Eng Int Syst (2024) 5: 465–475

Engineering
Intelligent Systems

Design of Interface Display Optimization Algorithm for In-vehicle Interaction System Based on Artificial Intelligence

Shujuan Qu*

Department of Art and Design, Zibo Vocational Institute, Zibo 255300, Shandong, China

With the development of vehicle intelligence, the in-vehicle interaction system becomes an important means of information exchange between drivers and vehicles. The traditional in-vehicle interaction system has problems such as inaccurate information display and poor user experience. The purpose of this study is to use the algorithm optimization of artificial intelligence to improve the interface display of in-vehicle interaction system, enhance the user experience and improve safety. Firstly, the user's preferences, habits and needs are determined; these will constitute the original user data set, and deep learning algorithms are used to construct the user profile in order to optimize the personalized interface. After that, wavelet transform was applied to carry out multi-scale redrawing and rendering of images to enhance the visual effect of interface image display. Finally, a collaborative filtering algorithm was used to construct an intelligent recommendation model. The items in the recommendation set were arranged according to the weighted degree of recommendation from the largest to the smallest, so as to realize the intelligent recommendation and optimization of the interface information being displayed. In order to verify the effect of the interface display optimization algorithm of in-vehicle interaction system based on artificial intelligence, this study evaluated the optimized display interface in terms of user satisfaction, operation efficiency, error rate and interaction effect. The evaluation results showed that in the user satisfaction survey, the proportion of users who are satisfied and very satisfied with the personalized level, comfort level, and information readability of the optimized display interface was 61.0%, 50.5%, and 50.0%, respectively. The research results indicate that the interface display optimization algorithm based on artificial intelligence for in-vehicle interaction systems can effectively meet the different needs of users and help improve the safety of the driver.

Keywords: Algorithm optimization, interface display, artificial intelligence, in-vehicle interaction system, deep neural network

1. INTRODUCTION

With the development of information technology, in-vehicle interaction systems have been widely used [1]. However, due to the diverse functions of automobiles and the complex traffic environment, the display interface of in-vehicle interaction systems still has certain defects in terms of practical use, such as excessive information capacity, poor image data display, and failure to consider the special characteristics of elderly users, all of which has a great impact on user experience and safe driving. Therefore, user-centered optimization of the interface display of in-vehicle interaction systems has become an important direction for the development of vehicle intelligence [2]. With the mature development of computer science theory, artificial intelligence technology has achieved great success [3–4]. It has high adaptability and accuracy. Artificial intelligence technology is the core when designing optimization algorithms for the interface display of the in-vehicle interaction system, in order to display information that better meets user needs, and achieve personalized information recommendation and accurate image recognition

*Email: qsj19820527@163.com

and classification. This has important practical significance and value for improving the visual effect of interface display, improving driving safety, and enhancing user satisfaction.

With the development of intelligent vehicles, the role of in-vehicle interaction systems in improving user-vehicle interaction is becoming increasingly significant. Zhang explored the optimization of information exchange in-vehicle interaction systems and proposed an adaptive backoff algorithm. This algorithm considered the number of retransmissions and the level of network busyness to select an appropriate competition window. Finally, he used network simulation tools to simulate different scene models of in-vehicle self-organizing networks and studied the impact of different access modes on service quality. The simulation results showed that this algorithm can significantly improve the packet loss rate by sacrificing smaller latency when there are more vehicle nodes [5]. Detjen Henrik analyzed human needs and system acceptance in the context of automated driving. After that, based on the literature review, the current interaction between the driver in the vehicle and the vehicle, as well as related human performance issues, were summarized [6]. Liao Yuan conducted a cross-regional study on driving behavior and technology preferences in typical driving scenarios through operational tests, which contributed to the optimal design of the in-vehicle interaction system. Yuan found that users' preferences for the functions of the in-vehicle interaction system were related to relative driving risk perception and decision-making, thus providing a reference for the optimal design of the in-vehicle interaction system [7]. Zeng Qingshu developed an integrated evaluation hierarchy and corresponding set of integrated evaluation carriers and decision modes for an in-vehicle interaction system to improve the interaction experience and usability of the HMI (Human Machine Interface) interface, and conducted a comprehensive evaluation of the rapid prototype electric vehicle user interface, thereby improving the quality of interaction system design [8]. Currently, in-vehicle interaction systems have made good progress, but with the complex development of vehicle driving environments, appropriate improvements and optimizations need to be made in the design of in-vehicle interaction systems. Current research has not taken into account the issue of user comfort when driving.

The development of artificial intelligence technology provides more opportunities for optimizing in-vehicle interaction systems. Jianan Lyu believed that the widespread application of intelligent technology in automobiles has brought about significant changes in human-computer interaction. He studied the impact of human-computer interaction mode on driving safety, comfort and efficiency from the perspectives of physical interaction of artificial intelligence, touch screen control interaction, augmented reality, etc. Finally, he proposed a human-computer interaction design method for on-board systems based on existing technologies, which has certain guiding significance for the current design of human-computer interaction interface for on-board systems [9]. Liu Baojing proposed an artificial-intelligence-based in-vehicle interaction system that combines high-speed, robust, and low latency networks with artificial intelligence technology. The in-vehicle interaction system was optimized through intelligent image analysis and fifth generation mobile communication technology. Finally, experiments showed that the proposed system can effectively improve user comfort when driving [10]. With the assistance of artificial intelligence technology, in-vehicle interaction systems have achieved further development, although most studies have not addressed practical application problems to provide more effective guidance for in-vehicle interaction systems. They have explored only the application of artificial intelligence technology for the optimization of in-vehicle interaction systems from a theoretical perspective.

In order to improve the accuracy and visual effect of information recommendation in-vehicle interaction systems, and ensure user driving safety, this study conducted effective research on the design of interface display optimization algorithms for in-vehicle interaction systems using artificial intelligence. The optimization effect of the final display interface was evaluated in terms of: user satisfaction, operational efficiency, error rate, and interaction effect. With the support of artificial intelligence, the optimized display interface of the in-vehicle interaction system can effectively meet the diverse needs of users and improve their operational efficiency and accuracy. In practical applications, the proposed optimization algorithm has strong feasibility in ensuring user driving safety and improving user interface interaction.

