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Prediction of User Behavioral Intentions Based on Structural Equation Modelling in AI Painting Cognitive Conditions

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Abstract

The in-depth development of AI painting cognitive technology and the intelligent algorithm has made user intention analysis a hot spot in user research and also made the problem of willingness prediction the focus of psychology and economics. The original user intention method cannot solve the problem of user intention judgment under massive data, and the prediction accuracy of behaviour intention needs to be higher. Therefore, this paper proposes a structural variance model to analyze the user's behaviour willingness under the cognitive conditions of AI painting. Firstly, AI painting cognition is used to analyze user behaviour data, behaviour classification is carried out according to AI painting mental conditions, and irrelevant user intention data is deleted. Then, according to the user behaviour data classification results, it is compared with the previous user willingness analysis method. The different behaviour willingness domains are deeply excavated to output the behaviour willingness with a higher probability. MATLAB shows that the PLS-SEM structural equation model can improve the accuracy of user intention prediction; the accuracy rate reaches 86.5%, shorten the prediction time of user behaviour, and control it within 15 seconds to meet the needs of user behaviour prediction.

Keywords: AI Painting Cognition, Structural Equations, User Behaviour Data, Forecast

1. Introduction

The emergence of AI painting platforms such as Hugging Face and Wehui has changed users' painting behaviour and traditional painting research. Many foreign painting websites attach great importance to analyzing users' willingness to paint behaviour to improve AI painting platforms. According to the survey data in 2022 [1], the number of visits to the sygil-webui painting platform is 1,232,4511 times per day. The satisfaction rate of AI portraits is low, indicating that the AI painting platform is inaccurate in predicting user behaviour [2], resulting in the prediction of user behaviour willingness becoming the focus of current research [3]. Although the establishment of AI painting databases such as personality painting and traditional painting can realize cluster analysis of user behaviour data, there are problems such as high complexity and long prediction time of user behaviour prediction [4].Most of the user's behaviour willingness is semi-structured and unstructured data, and a nonlinear relationship between the data and the user's AI painting cognition is also different. Under personalized requirements [5], complex psychology and random requirements, the AI painting platform will have problems such as a low satisfaction rate and poor accuracy. The PLS-SEM structural equation model has better complex data processing capabilities [6], realizes the mining of cognitive information and behavioural data, integrates the cognitive conditions of AI painting into the data module, and maps it with user behaviour data [7]. At the same time, the circular analysis of user behaviour results is carried out to verify the feasibility and rationality of corresponding user behaviours and the accuracy of prediction results [8]. Some scholars apply the cognitive theory of AI painting to predict user behaviour willingness and try to judge user behaviour willingness [9]. The results show that the cognitive theory of AI painting has an auxiliary effect on predicting user behaviour intention. Still, the problem of inaccurate prediction occurs in the middle and late stages [10]. The PLS-SEM structural equation model belongs to the equation in the field of sociology, widely used in management, computer, and other fields, the equation can process multiple dependent variables at the same time, and the measurement error of the varying requirements is low and can realize the analysis of unstructured data. At the same time, the structural variance can deal with the relationship between different variables and the internal structure of the variables and realize the result analysis of large elasticity [11], which is suitable for statistical and behavioural research. In addition, structural equations can realize the fitting analysis of the results, and the predicted results can be fitted with the actual statistical results [12]. The structural equation is mainly used in the following aspects to analyze user behaviour willingness: (1) adjusting the elastic parameters in user behaviour prediction and changing the direction of user behaviour prediction. Some scholars have studied online behaviour and compared three behaviour prediction methods. The results show that the structural equation has a wider range of applications and can realize the analysis of massive behavioural data and the comprehensive judgment of user behaviour prediction [13]; (2) Compare with other ways. Some scholars propose a method to improve the previous user willingness, use the previous user willingness method to intelligently classify online shopping [8], and calculate the user behaviour data according to the willingness probability to improve the calculation speed. However, this method is greatly affected by the random will of users, and the willingness analysis cannot be realized [9]. Starting from the complexity of user behaviour data, the PLS-SEM structural equation model is used to analyze semi-structured behaviour willingness data processing. The semi-structured and unstructured classification methods are compared [14]. , which proves that the structural equation has high accuracy in analyzing the data; (3) Compared with the B/C model, the hierarchical method predicts user behaviour data to improve the accuracy and rationality of the analysis method, but the result is still inferior to the structural equation [15]. The above analysis shows that although various intelligent algorithms can make comprehensive judgments on user behaviour data, the judgment results are unsatisfactory and cannot be adapted to the analysis of massive user behaviour data [16]. Therefore, the current prediction problem of user behaviour willingness needs to solve the probability calculation problem, simplify the complexity of prediction, and choose to improve the AI painting cognitive platform more accurately [17]. In this paper, the user behaviour data is calculated using structural equations, then the user behaviour willingness is accurately selected, and the appropriate methods are verified. Based on the above reasons, this paper analyzes user behaviour data, synthesizes AI painting cognition, analyzes the key points, elasticity points, and cycle points of user behaviour, and forms a behaviour prediction set, aiming to improve the accuracy of user behaviour prediction

