ability of consumers' online purchasing behaviour characteristics. On this basis, with the XGBoost model and the Pearson correlation coefficient, the sample data features and labels output by XGBoost are normalised. Assuming there are two data variables M, N, the Pearson correlation between the two variables is:

$$\partial_{M,N} = \frac{\sum (M - \bar{N})}{\sqrt{\sum (M - \bar{M})^2}} \tag{3}$$

In the above formula, g_{max} represents the maximum value of the data distribution clustering of consumer online purchasing behaviour characteristics; g_{mid} represents the average granularity of consumer online purchasing behaviour characteristics. According to equation (4), the feature set after clustering processing is shown in Table 1.

Table 1 Feature set after clustering

Consumer characteristics	*Commodity characteristics*
Consumer ID	Commodity category ID
The number of times consumers click on the product	Commodity clicks
Number of types of products clicked by consumers	Commodity purchased
The number of times consumers like the product	Likes of the product
Number of times consumers have joined the shopping cart	Number of consumers who bought goods
Number of consumer purchases	Number of consumers of electrical products
Number of types of goods purchased by consumers	Number of consumers who clicked on the product

So far, the extraction of characteristic data of consumers' online purchase behaviour is completed. On this basis, the EMD method is used to reduce the noise of the characteristic data.

2.2 Data denoising of consumer online purchase behaviour characteristics

Based on the above collected data of consumers' online purchase behaviour, there are many noises in the characteristic data, which disrupt the prediction of consumers' online purchase behaviour. Therefore, it is necessary to denoise the collected data of consumers' online purchase behaviour (Nosov et al., 2021).

In order to improve the sensitivity of the response to changes in consumer online purchasing behaviour characteristic data, and avoid the confusion of predicted consumer online purchasing behaviour, this study uses soft and hard thresholds to construct a threshold function to reduce consumer online purchasing behaviour characteristic data. The steps of denoise processing are as follows:

The calculation formula of the soft threshold is:

$$f(x) = \begin{cases} sgn(x)|x| > \partial \\ 0 \qquad |x| \le \partial \end{cases} \tag{5}$$

The calculation formula of the hard threshold is:

$$f(x) = \begin{cases} x|x| > \partial \\ 0\,|x| \le \partial \end{cases} \tag{6}$$

According to the calculation results of equation (5) and equation (6), a new threshold function is constructed, and its expression formula is:

$$f(x) = \begin{cases} sgn\left[|x| - \dfrac{\tau\partial}{1 + sgn(x)} \right] \\ \qquad\qquad 0 \end{cases} \tag{7}$$

In the above equation, ∂ represents the threshold; τ represents a variable parameter, and the parameter is within the interval [0, 1].

Due to the certain correlation between the threshold and the noise of the characteristic data, the EMD method is used to divide the decomposition scale of the characteristic data of consumer online purchase behaviours. Increasing the threshold can remove the noise of the characteristic data (Sarker et al., 2018). The calculation formula is:

$$\gamma = f(x) + \frac{N\sqrt{2lnf(x)}}{e^2 \cdot T_m} \tag{8}$$

In the above equation, N represents the noise variance of consumers' online purchase behaviour characteristics; e represents the decomposition scale of consumers' online purchase behaviour characteristics.

The EMD method is used to obtain the instantaneous frequency of consumer buying behaviour, and the characteristic data signal is denoised, the interactive data is eliminated, and the effective characteristic data is retained.

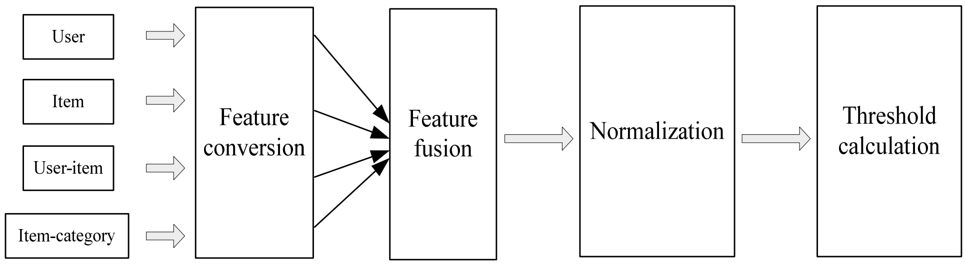
At this point, the data extraction and noise reduction of consumer online purchase behaviour have been completed, which has improved the accuracy of behaviour prediction to a certain extent. On this basis, data mining methods are used to construct a consumer online purchase behaviour prediction model to improve the forecasting effect.

