INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 21, Issue: 1, Month: February, Year: 2026
Article Number: 7067, https://doi.org/10.15837/ijccc.2026.1.7067

Evaluating User Satisfaction in Automotive Cockpits Using a Fuzzy Evaluation Model

Mingju Yao, Zhiyuan Li

Mingju Yao*
School of Intelligence Technology
Geely University of China, China
No.123, Chengjian Avenue, Chengdu City, China
*Corresponding author: 370604206@qq.com

Zhiyuan Li
School of Intelligence Technology
Geely University of China, China
No.123, Chengjian Avenue, Chengdu City, China
lizhiyuan@guc.edu.cn

Abstract

The assessment of user experience satisfaction in intelligent automotive cockpits is pivotal for enhancing vehicle design and user interaction. This study introduces a fuzzy comprehensive evaluation model that integrates the Analytic Hierarchy Process (AHP), entropy weight method, and fuzzy evaluation method to systematically analyze user satisfaction. By combining subjective and objective data, the model quantifies user perceptions across multiple dimensions, including cockpit layout, design aesthetics, and information interface usability. Empirical testing involving 20 participants validated the model's effectiveness, revealing key areas for improvement, such as steering wheel and seat design, while demonstrating consistency between subjective feedback and objective metrics. The results highlight the model's ability to provide actionable insights for automotive manufacturers, facilitating the development of more intuitive and user-centric cockpit systems. Future research will expand the evaluation framework to include diverse seating positions and additional cockpit features, further refining the assessment methodology.

Keywords: Intelligent car cockpit,fuzzy comprehensive evaluation model, Analytic Hierarchy Process, entropy method,user experience,human-machine interaction.

1 Introduction

In recent decades, the automotive industry has undergone a profound transformation driven by advancements in the Internet of Things (IoT), autonomous driving, vehicle-to-vehicle communication, and artificial intelligence (AI). These innovations have shifted vehicles from mere transportation tools to sophisticated mobile environments, with the intelligent cockpit emerging as a critical interface for user interaction[10][12]. Modern cockpits integrate infotainment systems, voice commands, touchscreens, and personalized settings, aiming to enhance driving safety, comfort, and overall user experience[19].

Despite these technological advancements, evaluating user satisfaction in intelligent cockpits remains a significant challenge. Current research primarily focuses on aesthetic cognition, intention styles, and perceptible interior features, often relying on subjective methods such as questionnaires and interviews [9] [20]. While these approaches capture user perceptions, they suffer from three key limitations. First is lack of objectivity, traditional methods depend heavily on self-reported data, which can be biased by users' varying levels of experience and articulation skills. Second is limited data dimensionality ,Surveys and interviews yield qualitative or low-dimensional quantitative data, making it difficult to extract meaningful insights from large datasets. The last is insufficient integration of multidisciplinary factors , Existing studies rarely combine insights from human-computer interaction, psychology, and automotive engineering, leading to fragmented evaluations.

To address these gaps, this study proposes a fuzzy comprehensive evaluation model that integrates the Analytic Hierarchy Process (AHP)[3], entropy weight method, and fuzzy mathematics. This hybrid approach:Quantifies subjective perceptions through structured fuzzy membership functions.Balances expert knowledge (AHP) with data-driven weighting (entropy method) to enhance objectivity.Combines both subjective and objective data as EEG, eye tracking, and Likert-scale surveys for a holistic assessment.

By systematically analyzing cockpit layout, design aesthetics, and information perception, this research provides a scientifically robust framework for evaluating and optimizing intelligent cockpit designs. The findings offer actionable insights for automotive manufacturers, helping them refine cockpit interfaces to better align with user needs.

Future work will expand the model's applicability by incorporating multi-seat evaluations as passenger perspectives and additional cockpit features as ambient lighting to further enhance assessment accuracy.

2 Literature review

Current research on evaluation methods for user satisfaction with intelligent car cockpit design experiences primarily focuses on aesthetic cognition, intention styles, and perceptible interior features, often relying on subjective tools such as questionnaires and interviews. While these approaches capture user perceptions, they face limitations in objectivity, data dimensionality, and interdisciplinary integration. To address these gaps, various established evaluation methodologies have been proposed, including the Analytic Hierarchy Process (AHP)[13], Principal Component Analysis (PCA), Fuzzy Comprehensive Evaluation (FCE)[8], and the entropy-based Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). A structured comparative analysis of these methods is provided in table 1, highlighting their applicability and limitations in automotive cockpit evaluations.

Recent studies emphasize the growing role of fuzzy theory in addressing uncertainty in user experience assessments. For instance, Yang et al. (2022) applied FCE to evaluate cockpit comfort, demonstrating its efficacy in translating subjective feedback into quantifiable metrics[22]. Similarly, Zadeh's foundational work on fuzzy sets (1978) underscores its utility in handling imprecise human judgments, a critical aspect of automotive cockpit evaluations[24]. However, standalone fuzzy methods often lack integration with objective data, limiting their robustness.

The limitations of these methods highlight the need for hybrid models. AHP's reliance on expert judgment risks subjectivity, while TOPSIS's purely data-driven approach may overlook contextual nuances[1]. PCA, though useful for dimensionality reduction, fails to capture hierarchical relationships. FCE alone struggles with balancing subjective and objective inputs. To bridge these gaps, this study integrates AHP, entropy weighting, and FCE into a unified framework. The proposed model synergizes AHP's structured hierarchy and TOPSIS's entropy-based objectivity with FCE's fuzzy logic, addressing biases, enhancing data integration, and enabling multidimensional analysis. By combining expert insights (AHP), data-driven weights (entropy), and fuzzy membership functions (FCE), the model mitigates individual method shortcomings, offering a holistic and adaptable solution for cockpit evaluations.