2. Related Concepts

2.1 Structural Equation Model

The structural equation is a comprehensive calculation method, with the help of fuzzy analysis of equations and probability calculation for behaviour data analysis, which can solve the problem of directivity of behavioural data [18], realize the comprehensive analysis of unstructured and willing direction in user behaviour, and improve the accuracy of analyzing user behaviour willingness. Compared with other methods, structural equation models have a more comprehensive analysis range and can realize massive data analysis. Structural equation models are widely used in computers, management, aviation and other fields but are less used in predicting user behaviour willingness. To analyze user behaviour data more objectively, the cognitive conditions of AI painting of structural equation models are quantitatively described, and the results are as follows.

AI cognitive computing: AI mental condition is x_{ij}, the cognitive structure is y_{ij}, the association function between cognitions is, the correlation coefficient is, and the AI computing centre of the data is, then the calculation of AI cognition is shown in equation (1). $k \in n$ ς_{ij}

$$\varphi(x)=\begin{cases}\frac{x^2_{ij}+y_{ij}}{2}, cronbach<0.7\\ \frac{x_{ij}\cdot\sum y_{ij}}{\sum\varsigma_i}, cronbach>0.7\end{cases} \tag{1}$$

When, $\overline{x_{ij}}=\sin\theta\cdot x_{ij}<\max(\sum\varsigma_{ij})$ $\overline{x_{ij}}=\sin\theta\cdot x_{ij}$ and is the random variability of AI cognition.

Classification of User Behaviour Data

Willingness characteristics of user behaviour: The willingness characteristic judgment function is $\varphi(x\cdot k)$ and belongs to the willingness classification function $f(x)$, and the characteristic judgment of user behaviour data is shown in equation (2).

$$\int_{x\in d_{ij}} k\cdot f(x)'\cup P_j(x) \tag{2}$$

Willingness probability calculation: Assuming that the user behaviour data is x_{it}, the user's willingness probability is a function of $Dim(x)$, and the willingness probability is calculated as shown in equation (3).

$$Dim(f(x))=lin(\frac{n}{\sum x_i}) \tag{3}$$

Where p represents the highest probability point where the intention occurs, and the result is in the range [0,1].

3. Preprocessing of User Behaviour Willingness Data

3.1 Initialization of User Behaviour Data

The initial user behaviour data is mainly natural language data and presents random distribution, so coefficients should transform the data to reduce the impact of randomness on the calculation prediction results. In addition, randomized data will impact user behaviour willingness prediction, so the willingness data should be mapped to the randomized list, as shown in Figure 1.

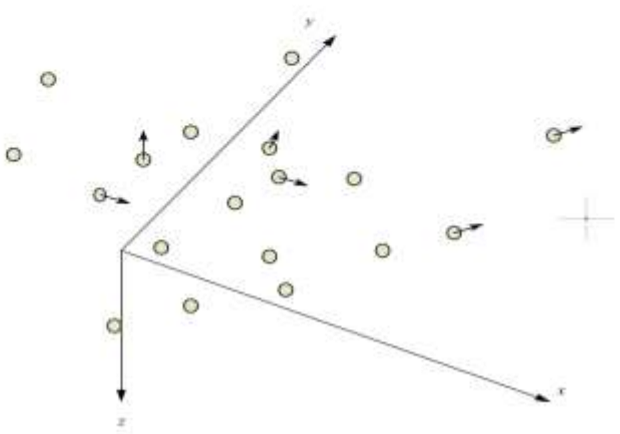

Figure 1. Probability of Willingness to Behave in User Behaviour

It can be seen from Figure 1 that the distribution of user behaviour willingness data is relatively messy and presents a specific directionality, which is due to a large number of natural languages. Among them, the willingness data is evenly distributed among the user behaviour data, indicating a certain probability of willingness, which can be preprocessed by coefficient transformation. Overall, the user behaviour data presents a random and discrete distribution, and the conversion process can be completed through coefficient conversion.