2. OPTIMIZATION ALGORITHM DESIGN FOR INTERFACE DISPLAY OF IN-VEHICLE INTERACTION SYSTEM

2.1 Personalized Interface Optimization Based on User Profile

The user behavior data of the in-vehicle interaction system includes basic user information, display interface application data, environmental data, static and dynamic historical information about the vehicle, and control data. To some extent, these data indicate the user's habits and preferences for the display interface of the in-vehicle interaction system under different driving scenarios. If the user behavior data is connected with the user needs, and processed by integration, classification, etc., the user behavior data can be abstracted and labeled. The resulting user behavior data model is called the user profile [11].

Through the analysis of user's usage habits, function preferences and corresponding historical operations, this study established, processed and analysed the user's original data set. In this study, deep neural network algorithms were used to extract features from the dataset, achieving fine constructions of user profiles. Based on classification results, label features of user preferences for displaying interface operations in the in-vehicle interaction system were added, and personalized interface display methods were designed for different users. The overall framework for personalized interface optimization based on user profiling is shown in Figure 1.

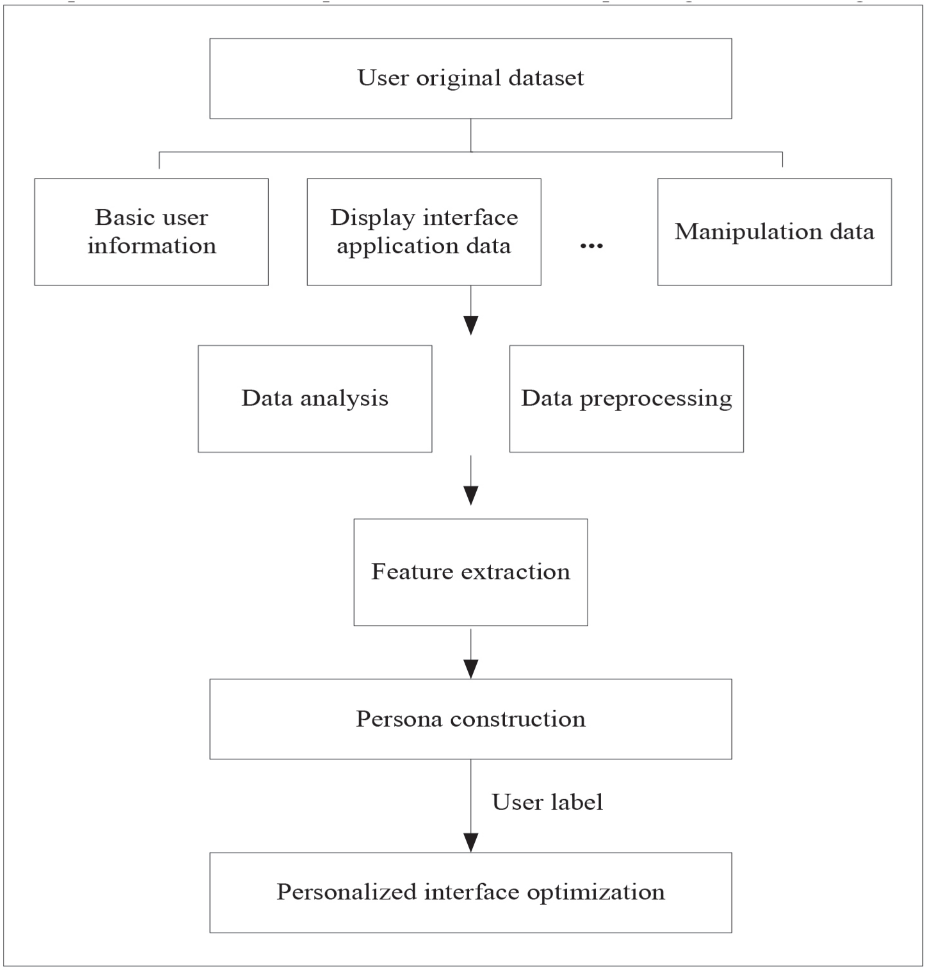

Figure 1 Overall framework for personalized interface optimization based on user profile.

Table 1 User data table.

Field name	Field description	Field type	Length	Is it empty
User-identification	User name or identification	Varchar	50	No
Behavior-type	User actions on the display interface	Varchar	50	No
User-location	User geospatial location information	Integer	50	No
Behavioral-time	The time when the user performs operations on the display interface	Datetime	20	No
User-attitude	User preferences	Varchar	100	No
Vehicle-status	Vehicle in static or dynamic state	Tinyint	50	No

Taking the user behavior data of an automobile brand as the original data set, a user data table was constructed, as shown in Table 1, and the historical behavior data of known users in a certain period of time was analyzed and processed.

In the optimization of personalized display interfaces, data analysis and processing are the first and most crucial steps as they affect the final optimization results. In the actual driving environment, the user's historical behavior data is often incomplete and therefore requires some processing, which is executed in two steps. Firstly, it is necessary to correct possible errors in the obtained behavioral data. This involves checking data consistency and handling missing values, so that the features of user behavioral data can be effectively mined. Secondly, a detailed analysis of data features must be conducted in order to understand their overall distribution, so as to provide valuable information for the establishment of user profiles.

When correcting possible errors in the behavioral data, this study estimated the outlier distribution of the data based on the average statistics obtained from the data. Firstly, the behavioral data related to users' browsing, operating, and implementing other driving functions on the display interface of the in-vehicle interaction system during their daily driving process were collected. The total amount of behavioral data presented by each user during the driving process was calculated, and those behavioral data that were significantly above or below the average level were filtered and excluded. In regard to incomplete data, the problem of missing sample