Table 1: Comparative Analysis of Evaluation Methods

Method	Advantages	Limitations	Applicability in Cockpit Evaluation
AHP	Combines qualitative and quantitative analysis; hierarchical structuring.	Subjective bias in expert ratings; struggles with large-scale indicators.	Suitable for prioritizing design factors but limited in handling complex datasets.
PCA	Reduces data dimensionality; identifies principal components.	Requires large sample sizes; loses interpretability of original variables.	Less effective for holistic user experience assessments with multifaceted factors.
FCE	Handles vagueness via fuzzy logic; quantifies subjective perceptions.	Membership function design may introduce subjectivity.	Ideal for ambiguous metrics like aesthetics but requires robust fuzzy rules.
TOPSIS	Objective weighting via entropy; ranks alternatives relative to ideal solutions.	Sensitive to normalization methods; ignores correlations between criteria.	Effective for benchmarking but overlooks interdependencies in cockpit design.

This integration aligns with emerging trends in intelligent cockpit research. For example, Li et al. (2023) emphasized the importance of hybrid models in capturing both quantitative physiological data (e.g., EEG, eye tracking) and qualitative user feedback[6]. Similarly, Xuan and Deng (2023) highlighted the value of fuzzy systems in processing heterogeneous data streams, a key requirement for modern automotive interfaces[21]. By building on these advancements, the proposed framework advances beyond traditional siloed approaches, providing a scalable methodology for iterative cockpit design optimization.

3 Research methods

This study aims to construct a user-centered evaluation system and evaluation methods for testing user satisfaction with car cockpit design experiences through analyzing domestic and international development trends of car cockpits, the semantics and perceptible features of intelligent car cockpit designs, and combining domestic and international user evaluation methods. Based on the constructed evaluation system and methods, we will conduct practical case tests to objectively explore user satisfaction with car cockpit design experiences. The specific objectives are as follows:

(1) Based on the current research status domestically and internationally, investigate the relationship between the perceptible features of intelligent car cockpit designs perceived by users and users' multidimensional perception, as well as the relationship between users' multidimensional perception and user experience satisfaction[17]. This will provide a theoretical foundation for testing and evaluation methods.

(2) Based on the multidimensional representation of users and satisfaction theory research, establish a test indicator system, testing methods, and testing procedures for user satisfaction with intelligent car cockpit design experiences.

(3) Based on the test indicator system and methods for user satisfaction with intelligent car cockpit design experiences, establish a fuzzy comprehensive evaluation model for user satisfaction.

(4) Conduct practical case tests on the established fuzzy comprehensive evaluation model to scientifically and objectively evaluate users' experiential perceptions and verify the feasibility of the evaluation model.

Through experiential calculations conducted within the same evaluation method, the experiential levels of different vehicle cockpits can be understood[18]. Unlike traditional statistical methods, the results of comprehensive evaluation methods can reveal problems and improvement directions in the cockpit's experiential aspects[14]. This provides scientific and objective theoretical support for cockpit design within enterprises, offers objective opinions for design decisions, reduces decision-making errors caused by subjective factors, and more accurately assesses user satisfaction with product experiences.

The fuzzy comprehensive evaluation model synergizes the Analytic Hierarchy Process (AHP), the Entropy Weight Method (EWM), and Fuzzy Comprehensive Evaluation (FCE). The steps for constructing this model are as follows:

Firstly, establish the factor set and evaluation set for comprehensive evaluation, utilizing the Analytic Hierarchy Process to filter evaluation indicators.

Secondly, construct fuzzy functions based on the principles of the fuzzy evaluation method.Next, standardize the evaluations of the indicators within the system.Subsequently, select the assignment method to establish fuzzy membership functions, aligning with the evaluation objectives and the characteristics of the indicators.Following this, construct the fuzzy judgment matrix and compute the weights.Finally, assemble the fuzzy comprehensive evaluation model.

When applied to assess user satisfaction with intelligent car cockpits, this fuzzy comprehensive evaluation model combines multiple evaluation methods, quantifying subjective evaluations and thereby reducing the error introduced by subjective factors. The resulting comprehensive evaluation value can be used for comparison with other evaluation objects. The results are clear, definitive, and easy to understand. The research process is shown in Figure 1.

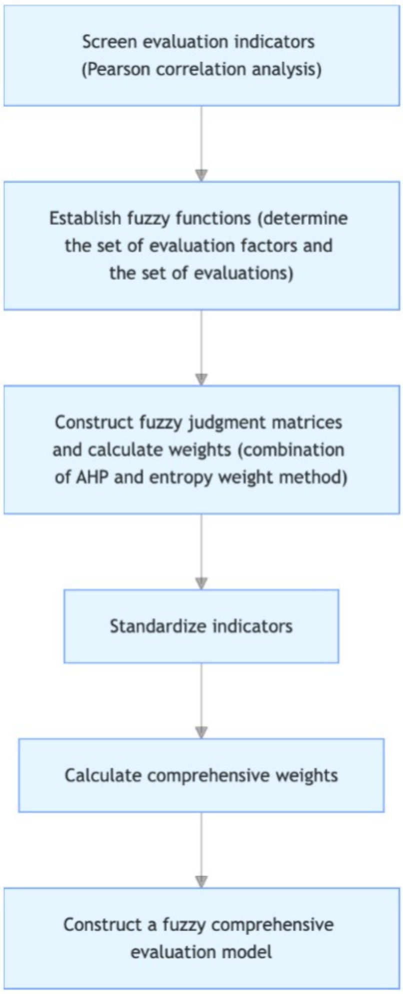

Figure 1: research process

3.1 Selection of Evaluation Indicators

In the evaluation of user experience in automotive cockpits, evaluation metrics are often correlated. An excessive number of metrics can lead to substantial computational demands during comprehensive evaluations. For example, when assessing the comfort of an automotive cockpit, metrics such as the softness of the seat, the adjustable angle of the backrest, and the size of the interior space may be interrelated. If all these highly correlated metrics are included in the evaluation system, it will not only increase the complexity of calculations but may also affect the accuracy of the evaluation results due to the repeated consideration of certain factors. To address this, the evaluation system needs to be simplified to maintain effectiveness while reducing unnecessary computational load.