3.2 Predictive Calculation of the User's Willingness to Behave

There are three main types of user behaviour willingness prediction: subjective, accurate, and comprehensive willingness prediction. The mathematical description of the above three predictions is as follows.

The AI painting cognitive library mainly analyzes the choice of subjective will prediction. The portrait is called according to user behaviour data, and its calculation is shown in equation (4).

$$F_1(\vec{x}) = n \cdot \sum_{i=1}^{n} [\vec{x}_i^{\,2}]^3 \tag{4}$$

Objective willingness prediction is to calculate the cognition of AI painting through interference factors and combine the artist expert library to complete the selection of user behaviour prediction. Its calculation is shown in equation (5).

$$y_2(x) = \sum_{i=1}^{n} [x_i^2 - \sin(2\pi\theta)]^3 \tag{5}$$

User behaviour intention prediction is to use the non-artist library for willingness data, fuse user behaviour data, and realize the prediction and mining of behaviour intention, which is calculated as shown in equation (6).

$$z(x) = -\log\{-0.2\sum_{i=1}^{n} \sqrt[k]{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\} + line^n \tag{6}$$

Where n is the number of times the probability of the user's willingness to act; The value range of $F_1(x)$ the probability is {-1,1}, and the value range of $y_2(x)$ is {-2,2}; The value range of $z(x)$ is {-3,3}.

3.3 Prediction of Randomness of User Behavior

The structural variance is related to the prediction of user behaviour data, so it is necessary to conduct random analysis of user behaviour, including artist library prediction, non-artist library prediction, interference factor prediction, user portrait prediction, etc.; the specific calculation is as follows:

1) Artist library prediction in user behaviour, calculated as shown in formula (7).

$$y_{ij}(t+1) = \omega \cdot y_{ij}(t) + \sum c_i \cdot r_1 \tag{7}$$

2) Non-artist library predictions in user behaviour data, calculated as shown in equation (8).

$$y_{ij}(t+1) = \omega \cdot y_{ij}(t) + \max \sum_{i,j=1}^{n} g_{ij}{}^{k}[x(t)] \tag{8}$$

3) Prediction of interference factors in user behaviour data, calculated as shown in equation (9).

$$y_{ij}(t_i) = n \cdot \frac{[\delta \cdot \sum_{i,j,k=1}^{n} g_{ij}{}^{k}\{x(t) \cdot f(P_j[x(t)]\}}{\max \sum_{i,j=1}^{n} g_{ij}{}^{k}[x(t)]} \tag{9}$$

4) User portrait prediction in user behaviour data, calculated as shown in formula (10).

$$y_{ij}(x) = \sum_{i=1}^{2} c_i r_i g_{ij}^{k} \cup x(t) \cdot f(P_j[x(t)]$$

(10)

Among them, the artist library call coefficient is c_1 r_1 the standardized processing of behaviour data and ω the probability of behaviour willingness.

In terms of the PLS-SEM structural equation model predicting user behaviour willingness, on the one hand, the structural equation calculation is carried out for natural language data and semi-structured data, which expands the collection scope of user behaviour data and realizes the probability calculation of user behaviour analysis. On the other hand, the intention is analyzed in reverse, and the user behaviour willingness set is formed through the structural equation and AI painting. The integration of AI painting cognition and structural equation results is realized. To improve the accuracy of intention prediction, the limiting coefficient should be added to the cognitive conditions of AI painting. Among them, the cognitive coefficient of AI painting α and the coefficient of art expert is β , and the specific calculation is shown in equation (11).

$$\begin{cases} \alpha = \dfrac{Line_t^{d} - 1}{Line_T^{D}} \\ \beta = \sum_{d=1}^{D} [\dfrac{(w_{\max} - \sum_{t=1}^{T} \Delta w_i)}{(\sum_{t=1}^{T} \Delta w_i - w_{\min})}]^{d} \end{cases}$$

(11)

Where e is the adjustment coefficient between art experts and non-art experts, T is the maximum amount of user behaviour data, d is the number of predictions, and D is the sub-prediction result.