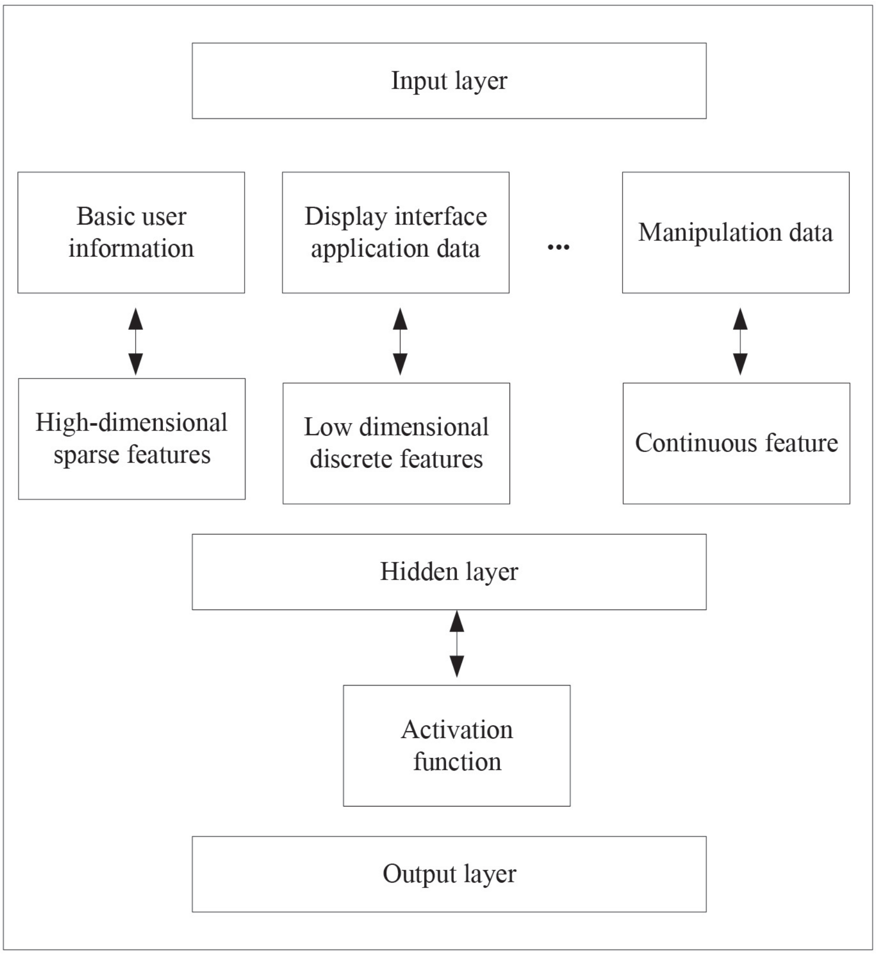

Figure 2 Constructing a nonlinear model using deep neural networks.

features was solved by assigning values. In this study, the missing values in the user behavior dataset were replaced by the mean of the feature values.

To take into account the different driving scenarios and the complexity of driver behavior in terms of user in-vehicle interaction system display interface, for feature extraction, this study used deep neural networks to construct a nonlinear model to extract features from the dataset, as shown in Figure 2.

Firstly, independent feature extraction methods are used for the input layer. Each high-dimensional sparse feature is mapped to a low-dimensional space, making it a low-dimensional feature value. Finally, it is concatenated with continuous features and input into the next layer for training.

In the hidden layer, the Rectified Linear Unit function is used as the activation function to realize the information transmission and feedback of the network. The forward propagation formula of the neural network is expressed as [12–13]:

$$u^{(k+1)} = f\left(w^{(k)} \cdot u^{(k)} + v^{(k)}\right) \tag{1}$$

where $w^{(k)}$ represents the layer k to layer $k+1$ weight matrix; $u^{(k+1)}$ is the output of layer $k+1$ neurons; $v^{(k)}$ is the offset from layer k to layer $k+1$.

The optimization goal of deep neural network training is to minimize the value of loss function by adjusting model parameters [14–15]. The loss function is set as a cross entropy function to minimize the loss as a binary classification problem. The formula can be written as:

$$B = -\frac{1}{A}\sum_{a}\left[t \ln u + (1-t)\ln(1-u)\right] \tag{2}$$

where a represents the sample, and A represents the total number of samples; t represents the true category to which the sample belongs, and u represents the output category of the neuron.

On this basis, the first-order moment estimation and second-order moment estimation methods are used to dynamically adjust the learning rate of each parameter to control the speed of parameter update. The update process is expressed as:

$$\delta_{t+1} = \delta_t - \frac{\hat{h}_t}{\sqrt{\hat{s}_t} + \theta} \times \varepsilon \tag{3}$$

In Formula (3), the definitions of each variable are shown in Table 2.

Finally, the overall personalized interface optimization is completed based on the label characteristics of user preferences for interface operations displayed on the in-vehicle interaction interface. The final effect is shown in Figure 3. This personalized interactive interface can be planned and transformed according to the different driving scenarios of drivers, providing them with more suitable interface control modes.

Table 2 Variable interpretation of Formula (3).

Sequence	Variable	Meaning
1	δ_t	Parameters that need to be updated
2	$\hat{h}_t$	Correction of first order moment estimation by updating process algorithm
3	$\hat{s}_t$	Correction of second order Moment estimation by updating process algorithm
4	θ	Constants that ensure numerical stability

Figure 3 Personalized display interface of in-vehicle interaction system.

2.2 Image Display Optimization Based on Deep Learning

The display interface of the in-vehicle interaction system is generally implemented by calling the application programming interface, and the presentation of images requires a series of complex processes. In real application scenarios, when some images need to be presented in a centralized manner on the display interface, if the difference in highlight resolution is significant, this would cause the centralized display effect of the images to be less than ideal; for instance, the images might not be clear. This not only affects the user's functional experience, but also endangers the safe driving of the user group, especially the elderly. Hence, in this study, by means of algorithm optimization, the display interface image was enhanced.

Taking the image display of the navigation function of the in-vehicle interaction system in the interface as an example, P_I is the original image to be displayed, and P_N is the noisy image, as shown in Figure 4. N is noise, and the observation mode can be expressed as:

$$P_I = P_N - N \tag{4}$$

In Figure 4, the mathematical model of the noisy image in the interface of the navigation function of the vehicle interactive system is Gaussian noise. The image is transformed into a real number domain, that is, a frequency domain, through a discrete cosine transform [16]:

$$g(x, y) = \frac{2}{M} d(x) d(y) \sum_{m=0}^{M-1} \sum_{n=0}^{M-1} P_I(m, n) \times \cos\left[\frac{\pi}{2M}(2m+1)x\right] \cos\left[\frac{\pi}{2M}(2n+1)y\right] \tag{5}$$

Among them, there are:

$$d(x) = \begin{cases} \frac{1}{\sqrt{2}}, & x = 0 \\ 1, & x = 1, 2, \cdots, M-1 \end{cases} \tag{6}$$

$$d(y) = \begin{cases} \frac{1}{\sqrt{2}}, & y = 0 \\ 1, & y = 1, 2, \cdots, M-1 \end{cases} \tag{7}$$

$g(x, y)$ is the frequency domain coefficient of $M \times M$.