This paper employs Pearson correlation analysis to filter evaluation metrics. The reason is that this method can precisely measure the linear correlation degree between variables. In the actual scenario of automotive cockpit evaluation, we hope that the retained metrics can reflect different aspects of the cockpit's characteristics and contain no redundant information. For instance, when evaluating the interaction design of the cockpit, the response speed of the touch screen and the convenience of operation are two important aspects. If these two metrics are highly correlated, retaining one of them can represent the information of these two aspects to a certain extent, thus simplifying the evaluation system. Through Pearson correlation analysis, we can identify which metrics are independent of each other within the same dimension. Then, we only retain these non - correlated metrics to represent different aspects of that dimension, effectively reducing the computational burden and improving the evaluation efficiency.

This approach also mitigates the limitations of the Analytic Hierarchy Process in systems with numerous evaluation metrics. When the number of evaluation metrics is large, the process of determining weights in the Analytic Hierarchy Process becomes complex, and the results of consistency tests vary greatly, making evaluation calculations difficult. Pearson correlation analysis can optimize the metrics at the screening stage, making the metrics entering the subsequent evaluation model more concise and reasonable, and enhancing the effectiveness of the entire evaluation model. For example, for an index system screened by Pearson correlation analysis, when using the Analytic Hierarchy Process to determine weights, the calculation process will be more straightforward, and the consistency test will be easier to pass. The final evaluation results can more accurately reflect users' experience satisfaction with the automotive cockpit.Pearson correlation coefficient analysis can describe the relationship between two continuous variables and perform point - biserial correlation analysis to describe the relationship between a continuous variable and a dichotomous variable. In this study, Pearson correlation coefficient analysis is used to calculate the relationship between two variables[7]. The Pearson correlation coefficient between the variables is defined as the ratio of their covariance to the product of their standard deviations, as shown in formula 1.

$$\sigma_{x,y} = \frac{cov(X,Y)}{\sigma_x \sigma_y} = \frac{E[(X-\mu X)(Y-\mu Y)]}{\sigma_x \sigma_y} \tag{1}$$

The population correlation coefficient is denoted by σ. The sample covariance and standard deviations are used to obtain the Pearson correlation coefficient, commonly denoted by r as shown in formula 2.

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{Y})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \tag{2}$$

The Pearson correlation coefficient ranges from -1 to 1. A coefficient between 0 and 1 indicates a positive correlation, with higher values signifying stronger correlation. Conversely, a coefficient between -1 and 0 indicates a negative correlation, with values closer to -1 signifying a stronger negative correlation. A correlation coefficient near 0 implies a weak correlation.The user experience evaluation index system for automotive cockpit design is classified into the target layer, criterion layer, sub - criterion layer, and indicator layer[5]. Based on their relationships, the overall goal, considered factors, and influencing factors are categorized into the target layer, criterion layer, and indicator layer, respectively. These layers are then graphically represented[4].

The target layer refers to the ultimate evaluation objective. The criterion layer consists of elements that make up the evaluation objective. The sub-criterion layer includes factors that constitute the criterion layer, while the indicator layer comprises specific metrics that reflect the factors in the sub-criterion layer. These include satisfaction with the automotive cockpit layout, vehicle interior design satisfaction, and satisfaction with the layout and perceptual shape of automotive information. The criterion layer is divided based on different evaluation targets and directions, with the sub-criterion layer representing different categories within these directions. The detailed hierarchy is illustrated in Figure 2.

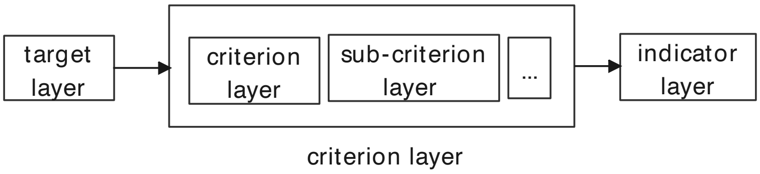

Figure 2: Evaluation hierarchy

3.2 Construction of Fuzzy Functions

The purpose of the user satisfaction test evaluation for automotive cockpit design experience is to understand the specific feelings of users during their experience in the cockpit[6]. Therefore, the fuzzy comprehensive evaluation method is chosen. Fuzzy comprehensive evaluation involves the fuzzy calculation of both subjective and objective data from users' cockpit experiences to derive their overall feelings, transforming subjective data into objective results. According to the fuzzy comprehensive evaluation theory, the user satisfaction test evaluation index system for automotive cockpit design experience is a multi-level fuzzy comprehensive evaluation.

The evaluation factor set is a collection of elements that influence the evaluation object, which can be understood as the indicators at each level in this context. The set is typically denoted by U. In this study, due to the complexity of the three-level, four-tier evaluation system, there are numerous evaluation factor sets.

To evaluate user satisfaction with automotive cockpit design experience, the evaluation factor set for the subjects is defined as A = Layout B1, Design B2, Information Layout and Perceptual Shape B3. These three evaluation factors, used as the target layer, assess user satisfaction with the automotive cockpit experience. Here, $A = B1 \cup B2 \cup B3$, and $B1 \cap B2 = \emptyset$,$B2 \cap B3 = \emptyset$, $B1 \cap B3 = \emptyset$.

For example, the criterion layer 1 evaluation factor set is defined as: B1 = {Steering Wheel U_{11}, Central Control Area U_{12}, Auxiliary Instrument Area U_{13}, Seat Area U_{14}, Physical Button Area U_{15}}, B2 = {Steering Wheel U_{21}, Instrument Area U_{22}, Seat Area U_{23}, Auxiliary Instrument Area U_{24}, Central Control Area U_{25}}, B3 = {Central Control Area U_{31}, Instrument Area U_{32}}.These factor sets represent the various components that collectively determine user satisfaction in the automotive cockpit design experience.