3.4 3.4 The Prediction Process of the User's Willingness to Behave

The PLS-SEM structural equation model uses qualitative methods to predict user behaviour data and behaviour prediction through probability calculation, and the specific selection process is shown in Figure 2.

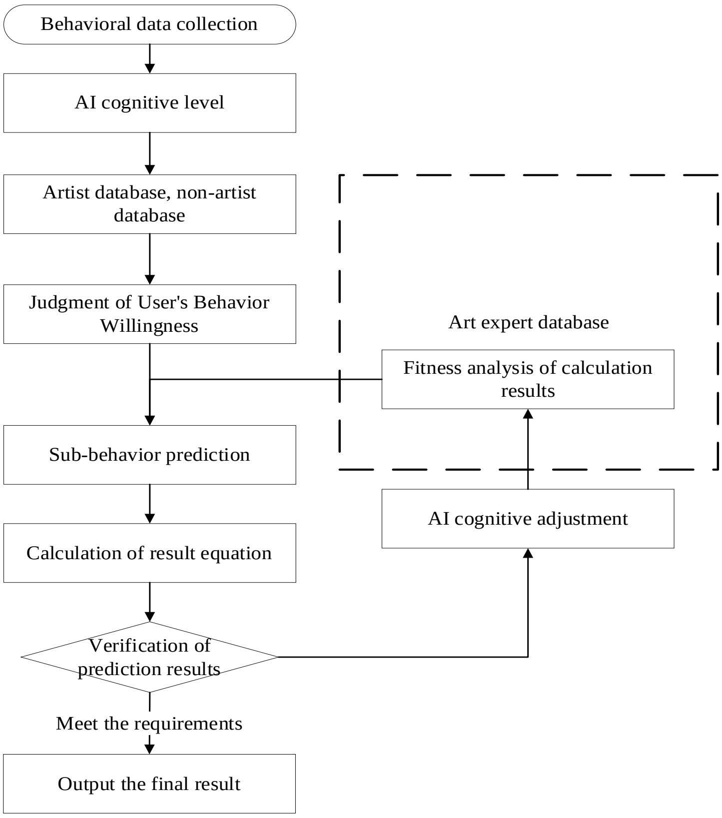

Figure 2. The Prediction Process of User Behaviour Data by Structural Equation Model

Step 1: Determine the set of willingness and user behaviour data, analyze the problem of user behaviour data according to the characteristics of willingness, and determine the collection of user behaviour data. At the same time, the initialization data and constraints of user behaviour data are converted and mapped to the wish list.

Step 2: Data processing of user behaviour data. Factor conversion processing on behavioural data. A vector replaces the direction of the will, the maximum angle is $\theta = \pi$, the minimum angle is $\theta = 0$, and the maximum number of depths is $n = 100$.

Step 3: Generate the prediction function. The PLS-SEM structural equation model calculates the user portrait data and the structural equation server, and the initial weights and constraints are set to make predictions. Formulas carry out data mining (1) ~ (7) and the prediction coefficients of different behaviours.

Step 4: Maximum probability prediction of user behaviour data and sub-prediction result judgment. According to the amount of user behaviour data and data structure, select the user behaviour willingness with the highest probability.

Step 5: The constraints of AI painting cognition. Obtain personal behaviour prediction, accurate and comprehensive prediction, and verify prediction results.

Step 6: Comprehensive prediction of user behaviour data volume. After determining the set of wills, the willingness with the highest probability is selected. The prediction is mined with the artist database to verify the accuracy of the sub-prediction and the degree of compliance with the cognitive constraints of AI painting.

Step 7: Whether the prediction intention data collection and user behaviour data collection are all analyzed. If all data sets are analyzed, repeat steps 2~6; otherwise, output the best prediction and constraints.

4. Actual Cases of User Behaviour Willingness Prediction

4.1 Data of User Behaviour Data

Taking the user behaviour data of AI painting platforms such as Hugging Face and Wehui as an example, this paper collects the AI painting behaviour data of 120 users from December 2021~December 2022. Some of the data was lost because it needed to be saved and later supplemented with an artist database. The total data collected was 1.2G, of which image data accounted for 20%, natural language data accounted for 20%, and random data accounted for 35%. The content of the intention includes the willingness to paint, the willingness to reuse, the form of painting, the amount of painting, etc. User behaviour data includes platform usage data, behaviour data and verification data, etc.; the specific data is shown in Table 1.