3 Predictive model of consumer online purchase behaviour based on data mining

In order to improve the effect of consumer online buying behaviour prediction, data mining methods are used to establish a consumer online buying behaviour characteristic system, and according to the behaviour characteristic fusion selection methods, a consumer online buying behaviour prediction model is constructed.

In order to solve the problem of long time for behavioural consumers to predict online purchasing behaviour, a consumer online purchasing behaviour characteristic system is established on the basis of obtaining effective data on consumer online purchasing behaviour characteristics, and a data matrix is used to normalise the purchasing behaviour characteristic data (Sobol et al., 2018). The constructed behaviour characteristic system is shown in Figure 2.

Figure 2 Consumer's online purchase behaviour characteristic system



It can be seen from Figure 2 that the characteristics of consumer online purchase behaviour are counted from the four dimensions of user, item, user-item, and item-category, and on this basis, the characteristics of the purchase behaviour are transformed, and the characteristics are fused by function transformation and combination methods. The four types of basic characteristics are merged through SQL. At this time, it should be noted that the dimensions and dimensional units of different behaviour characteristics are not unified (Balamurugan and Selvalakshmi, 2019). Therefore, it is necessary to carry out unified processing to the characteristics of consumer online purchase behaviour to improve the recognition of behaviour characteristics.

Based on the above analysis, the data matrix principle is used for normalisation processing, and the processing process is as follows:

Step 1 Build the original matrix

Obtain the original data according to the characteristic data extraction process of consumer online purchase behaviour in Section 2, and establish the corresponding original matrix, which is represented by B:

$$B = \begin{bmatrix} B_{11} & \cdots & B_{m} \\ \vdots & \ddots & \vdots \\ B_{n1} & \cdots & B_{nm} \end{bmatrix} \tag{9}$$

Step 2 Normalise the data of the original matrix

The so-called normalisation process is to use the sine cosine method to obtain the optimal and worst schemes among the finite schemes, and to calculate the distance between the data object and the scheme, as a basis for evaluation (Fetscherin, 2019).

Step 3 Use the entropy method to avoid behavioural data deviation caused by human factors

Determine the matrix interval weight range based on the interval fuzzy preference relationship, and perform the fuzzy processing on the weight. The weight transformation formula is:

$$\vartheta_j \rightarrow (\vartheta_{j1}, \vartheta_{j2}) \tag{10}$$

In the above equation, ϑ_{j1} represents the upper limit of the fuzzy matrix interval; ϑ_{j2} represents the lower limit of the fuzzy matrix interval.

Assuming that the weight vector of all consumers' online purchase behaviour characteristics is φ, then the entropy value of the upper and lower bounds of the fuzzy matrix interval is calculated as:

$$W = ((w_{11}, w_{12}), (w_{21}, w_{22}) \ldots (w_{j1}, w_{j2})) \;\; 1 \leq j \leq n \tag{11}$$

In the above equation, w_{jn} represents the entropy value of the j-th consumer's online purchase behaviour feature on the n-th vector.

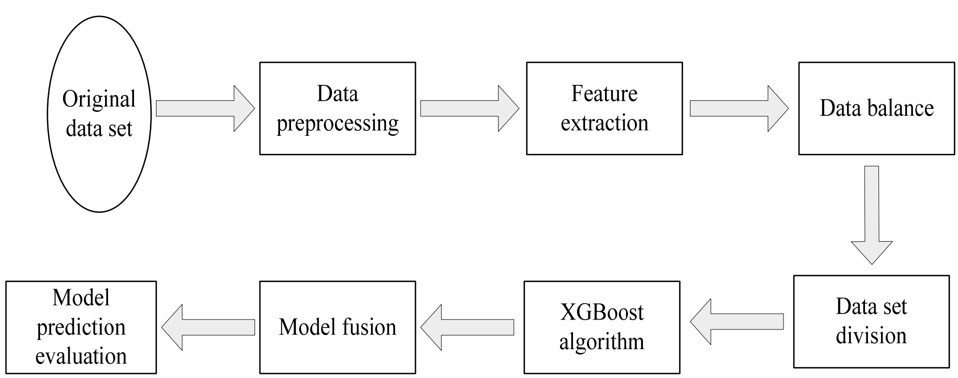
3.1 Construction of consumer online buying behaviour prediction model based on data mining