Based on specific evaluation levels, an evaluation factor set is established. The comment set mainly consists of various possible evaluation results for the subjects being evaluated, typically expressed as:

$$V = \{V_1, V_2, V_3, V_4, ..., V_{n-1}, Vn\} \tag{3}$$

Among them, V_n (n=1, 2, 3, ..., n-1, n) represents various possible evaluation outcomes, with n being the total number of evaluation results. Generally, the evaluation results are divided into 3 to 5 levels based on the evaluation purpose, with each evaluation level corresponding to a fuzzy subset in the comment set. The comment set can be established as 3-level, 5-level, or 7-level based on the evaluation requirements.

3.3 Establishing Fuzzy Membership Functions

Based on the user satisfaction evaluation set for automotive cockpit design experience V={very dissatisfied, dissatisfied, neutral, satisfied, very satisfied}, and considering the evaluation objectives and indicator characteristics, the assignment method is chosen to establish the fuzzy membership functions[22].

In the context of automotive cockpit evaluation, the relationships between user satisfaction ratings and evaluation indicator values are complex and do not exhibit simple monotonicity. To accurately model these relationships, specific types of fuzzy membership functions are selected based on the characteristics of different satisfaction levels and the nature of the automotive cockpit evaluation data.

For the "very dissatisfied" category, a left - shoulder membership function is assigned. In the automotive cockpit design, when an indicator value (such as the response time of in - car infotainment systems) is extremely poor, users are very likely to be very dissatisfied. For example, if the touch screen of the infotainment system has a response time longer than 0.3 seconds, users will be extremely unhappy. The left - shoulder function can well represent this situation where dissatisfaction reaches a maximum at very low indicator values and gradually decreases as the value improves.

The "dissatisfied", "neutral", and "satisfied" levels are assigned trapezoidal membership functions. Take the user - interaction - related indicators in the automotive cockpit as an example. When evaluating the ease of use of the steering wheel controls, there is a transition area between different satisfaction levels. A trapezoidal function can accurately and clearly reflect the differences in membership between adjacent numerical values in this transition area. For instance, when the number of steps required to perform a common operation on the steering wheel is between 2 and 4, users may have a "neutral" attitude. As the number of steps decreases to 1 or increases to 5, the membership degree of the "neutral" level gradually decreases, while the membership degree of the "satisfied" or "dissatisfied" level increases. The trapezoidal function can smoothly represent these gradual changes in user satisfaction.

The "very satisfied" category is assigned a right - shoulder membership function. In automotive cockpit design, when an indicator value (such as the clarity of the head - up display) is extremely good, users are very likely to be very satisfied. For example, if the contrast ratio of the head - up display is above 0.9, users will be extremely satisfied. The right - shoulder function can well represent this situation where satisfaction reaches a maximum at very high indicator values and gradually decreases as the value deteriorates.

The expressions for the fuzzy membership functions are shown in formula 4 to 8.

$$r_1(\mu_1) = \begin{cases} 1 & 0 \leq \mu < 0.1 \\ \frac{0.3-\mu}{0.2} & 0.1 \leq \mu < 0.3 \\ 0 & \mu \geq 0.3 \end{cases} \tag{4}$$

$$r_2(\mu_2) = \begin{cases} 0 & 0 \leq \mu < 0.1 \\ \frac{\mu-0.1}{0.2} & 0.1 \leq \mu < 0.3 \\ 1 & 0.3 \leq \mu < 0.4 \\ \frac{0.5-\mu}{0.1} & 0.4 \leq \mu < 0.5 \\ 0 & \mu \geq 0.5 \end{cases} \tag{5}$$

$$r_3(\mu_3) = \begin{cases} 0 & 0 \leq \mu < 0.4 \\ \frac{\mu-0.4}{0.1} & 0.4 \leq \mu < 0.5 \\ 1 & 0.5 \leq \mu < 0.6 \\ \frac{0.7-\mu}{0.1} & 0.6 \leq \mu < 0.7 \\ 0 & \mu \geq 0.7 \end{cases} \tag{6}$$

$$r_4(\mu_4) = \begin{cases} 0 & 0 \leq \mu < 0.6 \\ \frac{\mu-0.6}{0.1} & 0.6 \leq \mu < 0.7 \\ 1 & 0.7 \leq \mu < 0.8 \\ \frac{0.8-\mu}{0.1} & 0.8 \leq \mu < 0.9 \\ 0 & \geq 0.9 \end{cases} \tag{7}$$

$$r_5(\mu_5) = \begin{cases} 0 & 0 \leq \mu < 0.8 \\ \frac{\mu-0.8}{0.1} & 0.8 \leq \mu \leq 0.9 \\ 1 & 0.9 < \mu \leq 1 \end{cases} \tag{8}$$

Table 2: Judgement Matrix "1-9" scale

Factor i in relation to Factor j	Quantitative value
Equally important	1
Slightly important	3
Moderately important	5
Strongly important	7
Extremely important	9
Midpoint between two adjacent judgments	2, 4, 6, 8

Where r_1, r_2, r_3, r_4, r_5 represent the membership degrees corresponding to the ratings of very dissatisfied, dissatisfied, neutral, satisfied, and very satisfied, respectively, and μ represents the indicator value.

3.4 Establishing the Fuzzy Judgment Matrix

Firstly, starting from the second layer of the hierarchical structure model, it is necessary to construct a judgment matrix for each layer until the lowest level is reached. Given that qualitative index weights can be overly subjective, Saaty proposed the Consistency Matrix Method, which employs a "1-9" relative scale to reduce the difficulty of comparing indices of different natures and enhance objectivity. By comparing all indices pairwise and evaluating their importance, a matrix composed of these pairwise comparison results is called a judgment matrix[23].