Table 1. User Behaviour Data

Data structure	Data content	Amount of data	Percentage error	The sum of squared deviations
Database	Artist Database	84.61	85.33	85.91
	Non-artist database	84.04	82.77	82.98
AI painting platform	image	83.96	85.62	85.22
	colour	84.05	84.82	85.61
	structure	85.02	84.91	86.56
	anime	86.45	83.73	85.43
Processing	AI painting	85.72	84.07	82.61
	Regulate yourself	82.84	85.37	87.30
	Comprehensive painting	84.03	84.50	82.85
	Smart painting	87.40	86.84	84.08
	History painting	85.79	85.25	85.15

4.2 Reasonableness of User Behaviour Willingness Prediction

Rationality is an important content of user behaviour willingness prediction; the number of research objects in this paper is n=100, mining parameters D=6 times, data collection T=12 months, and AI level is 1~5. To improve the accuracy of the prediction results, the average of the 10 prediction results is taken, and the prediction results are calculated as shown in Table 2.

Table 2. Reasonableness of User Behaviour Data

Content	Parameter	AI painting environment	AI painting conditions	Willingness to act
AI cognition	artist	82.54	85.11	Class V
	Non-artist	85.11	84.02	
	Random data	85.76	83.99	
AI platform use	artist	85.30	85.14	Class V
	Non-artist	84.88	86.64	
	Random data	85.56	83.23	
Users are satisfied	artist	86.17	86.96	Class V
	Non-artist	85.37	85.34	
	Random data	87.63	83.40	

The reasonableness calculation process of the meaning of user behaviour is shown in Figure 3.

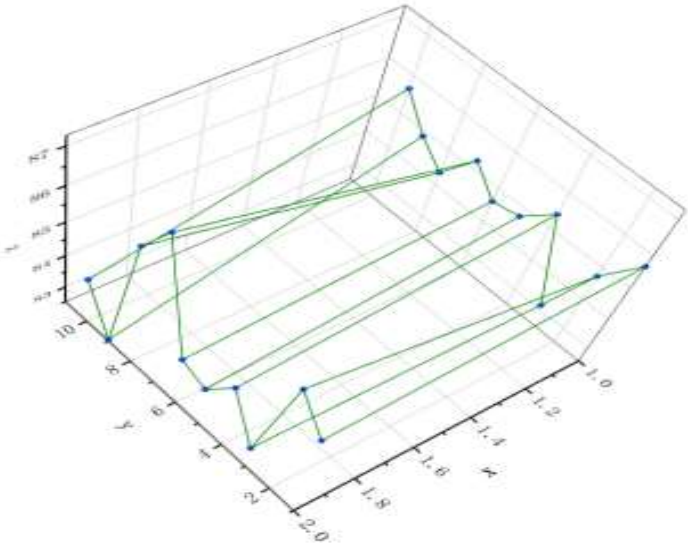

Figure 3. Reasonableness of User Behaviour Intention Data

It can be seen from Figure 3 that the user's willingness to behave is relatively strong, and it is at the V level, and the cognitive analysis of AI painting can be carried out.

4.3 Cognition of User Behaviour Willingness

User behaviour willingness is affected by AI cognition, so the AI cognitive level of user behaviour willingness is compared, and the specific simplified prediction results are shown in Figure 4.