According to the constructed consumer online buying behaviour characteristic system, data mining methods are used to construct a consumer online buying behaviour prediction model. After division of the obtained consumer online purchasing behaviour characteristic system into different levels in number levels, a certain level of behaviour sequence is assumed to be F, and q_m is used to represent the length of the consumer online purchasing behaviour sequence (Bechlioulis and Brissimis, 2019) (each length is taken between [0, 24] and is an integer), then data mining technology is used to classify the sample data of purchase behaviour sequence, and the classification label of the behaviour data under data mining is:

$$F = \begin{cases} F_0 = 0 \;\; \textit{Consumers will not buy} \\ F_1 = 1 \;\; \textit{Consumer purchase} \end{cases} \tag{12}$$

According to equation (12), the classification results of consumers' online purchase behaviour prediction are realised. On the basis of the results of consumers' online purchase behaviour feature data extraction, the prediction model of consumers' online purchase behaviour based on data mining is constructed. The framework of the model is shown in Figure 3.

Figure 3 The framework of consumer online purchase behaviour prediction model



Based on the model framework shown in Figure 3, the steps of building a data mining based consumer online purchase behaviour prediction model are as follows:

1 After extraction of the characteristics of consumers' online behaviour from the original dataset by feature extraction method, the training dataset and test dataset are divided (Nik et al., 2019).

2 The improved sample data balance method is used to process the training dataset, and the balanced data sample categories are obtained.

3 The features of consumers' online purchase behaviour in training dataset are fused, xgboost model is used as the base classifier, and the original data is normalised to complete the construction of feature system.

4 The training set is input into the base classifier to obtain the prediction results of consumers' online purchasing behaviour, and a new training set is obtained according to the characteristic system of purchasing behavior.

5 The new training set is input into the prediction model, and the prediction results are evaluated (Lee et al., 2021).

In conclusion, the prediction model based on data mining is highly sensitive to the noise reduction of the same class of sample data, and can help establish a good behaviour feature system and complete the construction of the prediction model. The actual effect of the designed model needs further experiments to verify.

4 Experimental analysis

In order to verify the effectiveness of the proposed model, comparative experiments are conducted.

4.1 Experimental scheme design

This experiment takes a large shopping mall as the experimental object, with the total number of samples of 50,850, the positive and negative ratio of 1:8, the division ratio of training set and test set of 0.5:0.5, and the total number of features of 181. The experimental environment parameters are shown in Table 2.

Table 2 Experimental environment parameters

Hardware environment		*Software environment*	
CPU	Intel(R), 2.6 GHz	Operating system	Windows10
Graphics card	NVIDA(R), 740M	Development environment	Python
RAM	12GB	Toolkit	Pandas, numpy

According to the above experimental environment settings, the design experiment plan is as follows: the design model in this paper and the Shin et al. (2018), Setia et al. (2020), and Rodgers et al. (2021) models are used as comparison methods to verify the effectiveness of the method proposed in this paper. Because the experiment will be affected by external conditions, the experimental results will have a certain deviation.

Therefore, in order to avoid deviations, it is necessary to ensure that all experimental conditions are consistent.

4.2 Experimental index design

The experiment mainly verifies the application performance of this model from three aspects: the prediction accuracy of consumers' online purchasing behaviour, the prediction time and the recall rate of the model. Among them, the calculation formula of prediction accuracy is as follows:

$$Z = \frac{Q_i}{Q_{all}} \times 100\% \tag{13}$$

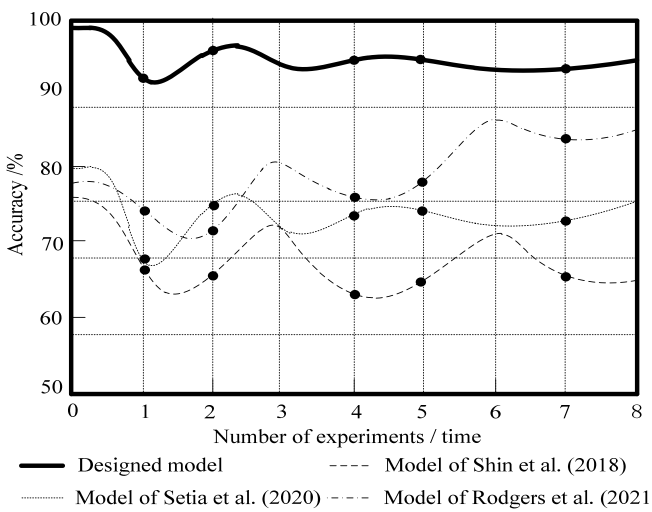
In the formula, Q_i represents the actual number of samples, Q_{all} represents the total number of predicted samples.