In the evaluation structure, constructing a judgment matrix at each layer is necessary to determine the weight of each factor. By performing pairwise comparisons of the n evaluation indices for a single evaluation object at the sub-criteria level, the comparison judgment matrix $A_k = (a_{ij}^{(k)})_{n\times n}$ can be obtained as illustrated in formula 9.

$$A_k = (a_{ij}^{(k)})_{n\times n} = \begin{pmatrix} a_{11}^{(k)} & a_{12}^{(k)} & \cdots & a_{1n}^{(k)} \\ a_{21}^{(k)} & a_{22}^{(k)} & \cdots & a_{2n}^{(k)} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1}^{(k)} & a_{n2}^{(k)} & \cdots & a_{nn}^{(k)} \end{pmatrix} \tag{9}$$

and the following conditions must hold:

- Positivity: $a_{ij}^{(k)} > 0$
- Reciprocity: $a_{ij}^{(k)} = \dfrac{1}{a_{ji}^{(k)}} \quad (i \neq j)$
- Unit Diagonal: $a_{ii}^{(k)} = 1 \quad (i = 1, 2, \ldots, n)$

Where, $a_{ij}^{(k)}$ represents the judgment matrix at the k-th level , that is, the index group number. i and j respectively represent the row index and the column index in the comparison judgment matrix,and the "1-9" scale shown in table 2.

The constructed judgement matrix is a consistent one, necessitating a consistency check to ensure that the scores assigned by experts do not exhibit logical contradictions.

The judgement matrix A has a maximum eigenvalue λ=n, with the remaining n-1 eigenvalues being zero. Any row or column of A is an eigenvector corresponding to the eigenvalue n, satisfying AW = nW. A matrix that meets these conditions is referred to as a consistent matrix.

If the pairwise comparison matrix is a consistent matrix, the normalized eigenvector corresponding to the largest eigenvalue n will be taken. However, in practice, it is difficult for the constructed pairwise comparison matrix to fully meet this requirement[15]. Therefore, if the pairwise comparison matrix is not a consistent matrix, the normalized eigenvector corresponding to its largest eigenvalue will be

Table 3: Random consistency index RI data

n	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51

used as the weight vector W. The formula for calculating the weight vector is shown in formula 10. This method of calculating the weight vector is called the eigenvalue method, which also allows the calculation of the numerical value of the largest eigenvalue using the formula.

$$AW = \lambda_{max} W \tag{10}$$

The consistency test index is shown in formula 11.

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} \tag{11}$$

where λ_{max} is the maximum eigenvalue, and n is the unique non - zero eigenvalue. If $CI = 0$, it indicates that the judgment matrix meets the consistency, if CI is close to 0, it indicates that the judgment matrix has a satisfactory consistency; the larger the CI, the worse the consistency. In order to balance the size of CI, the random consistency index RI is introduced, and the values of RI are shown in table 3.

Verify the consistency of the judgment matrix according to Formula 12.

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{12}$$

When $n < 3$, the judgment matrix is certain to be consistent, and there is no need to carry out a consistency test on it. When $n \geq 3$, if $CR < 0.1$, it indicates that the judgment matrix is consistent. if $CR \geq 0.1$, it indicates that the judgment matrix fails the consistency test, and the judgment matrix needs to be revised.

3.5 Standardization of Indicators

Before calculating the information entropy of the indicators, the data must be normalized. The purpose of data normalization is to remove the dimensions of the indicators and convert the indicator values to the range [0,1]. During the data normalization process, if the indicator is a positive indicator, it is calculated according to formula 13.

$$Y_{ijl} = \frac{u_{ijl} - min(\ u_{ijl})}{\max(\ u_{ijl}) - min(\ u_{ijl})} \tag{13}$$

If the indicator is a negative indicator, it is calculated according to formula 14.

$$Y_{ijl} = \frac{\max(\ u_{ijl}) - u_{ijl}}{\max(\ u_{ijl}) - min(\ u_{ijl})} \tag{14}$$

Where u_{ijl} represents the indicators under different evaluation directions;max(u_{ijl}) represents the maximum value in the indicator sample data; min(u_{ijl}) represents the minimum value in the indicator sample data;$ijl(i,\ l\ = 1, 2, ..., n; j = 1, 2, ..., m)$ represents the indicator number, where i represents the serial number of the evaluation direction, j represents the serial number of the evaluation object under the evaluation direction, and l represents the serial number of the evaluation indicator under the evaluation object, Y_{ijl} represents the normalized value.

3.6 Calculation of Comprehensive Weights

First, compute the proportion of the ijl-th indicator in the l-th sample relative to the total indicator value[16], as shown in formula 15.

$$p_{ijl} = \frac{Y_{ijl}}{\sum_{111}^{ijl} Y_{ijl}} \tag{15}$$

Subsequently, calculate the entropy value for the l-th indicator based on p_{ijl}, using formula 16.

$$E_{ijl} = -ln(n)^{-1} \sum_{111}^{ijl} p_{ijl} ln p_{ijl} \tag{16}$$

Here, $E_{ijl} \geq 0$ and if $p_{ijl} = 0$, then $E_{ijl} = 0$, E_{ijl} represents the entropy value of the ijl-th indicator, and n denotes the number of samples considered.

Then, compute the coefficient of variation for each indicator as shown in formula 17.

$$D_{ijl} = 1 - E_{ijl} \tag{17}$$

The formula for calculating indicator weights is presented as formula 18.

$$w''_{ijl} = \frac{D_{ijl}}{\sum_{111}^{ijl} D_{ijl}} \tag{18}$$

Initially, employ the AHP to determine the weights of the indicators[2]. Subsequently, utilize the Entropy Weight Method to calculate the weights of the indicators. Finally, compute the comprehensive weights using formula 19.

$$w_i = \frac{w'_i \cdot w''_i}{\sum_1^n w'_i \cdot w''_i} \tag{19}$$

Where w_i represents the comprehensive weight, w'_i denotes the weight calculated using the AHP, and w''_i indicates the weight derived from the Entropy Weight Method.