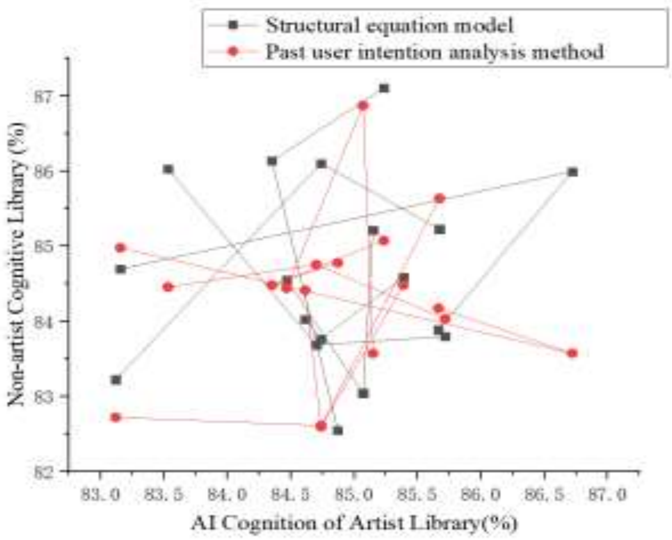

Figure 4. AI Cognition of User Behaviour Data

It can be seen from Figure 4 that the PLS-SEM structural equation model has a more significant influence on user behaviour willingness by AI painting cognition by about 41%, which is significantly higher than the previous user intention analysis method; in addition, the PLS-SEM structural equation model realizes the simplified calculation of AI cognition and minimizes the impact of user behaviour data, so as to ensure the accuracy of user behaviour willingness analysis. The main reason for the above problems is that the qualitative analysis of structural equation models can eliminate abnormal data and reduce natural language's impact on behavioural intention.

4.4 User Behaviour Willingness Prediction Time

The prediction time of user behaviour data is also an important content of behaviour willingness prediction. The painting cognition and artist behaviour should be calculated and compared with the previous user willingness method; the prediction results are shown in Figure 5.

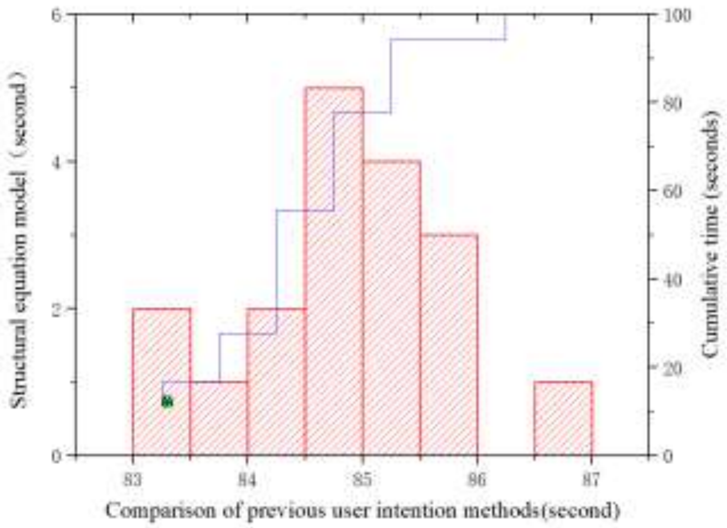

Figure 5. Prediction Time of User Behaviour Data

It can be seen from Figure 5 that compared with the previous user intention method, the prediction time of the PLS-SEM structural equation model on user behaviour data is shorter, and the calculation and prediction results of the PLS-SEM structural equation model are better than the previous user willingness method in terms of artist database. The reason is that the PLS-SEM structural equation model can realize the calculation of massive natural language data, and the user behaviour data is processed by coefficient transformation, simplifying the initial data volume of the PLS-SEM structural equation model.

4.5 Selection Accuracy of User Behaviour Willingness Prediction

To verify the implementation effect of the PLS-SEM structural equation model, the selection prediction results of user behaviour willingness prediction are analyzed, and the prediction results are shown in Figure 6.