On this basis, wavelet transform is used to transform image information into frequency domain information containing low-frequency and high-frequency components, and multi-scale redraws of the image are performed horizontally, vertically, and diagonally.

It is assumed that the two-dimensional scale space of the image to be displayed is E_o^2 and another two-dimensional scale space is represented as Q_o^2, then there is:

$$E_{o+1}^2 = E_o^2 \oplus Q_o^2 \tag{8}$$

where the image scale coefficient is represented as o, with a value range of 0, 1, 2, $\cdots$, and there is a sequence:

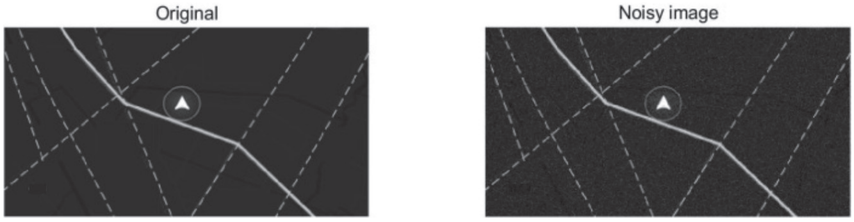

Figure 4 Original image to be displayed and noisy image.

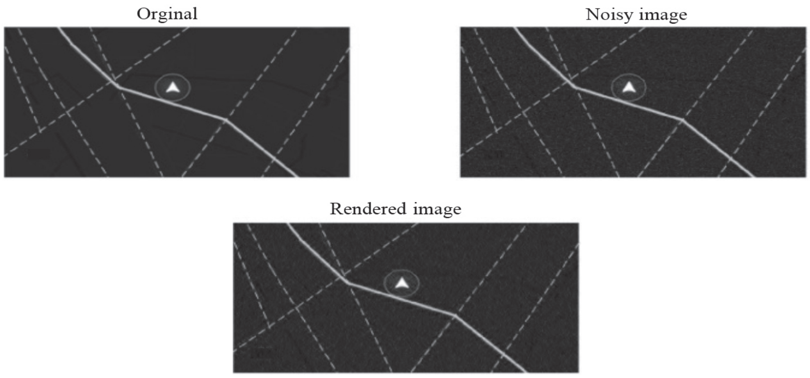

Figure 5 Rendered display image.

$$D^{o+1} = \left\{D^{o,1}_{r,c}\right\} r, c \in z \tag{9}$$

$$L^{o,1} = \left\{L^{o,2}_{r,c}\right\} r, c \in z \tag{10}$$

$$L^{o,2} = \left\{L^{o,3}_{r,c}\right\} r, c \in z \tag{11}$$

$$L^{o,3} = \left\{D^{o+1}_{r,c}\right\} r, c \in z \tag{12}$$

From the sequence, it can be concluded that:

$$g_{o+1} = \sum_{r,c} d^{o+1}_{r,c} \alpha_{o+1,r,c} \tag{13}$$

$$L_o = \sum_{r,c} L^{o,1}_{r,c} \beta^1_{o,r,c} + \sum_{r,c} L^{o,2}_{r,c} \beta^2_{o,r,c} + \sum_{r,c} L^{o,3}_{r,c} \beta^3_{o,r,c} \tag{14}$$

where α represents the transformed image scale coefficient, and β represents the wavelet coefficient; r and c represent the rows and columns of the corresponding coefficient matrix, then there are [17]:

$$D^{o+1}_{r,c} = \langle g, \alpha_{o+1,\ r,c} \rangle \tag{15}$$

$$L^{o,1}_{r,c} = \left\langle g, \beta^1_{o,r,c} \right\rangle \tag{16}$$

$$L^{o,2}_{r,c} = \left\langle g, \beta^2_{o,r,c} \right\rangle \tag{17}$$

$$L^{o,3}_{r,c} = \left\langle g, \beta^3_{o,r,c} \right\rangle \tag{18}$$

Sequence $D^o, L^{o,1}, L^{o,2}, L^{o,3}$ is a two-dimensional wavelet transform of D^{o+1}.

By following the algorithm steps and principles, the image of the display interface of the in-vehicle interaction system is processed and optimized, and then the image is rendered through the application programming interface of the in-vehicle interaction system. Finally, the optimized display image is obtained, as shown in Figure 5.

2.3 Optimization of Information Display Based on Intelligent Recommendation

The optimization of information display aims to improve the way information is presented in the current in-vehicle interaction system display interface. Specifically, in order to ensure that the amount of information and content differences presented in the display interface of the in-vehicle interactive system would not occupy too much cognitive and memory resources of the user, it is necessary to change and adjust the information and content presented in the display interface according to the user's habits, preferences, and specific driving situations, so as to ensure driving safety. At present, with the continuous development of intelligent technology, the functions of in-vehicle interaction systems have been expanded, and the number of display interface menus and information would continue to increase, which would have varying degrees of impact on user operation behavior.

On this basis, this paper constructed an intelligent recommendation model with the help of the Collaborative filtering algorithm, as shown in Figure 6. According to the user information browsing history, recommendation information table and other information to intelligently recommend relevant information and functions can provide more intelligent and personalized interface display.

It is assumed that R_a is the collection of resources that the user has browsed in the in-vehicle interaction system display interface, and M_n is the nearest neighbor model of the project, where the nearest neighbor of the project refers to other projects similar to the target project.