3.7 Construction of the Fuzzy Comprehensive Evaluation Model

Following the principles of fuzzy comprehensive evaluation, the synthesis of the fuzzy matrix yields the comprehensive evaluation result vector S [11]. The final comprehensive evaluation is determined by applying the maximum membership principle, as depicted in formula 20

$$S = W \circ R = (w_1, w_2, \cdots, w_n) \circ \begin{pmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \dots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{pmatrix} = (S_1, S_{2,} \cdots, S_n) \tag{20}$$

Where S represents the fuzzy comprehensive evaluation result vector, and $\circ$ denotes the fuzzy operation synthesis operator.

In this study chooses to use the weighted average method for calculations, where the value of S_n is determined by each r_{nn} in the R matrix and w_i. Each factor contributes to the comprehensive evaluation result, with varying degrees of contribution based on their weights. The operation rules of this operator are outlined in formula 21.

$$S_n = \sum_{i=1}^{n} w_i \cdot r_{nn} (n = 1, 2, \cdots, n) \tag{21}$$

According to the maximum membership principle, the final calculation results can be used to determine the evaluation grade.

4 Experiment and analysis

4.1 Experimental Context

The target vehicle for this test is a specific brand of sedan, with a testing duration of four working days. This test is a static real-vehicle test involving 20 participants who evaluate the experience of the sedan's cabin design. The test content primarily includes cabin layout, styling, and information perception on the in-vehicle display screen.

Participants were selected based on different test objectives and requirements. To enhance the accuracy and scientific validity of the test results, strict criteria were applied to the participants, including driving experience, potential user status of the product, and intentions to purchase a vehicle.

For the user satisfaction evaluation test of automotive cabin design experience, participants needed a certain level of familiarity with vehicle operations to understand the cabin layout sufficiently and prevent task misinterpretation and operational errors. Therefore, participants were required to have a driving license with a minimum of one year of driving experience and be potential users of the test vehicle. They also needed to clearly and explicitly express their feelings and thoughts. Based on these criteria, we selected 20 participants for each type, with a gender ratio of 2:1.

4.2 Test Scenario Setup

The test scenario was designed considering the lighting requirements for the eye tracker, with overcast conditions chosen as the testing environment. The test site was an open parking lot with sufficient lighting and no disturbances, as shown in Figure 3.

Figure 3: The experiment site

During the test, different participants were required to complete various tasks from different positions. For example, in the driver's task, the participant needed to perform the driver's cabin layout and design task from the driver's seat, while the primary investigator collected physiological data from the rear. Participants were equipped with an eye tracker, physiological sensors, and an EEG cap to execute the tasks.

Each participant completed the tasks in a specific order. During the test, the primary investigator provided no operational hints to the participants to ensure the standardization of the test.

4.3 Data Collection in Testing

During this test, both subjective and objective data were collected. The objective data included eye movement data, electromyography data, and electroencephalogram data. The subjective data consisted of subjective satisfaction ratings using a Likert scale, which participants filled out via a questionnaire on Wenjuanxing after completing their tasks.

The Datastream data acquisition system within the D-lab software was used for the synchronized collection and display of objective data. D-lab integrates several modules, including eye tracking with the Dakalis module, video behavior recording and analysis system, physiological indicator detection system, and the data acquisition system.

D-Lab allows for the simultaneous display of various objective data on a single timeline, enabling observation and analysis of different objective data points at the same time. During the test, subjective data were collected by asking participants to provide subjective ratings on their experience with the vehicle's cabin layout, design, information layout, and form perception.

In the test, participants needed to complete the cabin layout and design tasks from the driver's seat. The primary tester collected physiological data from the rear, while participants wore an eye tracker, physiological sensors, and an EEG cap to perform the tasks, as illustrated in Figure 4.

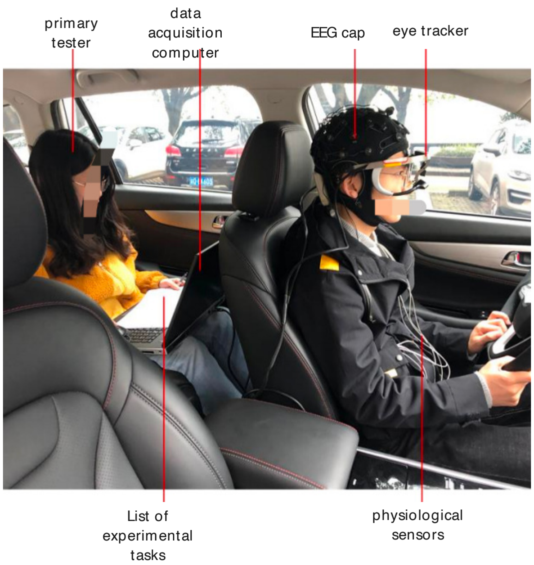

Figure 4: The experimental scene

Each participant completed tasks in a specific sequence, with no operational hints provided by the primary investigator during the test to ensure standardization. A total of 20 participants were involved in the formal test, based on the evaluation index system established in this study.

A total of 520 objective data points and 20 subjective data points were collected from the participants. Each participant contributed 49 valid data points, including 24 EEG data points, 10 eye movement data points, 5 EMG data points, and 10 operation data points. With 20 participants and 21 data sets per participant, the data to be analyzed were filtered accordingly.

4.4 Evaluation Result Analysis

The evaluation result analysis is divided into two parts. The first part focuses on individual user test data analysis, aiming to verify the feasibility of the testing method and evaluation model. The second part involves the analysis of overall user test data, with the primary goal of validating the effectiveness of the testing method and evaluation model, and summarizing the issues in the vehicle cabin design.

By analyzing the cabin experience data of a single participant, and evaluating the cabin from his perspective based on his subjective and objective data, the feasibility of the proposed method in this study is verified, and unique experience information for each participant can be obtained. This analysis is exemplified using Participant 1. Other participants can be analyzed following the same method.