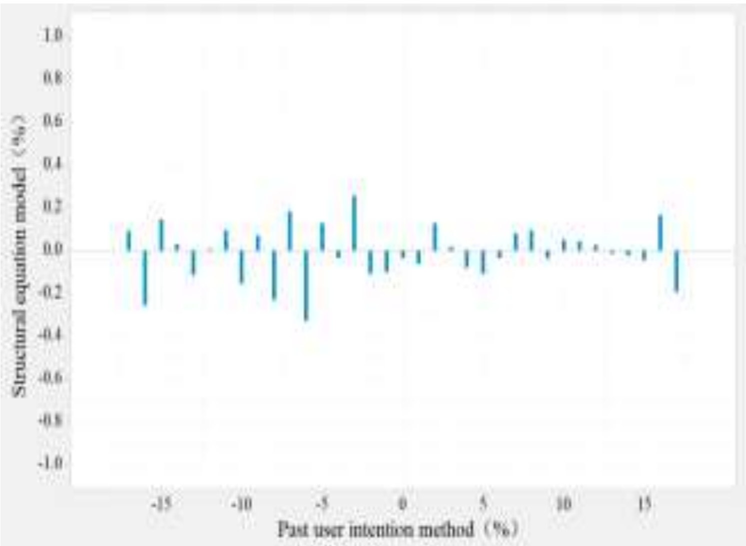

Figure 6. Test Prediction Results of Different Algorithms

It can be seen from Figure 6 that the calculation accuracy of the PLS-SEM structural equation model is higher than that of the previous user willingness method, and the change range is relatively small, indicating that the calculation and prediction results of the PLS-SEM structural equation model are relatively stable. Table 3 shows the prediction results of the user behaviour data of the PLS-SEM structural equation model.

Table 3. Summary of the Accuracy of Willingness Projections

The number of user wishes	accuracy	Willingness probability bias	Willingness to predict error rates
49	83.76	5.20	2
48	84.16	6.78	2
47	83.90	5.67	2
46	87.08	4.74	3
45	86.77	3.12	2
44	82.73	5.39	1
43	88.05	4.74	2
42	85.44	4.61	2
41	85.30	5.23	2
40	86.36	4.35	2
39	85.06	4.87	4
38	84.53	5.67	2

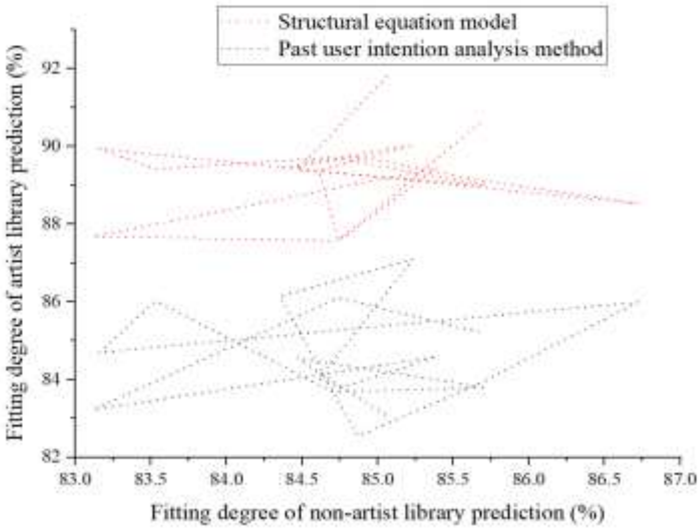

Figure 7. Fitness Prediction Results for Different Methods

It can be seen from Table 3 that the calculation accuracy of the PLS-SEM structural equation model before and after the coefficient conversion process is significantly improved, and the calculation deviation is significantly reduced after the coefficient conversion process. After the coefficient conversion process, the accuracy of user behaviour intention prediction gradually decreased, indirectly indicating that the intention prediction's accuracy improved. To further verify the accuracy of the PLS-SEM structural equation model in predicting user behaviour intention, the fitness values are compared, and the prediction results are shown in Figure 7.

It can be seen from Figure 7 that in terms of user behaviour willingness prediction fitness, the fitness after processing the PLS-SEM structural equation model is significantly better than the previous user willingness method, and the prediction of willingness fit and satisfaction are better than the previous user willingness method, and the reason is that the structural variance increases the synergistic coefficient and prediction weight of the prediction in different structural equation databases, and reduces the influence of local maximum probability prediction on the prediction results.

5. Conclusion

This paper proposes a prediction based on a structural equation model for the user behaviour data problem. This method combines structural equation calculation, constraint conditions, and weight coefficients to analyze user behaviour data to improve prediction accuracy. The prediction results show that the PLS-SEM structural equation model can predict user behaviour data, improve the accuracy of user behaviour willingness prediction, and shorten the selection time of prediction. Compared with the previous user intention method, the PLS-SEM structural equation model has a higher simplification rate and rationality for user behaviour data, which can meet the prediction requirements of user behaviour data. However, there are also certain limitations when making an intentional prediction. Structural variance needs to pay more attention to improving prediction ability, ignoring prediction consistency, and reducing prediction accuracy.

References

[1] E. Bokhari, "Clinical (In)Efficiency in the Prediction of Dangerous Behavior," *Journal of Educational and Behavioral Statistics*, 2023.