For each browsing item p, $p \in P_X$. After obtaining its K nearest neighbor set $C_p = \{p_1, p_1, \cdots, p_K\}$, the set is obtained by merging all C_p. After deleting the existing items in P_X from C, a candidate recommendation set is obtained. For each j belonging to the

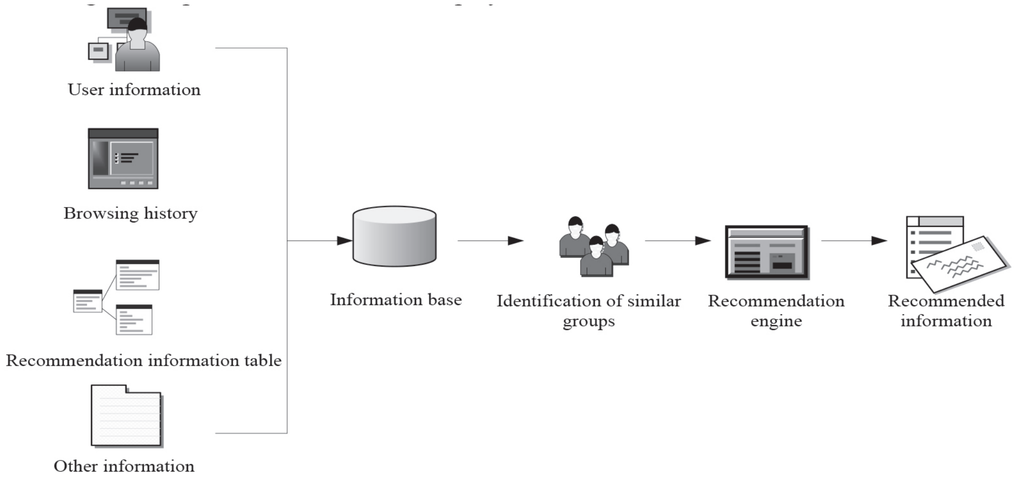

Figure 6 Intelligent recommendation model.

Table 3 Explanation of variables in Formula (22).

Sequence	Variable	Meaning
1	$\overline{S}_X$	The average score of user X on all items
2	$\overline{S}_j$	The average score of user j on all items
3	$C_{X,j}$	The collection of items jointly rated by user X and user j
4	C_X	The collection of items rated by user X
5	C_j	The collection of items rated by user j

recommendation set, the recommendation degree of j to X is calculated [18–19]:

$$rec\,(X, p) = \sum_{p \in P_X} sim\,(X, j) \tag{19}$$

where $sim\,(X, j)$ represents the similarity between the two browsing items.

The similarity calculation is as follows:

$$sim\,(X, j) = cos\,(X, j) = \frac{\overrightarrow{X} \cdot \overrightarrow{j}}{|X|\,|j|} \tag{20}$$

$$|X| = \sqrt{\sum_{K=1}^{C} X_K} \tag{21}$$

Among them, X_K is the rating given by user X to the K-th project. For those cases where data is sparse, the distance between users is mainly calculated through similarity.

Due to individual differences among users, different users have different evaluation criteria for a unified project. Therefore, even if different users have consistent ratings for a certain project, it does not mean that their preferences and application habits for the project are completely consistent among users. To solve this problem, it is necessary to make certain modifications to the similarity formula, which is mainly achieved by subtracting the average score:

$$sim\,(X, j) = \frac{\sum_{K \in C_{X,j}} \left(S_{X,K} - \overline{S}_X\right)\left(S_{j,K} - \overline{S}_j\right)}{\sqrt{\sum_{K \in C_X} \left(S_{X,K} - \overline{S}_X\right)^2}\sqrt{\sum_{K \in C_j} \left(S_{j,K} - \overline{S}_j\right)^2}} \tag{22}$$

The definitions of each variable are shown in Table 3.

Based on the weight of recommended values in the recommendation set, the project information is sorted from high to low, and the top items are used as the user's recommendation set. With the assistance of the recommendation model, the display interface of the in-vehicle interaction system can achieve diversified information recommendation, that is, it can no longer only push text content, but also personalized recommendations for images and videos related to user preferences. This not only effectively discovers users' potential preferences and improves the accuracy of display interface recommendations, but also makes it easier for users to obtain the information they need, improving their satisfaction with the display interface of the car interaction system.

3. EVALUATION OF THE EFFECTIVENESS OF OPTIMIZATION ALGORITHMS FOR DISPLAYING THE INTERFACE OF THE IN-VEHICLE INTERACTION SYSTEM

To verify the effectiveness of the interface display optimization algorithm for artificial intelligence based in-vehicle interaction systems, this article evaluated the optimization effect of the final display interface from four aspects: user satisfaction, operational efficiency, error rate, and interaction effect.

3.1 User Satisfaction

In the evaluation of user satisfaction, this article mainly used a questionnaire survey to investigate users' experience and feelings towards the optimized interface. Due to the fact that

Table 4 Basic user information.

Item	Classification	Number of people	Proportion (%)
Gender	Male	127	63.5
	Female	73	36.5
Age	18–30 years old	57	28.5
	31–50 years old	101	50.5
	Over 50 years old	42	21.0
Driving experience	1-3 years	94	47.0
	Over 3 years	106	53.0

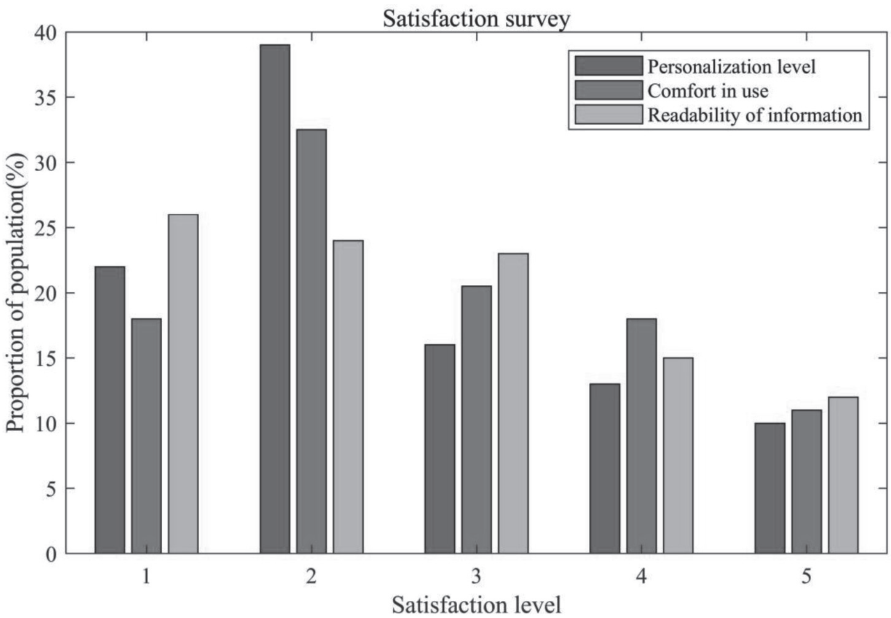

Figure 7 Satisfaction survey results.