4.3 Analysis of experimental results

4.3.1 Comparison of prediction accuracy

The accuracy of consumer online purchase behaviour prediction between the designed model and the traditional model is recorded, and the comparison result is shown in Figure 4.

Figure 4 Comparison of behaviour prediction accuracy

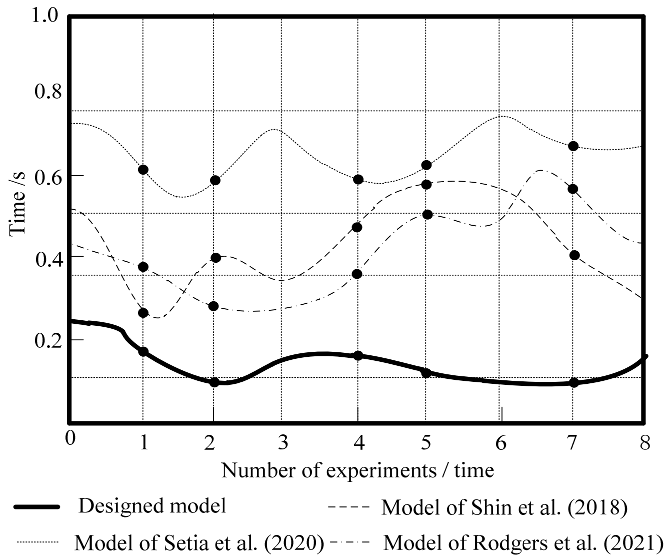


Through analysis of the above results, it is found that the consumer online buying behaviour prediction model designed this time has high accuracy in many experiments. The comparison found that the accuracy of the designed model is higher than that of the traditional model. The prediction accuracy is generally above 93%. This is because the model uses the proximity rule to update the centre of each clustering sample data to extract the characteristics of consumers' online purchase behaviour, thereby improving the accuracy of consumer behaviour prediction.

4.3.2 Prediction time comparison

The predicted time of consumer online purchase behaviour between the designed model and the traditional model is recorded, and the comparison result is shown in Figure 5.

Figure 5 Comparison of behaviour prediction time



By analysing Figure 5, we can see that in the previous experiments, the prediction time of consumer online purchase behaviour of the designed model is not much different from that of the traditional model. In other experiments, the behaviour prediction time of the traditional model is longer than that of the designed model. The behaviour prediction time of the model designed in this paper is generally less than 0.3 s. This is because this paper adopts the empirical model decomposition method to calculate the characteristic thresholds of consumers' online purchase behaviours, which reduces the influence of noise on behaviour predictions, improves the operating efficiency of the model to a certain extent, and shortenrs the prediction time of consumers' online purchase behaviours.

4.3.3 Comparison of model recall rate

The recall rate of the model designed by the statistics institute and the traditional model for predicting consumer online purchase behaviours is recorded, and the comparison results are shown in Table 3.

Through the analysis of the results in Table 3, it is concluded that the designed model has a relatively high recall rate when predicting consumers' online purchase behaviour, generally above 93%. The reason for this situation lies in the designed consumer online purchase behaviour prediction model. It has high prediction accuracy, and adopts data mining methods to divide the number of different sequences in the consumer purchase behaviour characteristic system, which improves the recall rate during the operation of the model to a certain extent. It can be seen that the designed model has certain practical application value.

Table 3 Comparison of model recall rate (%)

Number of experiments/time	*Designed model*	*Shin et al. (2018) model*	*Setia et al. (2020) model*	*Rodgers et al. (2021) model*
1	97	94	95	81
2	96	92	90	77
3	96	90	85	75
4	95	89	80	73
5	94	91	79	78
6	95	82	82	80
7	93	89	77	81
8	94	84	86	80

5 Conclusions

This paper proposes and designs a data mining based online purchasing behaviour prediction model. Data mining technology is used to mine and denoise the characteristics of consumers' purchase behaviour, and a prediction model of consumers' online purchase behaviour is established, which effectively solves the problems of low prediction accuracy, long prediction time and low recall rate of traditional models. This method has the following advantages

1. The prediction accuracy of the designed model is more than 93%, which is high
2. The prediction time of the designed model is always less than 0.3s, so the prediction speed is faster
3. The recall rate of the designed model is 90%, which shows that the model can accurately and effectively provide the prediction results of consumers' online purchasing behaviour.

Although this paper has conducted in-depth research on data mining and noise reduction of consumer online purchase behaviour prediction model, and achieved innovative results, there are still some problems to be further discussed. In the follow-up research, further research is needed to optimise the consumer online purchase behaviour prediction model, and promote the improvement and development of e-commerce industry.

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