[2] R. Syama, and C. Mala, "Context-aware behaviour prediction for autonomous driving: a deep learning approach," *International Journal of Pervasive Computing and Communications*, vol. ahead-of-print, no. ahead-of-print, 2022.

[3] K. Amasyali, and N. El-Gohary, "Machine learning for occupant-behavior-sensitive cooling energy consumption prediction in office buildings," *Renewable & Sustainable Energy Reviews*, vol. 142, 2021.

[4] J. M. Bowen, M. J. Haskell, G. A. Miller, C. S. Mason, D. J. Bell, and C. A. Duthie, "Early prediction of respiratory disease in preweaning dairy calves using feeding and activity behaviors," *Journal of Dairy Science*, vol. 104, no. 11, 2021, pp. 12009-12018.

[5] J. Kuzilek, Z. Zdrahal, and V. Fuglik, "Student success prediction using student exam behaviour," *Future Generation Computer Systems-the International Journal of Escience*, vol. 125, 2021, pp. 661-671.

[6] S. Shahriar, A. R. Al-Ali, A. H. Osman, S. Dhou, and M. Nijim, "Prediction of EV Charging Behavior Using Machine Learning," *IEEE Access*, vol.9, 2021, pp.111576-111586.

[7] P. Szabo, and B. Genge, "Efficient Behavior Prediction Based on User Events," *Journal of Communications Software and Systems*, vol. 17, no. 2, 2021, pp. 134-142.

[8] M. Alaeiyan, and S. Parsa, "A hierarchical layer of atomic behavior for malicious behaviors prediction," *Journal of Computer Virology and Hacking Techniques*, vol. 18, no. 4, 2022, pp. 367-382.

[9] A. Almeida, U. Bermejo, A. Bilbao, G. Azkune, U. Aguilera, M. Emaldi, F. Dornaika, and I. Arganda-Carreras, "A Comparative Analysis of Human Behavior Prediction Approaches in Intelligent Environments," *Sensors*, vol. 22, no. 3, 2022.

[10] P. K. Anyidoho, R. A. Davidson, T. Rambha, and L. K. Nozick, "Prediction of population behavior in hurricane evacuations," *Transportation Research Part a-Policy and Practice*, vol. 159, pp. 200-221, 2022.

[11] R. Budiarto, A. A. Alqarni, M. Y. Alzahrani, M. F. Pasha, M. F. M. Firdhous, and D. Stiawan, "User Behavior Traffic Analysis Using a Simplified Memory-Prediction Framework," *Cmc-Computers Materials & Continua*, vol. 70, no. 2, 2022, pp. 2679-2698.

[12] K. Furuhashi, T. Nakaya, and Y. Maeda, "Prediction of Occupant Behavior toward Natural Ventilation in Japanese Dwellings: Machine Learning Models and Feature Selection," *Energies*, vol. 15, no. 16, 2022.

[13] L. N. Grendas, L. Chiapella, D. E. Rodante, and F. M. Daray, "Comparison of traditional model-based statistical methods with machine learning for the prediction of suicide behaviour," *Journal of Psychiatric Research*, vol. 145, 2022, pp. 85-91.

[14] M. Hrama, V. Sidletskyi, and I. Elperin, "Intelligent automatic control of sugar factory evaporator operation using behavior prediction subsystem," *Ukrainian Food Journal*, vol. 11, no.1, 2022, pp. 148-163.

[15] V. Papathanasopoulou, I. Spyropoulou, H. Perakis, V. Gikas, and E. Andrikopoulou, "A Data-Driven Model for Pedestrian Behavior Classification and Trajectory Prediction," *IEEE Open Journal of Intelligent Transportation Systems*, vol. 3, pp. 328-339, 2022.

[16] A. Perisic, and M. Pahor, "Clustering mixed-type player behavior data for churn prediction in mobile games," *Central European Journal of Operations Research*, vol. 31, no. 1, pp. 165-190, 2023.

[17] G. Shmueli, and A. Tafti, "How to improve prediction using behavior modification," *International Journal of Forecasting*, vol. 39, no. 2, 2023, pp. 541-555.

[18] S. K. Tripathy, H. Kostha, and R. Srivastava, "TS-MDA: two-stream multiscale deep architecture for crowd behavior prediction," *Multimedia Systems*, vol. 29, no. 1, 2023, pp. 15-31.