Participant 1's objective experience levels are shown in table 4. The subjective scores range from 1 to 7, where 1 indicates very dissatisfied, 2 indicates dissatisfied, 3 indicates somewhat dissatisfied, 4 indicates neutral, 5 indicates satisfied, 6 indicates somewhat satisfied, and 7 indicates very satisfied. In the layout experience, tasks include the steering wheel area, center console area, co-pilot dashboard area, seat area, and physical button area. The objective experience levels calculated by the evaluation model and the participant's subjective evaluation levels are shown in table 4. The objective experience levels are categorized into five grades (very dissatisfied, dissatisfied, neutral, satisfied, very satisfied). From table 4 , we can discern Participant 1's satisfaction with the test vehicle's cabin. The

Table 4: No. 1 subject's objective experience level and subjective scores range

Area	objective experience level	subjective scores range
Layout	(0.284, 0.122, 0.355, 0.135, 0.103)General	6
steering wheel area	(0, 0.190, 0.379, 0, 0.431)Excellent	6
center console area	(0, 0.073, 0, 0.622, 0)good	5.5
co-pilot dashboard area	(0, 0.071, 0.929, 0, 0)General	5.5
seat area	(0, 0, 0.536, 0.464, 0)General	4.5
physical button area	(0.686, 0, 0, 0, 0.314)Extremely Unsatisfactory	6
Layout	(0.350, 0.246, 0.077, 0171, 0.155)Extremely Unsatisfactory	5
steering wheel area	(0.36, 0.64, 0, 0, 0)Unsatisfactory	5
Dashboard Area	(0.686, 0, 0, 0, 0.314)Extremely Unsatisfactory	5
seat area	(0.384, 0.302, 0, 0.314,0)Extremely Unsatisfactory	5
co-pilot dashboard area	(0, 0.192, 0.119, 0.314,0.350)good	4
center console area	(0.687, 0.039, 0.169, 0.106,0)Extremely Unsatisfactory	4
IP area	(0, 0.304, 0.169, 0.256,0.271)Unsatisfactory	4
Information Layout and Form Perception	(0.294, 0.03, 0.676, 0,0)General	6
center console area	(0.670, 0.068, 0.262, 0,0)Extremely Unsatisfactory	5
co-pilot dashboard area	(0, 0, 1, 0,0)General	6
Overall Satisfaction	(0.745, 0.568, 0.174, 0.093,0.054)General	5.63

overall satisfaction is neutral, with subjective satisfaction data scoring moderately well. However, the subjective scores are very evenly distributed, making it difficult to discern any distinct feelings the participant had after experiencing the cabin.

In terms of layout, Participant 1's objective satisfaction data is ranked as follows: steering wheel area > center console area > co-pilot dashboard area > seat area > physical button area. The subjective satisfaction data is ranked as: steering wheel area, physical button area > center console area, co-pilot dashboard area > seat area. The most contradictory area is the satisfaction with the physical button area. During testing, it was found that some participants took a long time to complete simple tasks in the physical button area because they couldn't locate the function controls. However, once they found the controls, they realized that the issue was due to their own oversight. This problem is rarely reflected in subjective satisfaction since, after identifying the control locations, the tasks became simple, hence the participants did not perceive an issue with the layout of this function. Therefore, objective data can reveal issues that participants may not be aware of. For instance, the relatively low objective satisfaction level in the physical button area, as shown by the distribution (0.686, 0, 0, 0, 0.314) which is ranked as "Extremely Unsatisfactory", contrasts with the relatively high subjective score of 6. This discrepancy highlights the importance of objective data in uncovering potential design flaws that might be overlooked in subjective evaluations.

In terms of styling, Participant 1's objective satisfaction data is ranked as: co-pilot dashboard area > steering wheel area > seat area, instrument cluster area, center console area. The subjective satisfaction data is ranked as: steering wheel area, instrument cluster area, seat area > co-pilot dashboard area, center console area. Most participants cannot clearly articulate their opinions or feelings about aesthetics, and their subjective data on aesthetics tends to be moderate, resulting in limited information that can be extracted. It is necessary to conduct a consistency check between the subjective and objective data. When there is consistency between the subjective and objective data, the objective data can be used for analysis.The differences in the rankings of objective and subjective satisfaction in the styling aspect indicate that there might be a lack of clear understanding among participants regarding aesthetic design elements, or that the evaluation criteria for aesthetics are more subjective and vary from person to person.

In terms of information layout and form perception, participants had a poor experience with the center console and a moderate experience with the instrument cluster, which aligns with the trend in subjective data. Post-test discussions with participants confirmed that there were issues with the information layout and form perception of the center console. The objective data for the center console in this aspect, such as (0.670, 0.068, 0.262, 0,0) being ranked as "Extremely Unsatisfactory", and the corresponding subjective score of 5, suggest that although the participants' subjective ratings are not extremely low, the objective data still points to significant problems in the center console's information layout and form perception, which might need further investigation.

In summary, Participant 1 rated the overall satisfaction with the test vehicle as average. The layout, information layout, and information perception were also rated as average, while the cockpit styling was rated very poorly, particularly in the instrument cluster and seat areas. Therefore, it can be concluded that Participant 1 was most dissatisfied with the styling of the instrument cluster and seats. Similarly, this model can calculate individual satisfaction levels, allowing for the identification of issues in intelligent vehicle cockpit design through objective user satisfaction ratings.

Using the aforementioned methodology, the subjective and objective data from 20 participants were analyzed to validate the effectiveness of the testing method and evaluation model. The experience levels of the participants regarding the cockpit of a certain sedan were obtained, including satisfaction ratings for layout, styling, information layout, form perception, and multiple sub-areas within these categories. Initially, a consistency analysis of the subjective and objective data was conducted, followed by an analysis of the results based on these data. The consistency check between subjective and objective experience data employed linear fitting, as illustrated in Figure 5, which primarily showcases the trend of subjective and objective ratings of cockpit experience from 20 users. The subjective data was derived from satisfaction questionnaire calculations, while the objective data was computed using the processing method described above.