the evaluation in this article mainly focuses on the display interface of the in-vehicle interaction system, the survey object of this questionnaire was mainly the driver. The survey content was mainly divided into two aspects: user basic information and user satisfaction. The survey content of user basic information mainly includes user gender, age, and driving experience. The content of the user satisfaction survey mainly includes the degree of personalization, comfort, and readability of information displayed on the interface of the artificial intelligence based in-vehicle interaction system. Satisfaction ratings were categorized on a scale of 1–5, indicating very satisfied, satisfied, fair, dissatisfied, and very dissatisfied, respectively.

A total of 210 questionnaires were distributed in this survey, and 10 invalid and incomplete questionnaires were removed. Finally, 200 valid questionnaires were collected, with a validity rate of approximately 95.24%. The basic user information is shown in Table 4, and the satisfaction survey results are shown in Figure 7.

According to Table 4, in terms of user gender, the majority of respondents in this survey were males, accounting for 63.5% of the total population; the proportion of women accounted for 36.5% of the total population. In terms of user age, drivers aged 31 to 50 were the majority, with a specific proportion of 50.5%; the proportion of drivers aged 18–30 was 28.5%, and the proportion of drivers over 50 was 21.0%. At the level of driving experience, the proportion of drivers aged 1–3 years was 47.0%, and the proportion of drivers aged over 3 years was 53.0%.

In Figure 7, the horizontal axis represents the satisfaction level, which is divided into 1–5 levels. The vertical axis represents the number of people. Generally speaking, the more people in the satisfied and very satisfied categories, the better the user's experience of using the car interaction system display interface. The survey results indicate that in regard to personalization, 61.0% of participants were either satisfied or very satisfied with the optimized display interface; in terms of user comfort and information readability, 50.5% and 50.0%, respectively, were satisfied or very satisfied with the optimized display interface. In the satisfaction survey, the number of users who were satisfied or very satisfied with the personalized level, comfort level, and information readability of the optimized display interface reached half or more of the total number. This indicated that the proposed optimization algorithm successfully took into account the different ages of users and their various demands and requirements in practical applications, thereby effectively improving the user experience.

3.2 Operational Efficiency

Operational efficiency refers to the time spent by users to complete specific tasks before and after the optimization of the display interface. In the actual driving process, the user's

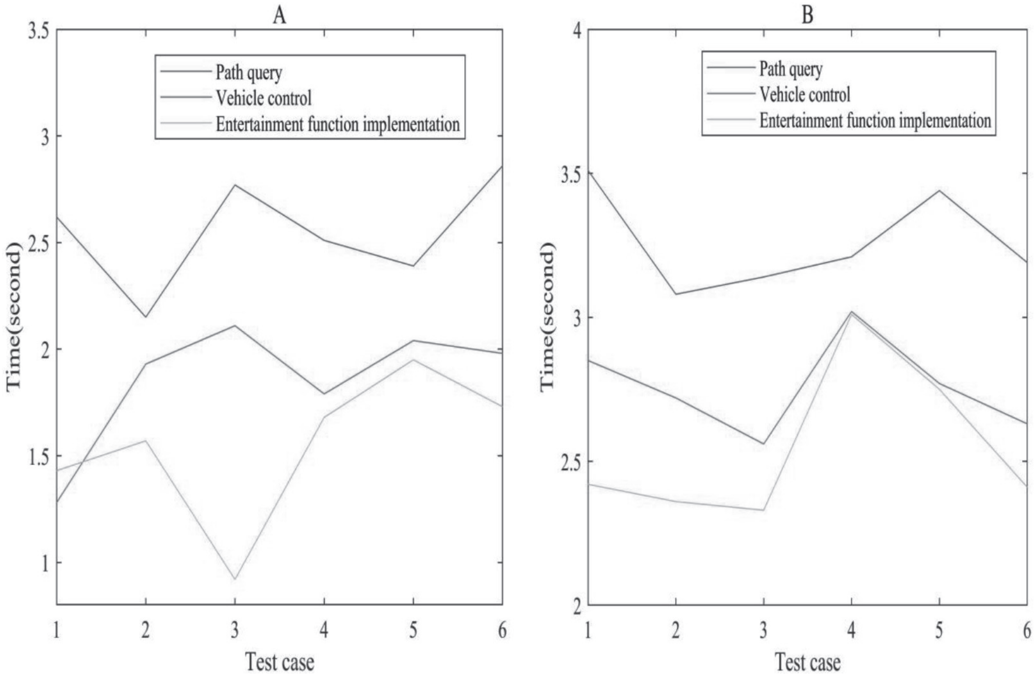

Figure 8 Evaluation results for operational efficiency.

operational efficiency in the display interface greatly affects driving safety. This study took the common path query, vehicle control, and entertainment function implementation in user driving scenarios as specific tasks for operational efficiency evaluation, and used user data as a test set to randomly select six test cases related to these three types of operations. The times spent by users completing specific tasks before and after the optimization of the display interface were compared and evaluated. The final results are shown in Figure 8.

Figure 8A shows the evaluation results for operational efficiency after optimization, while Figure 8B shows the evaluation results for operational efficiency before optimization.

In figures 8A and 8B, the horizontal axis represents the test cases for path query, vehicle control, and entertainment function implementation, while the vertical axis represents the time spent by the user in operation. In Figure 8A, the average time spent on the optimized display interface of the algorithm in the path query, vehicle control, and implementation of entertainment function test cases was approximately 2.55 seconds, 1.86 seconds, and 1.55 seconds, respectively. In Figure 8B, the average time spent on the optimized display interface under the test cases of path query, vehicle control, and the implementation of the entertainment function were approximately 3.26 seconds, 2.76 seconds, and 2.55 seconds, respectively. The evaluation results for operational efficiency before and after optimization showed that under the optimization of the algorithm proposed in this study, the user's operational efficiency in terms of the display interface had significantly improved. Users need to spend less time to complete the operation, which can help to ensure driver safety.

3.3 Error Rate

Error rate refers to the operation error rate of the user in the display interface. When the in-vehicle interactive system displays too many information elements or the interface layout is not user-friendly, the user operation error rate is expected to be higher. When determining the error rate, this study also focused on three types of operations: path query, vehicle control, and entertainment function implementation. Six test cases related to these three types of operations were randomly selected from user behavior data, and the error rate of user execution tasks before and after display interface optimization was compared and evaluated. The final results are shown in Figure 9.

Figure 9A shows the error rate evaluation results after optimization, and Figure 9B shows the error rate evaluation results before optimization.

In Figures 9A and 9B, the horizontal axis represents test cases for path query, vehicle control, and entertainment function implementation, while the vertical axis represents the error rate of user display interface operations. In Figure 9A, the average error rates of path query, vehicle control, and entertainment function implementation under different test cases were about 0.45%, 0.38% and 0.43%, respectively. In Figure 9B, the average error rates of the path query, vehicle control, and entertainment function implementation before optimization under different test cases were about 0.92%, 0.93% and 0.86%, respectively.

3.4 Interactive Effects

The interaction effect of the display interface of the in-vehicle interaction system is analyzed by examining user behavior data and operation records. Given the complexity of driving conditions and environments, this study set up 10 driving scenarios and evaluated the completion rate, usage level, and page bounce rate of user target functions at specific times under different driving scenarios. The results are shown in Figure 10.

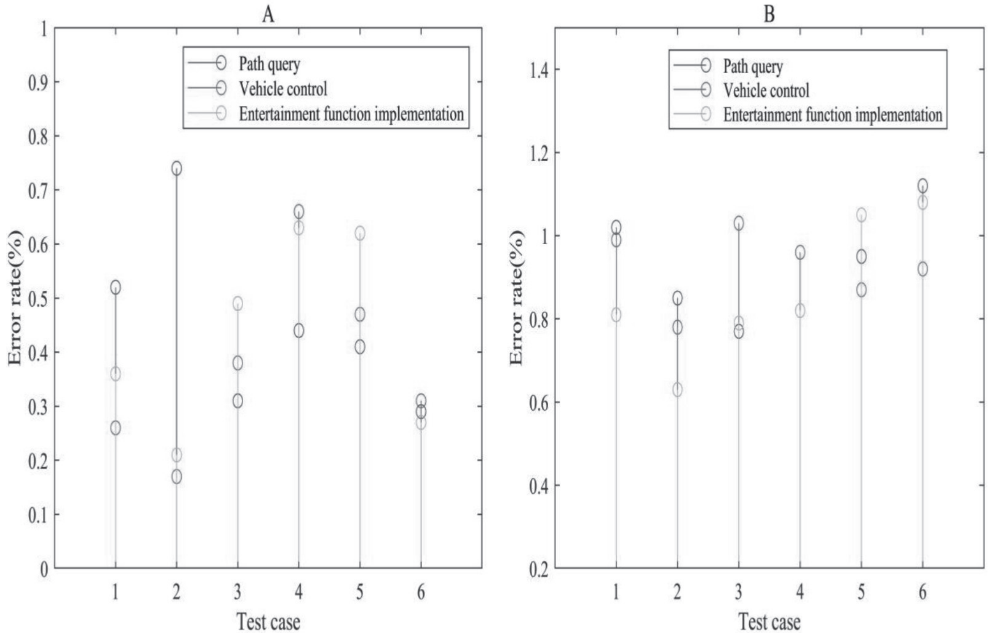

Figure 9 Error rate evaluation results.

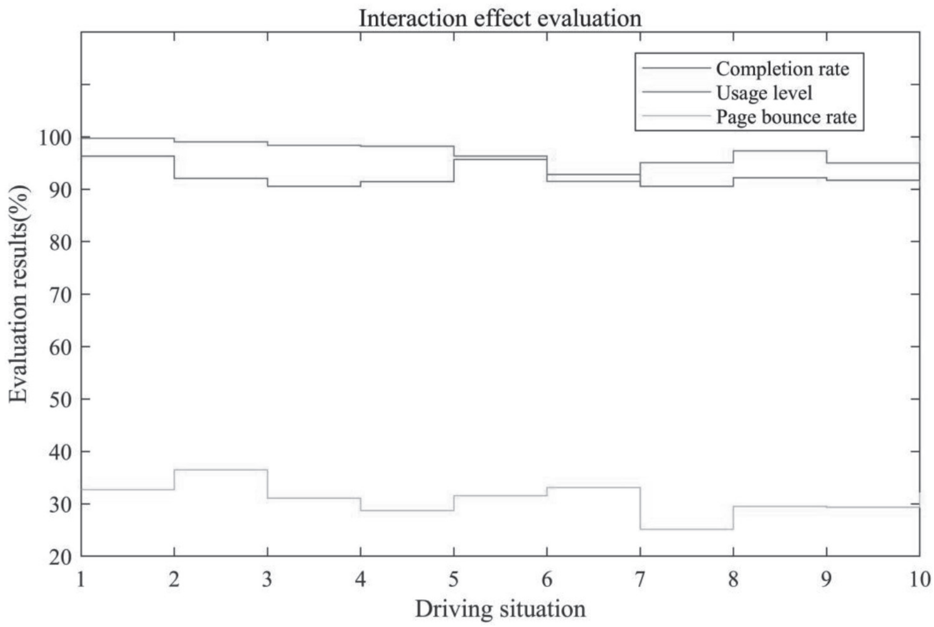

Figure 10 Evaluation results for interaction effects.

In Figure 10, the horizontal axis represents different driving scenarios, while the vertical axis represents the evaluation results of target function completion rate, usage level, and page bounce rate. The higher the completion rate and usage level of the target function, the better the interaction effect of the display interface. Page bounce rate refers to the number of page views by users who leave after reading only one page. The higher the page bounce rate, the lower the attractiveness of the page content to users, and the worse the interaction effect. The results indicated certain differences in the interaction effects under different driving scenarios. However, overall, the optimized in-vehicle interaction system display interface proposed in this paper had a relatively ideal interaction effect. For instance, the average completion rate of user target functions within specific time periods under different driving scenarios was about 92.37%; the average usage of functions was about 96.98%, while the average page bounce rate was about 30.97%. The evaluation of the interaction effects shows that the proposed optimized system can effectively improve the interaction between the display interface and users.

4. CONCLUSION

The development of automotive intelligence not only provides users with higher travel efficiency; it also makes safe driving a top priority in transportation [20]. The display interface centered on the in-vehicle interaction system effectively integrates vehicle information and functions, playing an important role in ensuring the safety of travelers when driving. In order to improve the application effect of the display interface of the car interaction system and enhance user satisfaction, this study conducted in-depth research on the optimization algorithm design of the car interaction system interface based on artificial intelligence [21–22]. This improved the user experience to a certain extent, and also significantly improved the efficiency and accuracy of user operation on the display interface, thereby enhancing the interaction effect between the car interaction system display interface and users. Although the design of interface display optimization algorithms for in-vehicle interaction systems based on artificial intelligence can help promote the intelligent and rational development of display interface design, this study has certain limitations. In future research, further improvements could be considered in terms of display interface scalability to meet the needs of different users and improve traffic safety.

REFERENCES

1. Lv, Zhihan, Liang Qiao, and Ilsun You. "6G-Enabled Network in Box for Internet of Connected Vehicles". IEEE Transactions on Intelligent Transportation Systems (2020).
2. Cao, Z., & Qian, L. (2023). Crowding Effect of Institutional Openness Based on Big Data Algorithm on the Efficiency of New Energy Technology Innovation. Frontiers in Bioengineering and Biotechnology, 11.
3. Haenlein, Michael, and Andreas Kaplan. "A brief history of artificial intelligence: On the past, present, and future of artificial intelligence". California Management Review, 61.4 (2019): 5–14.
4. Lu, Yang. "Artificial intelligence: a survey on evolution, models, applications and future trends". Journal of Management Analytics, 6.1 (2019): 1–29.
5. Zhang, Yuzhuo, Yuan Cao, Yinghong Wen, Liang Liang, Feng Zou. "Optimization of information interaction protocols in cooperative vehicle-infrastructure systems". Chinese Journal of Electronics, 27.2 (2018): 439–444.
6. Detjen, Henrik, Sarah Faltaous, Bastian Pfleging, Stefan Geisler & Stefan Schneegass. "How to increase automated vehicles' acceptance through in-vehicle interaction design: A review". International Journal of Human–Computer Interaction, 37.4 (2021): 308–330.
7. Liao, Yuan, Minjuan Wang, Lian Duan, Fang Chen. "Cross-regional driver–vehicle interaction design: an interview study on driving risk perceptions, decisions, and ADAS function preferences". IET Intelligent Transport Systems, 12.8 (2018): 801–808.
8. Zeng, Qingshu, Bing Jiang, and Qijun Duan. "Integrated evaluation of hardware and software interfaces for automotive human–machine interaction". IET Cyber-Physical Systems: Theory & Applications, 4.3 (2019): 214–220.
9. Jianan, Lyu, and Ashardi Abas. "Development of human-computer interactive interface for intelligent automotive". International Journal of Artificial Intelligence, 7.2 (2020): 13–21.
10. Liu, Baojing, Chenye Han, Xinxin Liu & Wei Li. "Vehicle artificial intelligence system based on intelligent image analysis and 5G network". International Journal of Wireless Information Networks, 30.1 (2023): 86–102.
11. Min, Tian, and Wei Cai. "Portrait of decentralized application users: an overview based on large-scale Ethereum data". CCF Transactions on Pervasive Computing and Interaction, 4.2 (2022): 124–141.
12. Bau, David, Jun-Yan Zhu, Hendrik Strobelt, and Antonio Torralba. "Understanding the role of individual units in a deep neural network". Proceedings of the National Academy of Sciences, 117.48 (2020): 30071–30078.
13. Cheng, Yu, Duo Wang, Pan Zhou, Tao Zhang. "Model compression and acceleration for deep neural networks: The principles, progress, and challenges". IEEE Signal Processing Magazine, 35.1 (2018): 126–136.
14. Cichy, Radoslaw M., and Daniel Kaiser. "Deep neural networks as scientific models". Trends in Cognitive Sciences, 23.4 (2019): 305–317.
15. Farrell, Max H., Tengyuan Liang, and Sanjog Misra. "Deep neural networks for estimation and inference". Econometrica, 89.1 (2021): 181–213.
16. Othman, Gheyath, and Diyar Qader Zeebaree. "The applications of discrete wavelet transform in image processing: A review". Journal of Soft Computing and Data Mining, 1.2 (2020): 31–43.
17. Mehra, Isha, Areeba Fatima, and Naveen K. Nishchal. "Gyrator wavelet transform". IET Image Processing 12.3 (2018): 432–437.
18. Fu, Mingsheng, Hong Qu, Zhang Yi, Li Lu, Yongsheng Liu. "A novel deep learning-based collaborative filtering model for recommendation system". IEEE Transactions on Cybernetics, 49.3 (2018): 1084–1096.
19. Cui, Zhihua, Xianghua Xu, Fei XUE, Xingjuan Cai, Yang Cao, Wensheng Zhang, et al. "Personalized recommendation system based on collaborative filtering for IoT scenarios". IEEE Transactions on Services Computing, 13.4 (2020): 685–695.
20. Lv, Zhihan, Liang Qiao, Ken Cai, and Qingjun Wang. "Big Data Analysis Technology for Electric Vehicle Networks in Smart Cities". IEEE Transactions on Intelligent Transportation Systems (2020).
21. Hu, Shan. Full Target K-Coverage Retention at the Boundary of Smart Sensor Networks. Engineering Intelligent Systems, Volume 32, Issue 2, Pages 139–147, March 2024
22. Hongjie, Chen, Chuan, Xiao. Longitudinal Deformation Analysis of High-Resolution Integrated Images Based on Multi-Sensors. Engineering Intelligent Systems, v 31, n 1, p 33–42, January 2023

Shujuan Qu was born in Yantai, Shandong, P.R. China, in 1982. She received a master's degree from Shandong University of Technology. She is currently working at the Zibo Vocational College. Her research interests include digital art, visual communication design and production.
E-mail: qsj19820527@163.com