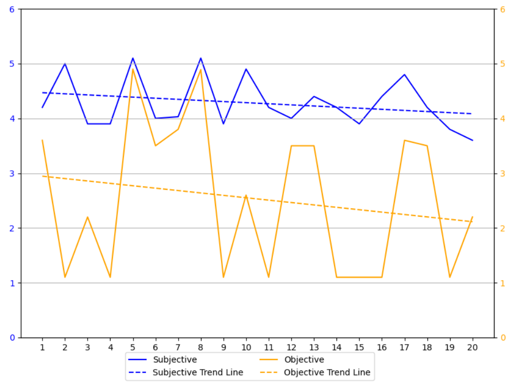

Figure 5: Distribution Diagram of Subjective and Objective Data on Overall Experience Satisfaction of Sedan Intelligent Cockpit

The consistency observed in the subjective and objective data from the 20 participants suggests that the testing method and evaluation model proposed in this study possess a certain level of validity. These findings can serve as a theoretical foundation for design and improvement in the field of intelligent vehicle cockpit design. As shown in Figure 6, the subjective and objective distribution of overall experience satisfaction levels for the cockpit of a certain sedan among 20 participants is presented. According to the data, the objective results indicate that 47% of users were dissatisfied with the sedan's cockpit experience, 35% found the experience average, and only 18% were satisfied with the design. Subjective data showed that 23% of users were dissatisfied, and only 18% were satisfied, aligning with the objective results. This indicates significant issues in the sedan's cockpit design, necessitating improvements based on user needs and experiences.

As illustrated in Figure 7 , the distribution of satisfaction levels for the three key elements in cockpit design is presented. It is evident from the figure that users were most dissatisfied with the layout design, with 59% expressing dissatisfaction, followed by 52% for styling design, and 35% for information layout and form perception design. This indicates that layout design is the area with the

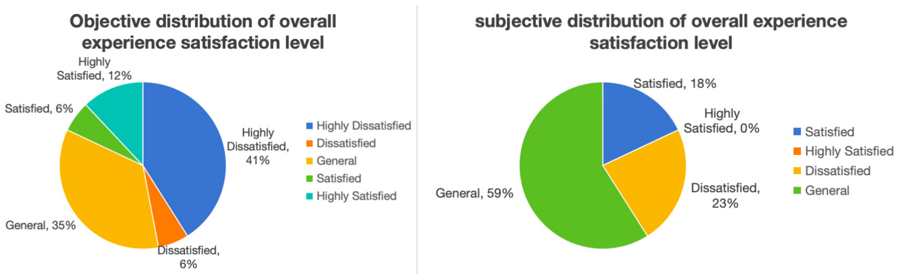

Figure 6: Subjective and objective distribution of overall experience satisfaction level

most significant issues requiring improvement. Subjective evaluations also showed 24% dissatisfaction and 23% satisfaction with layout design, consistent with the objective data. In styling design, 29% were dissatisfied and 24% satisfied, also aligning with the objective data. However, there was a discrepancy in the information layout and form perception design, where 41% of users were satisfied and 30% dissatisfied according to subjective data, contradicting the objective data. Therefore, the objective data for this element is deemed unreliable, and analysis should primarily rely on subjective data.

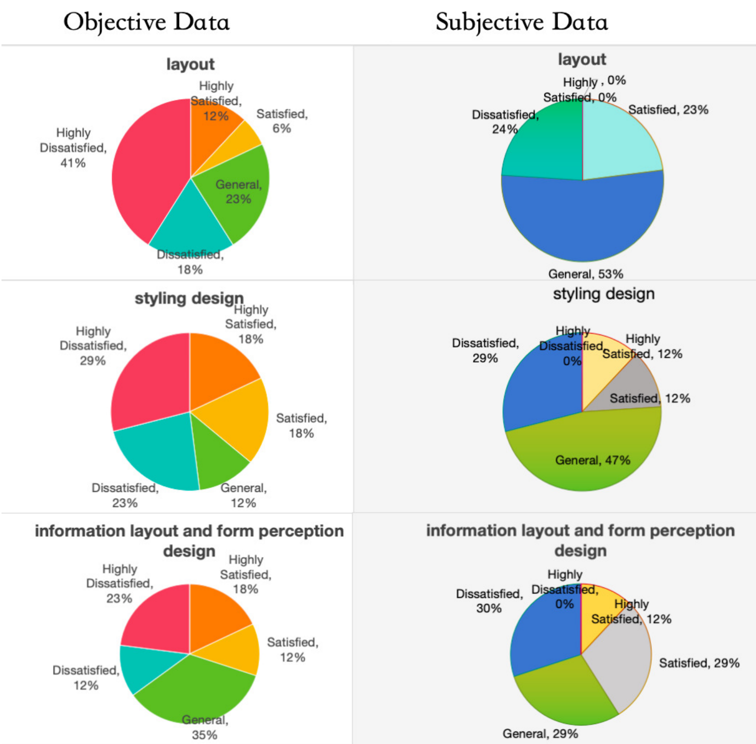

Figure 7: The distribution diagram of the satisfaction level for the three key elements in cockpit design

In the layout, the distribution of satisfaction levels for different layout areas is shown in Figure 8. Since there is consistency between subjective and objective data in both layout and styling design, objective data can be utilized for analyzing the layout design.

As indicated by the figure 8, 41% of users expressed dissatisfaction with the steering wheel area layout design, 69% with the central control area, 52% with the auxiliary instrument area, and 64% with the physical button area. The majority of users are dissatisfied with the central control area layout, and over half are dissatisfied with the auxiliary instrument and physical button layouts. Therefore, the central control area should be the first to undergo layout design adjustments in the sedan's design. The distribution of satisfaction levels for various styling areas is depicted in Figure 9.

According to Figure 9, 64% of users are dissatisfied with the steering wheel design, 29% with the instrument panel design, 64% with the seat design, 29% with the auxiliary instrument panel design, 53% with the central control design, and 53% with the IP area design. The majority of users are dissatisfied with the steering wheel and seat designs, while the auxiliary instrument panel design is

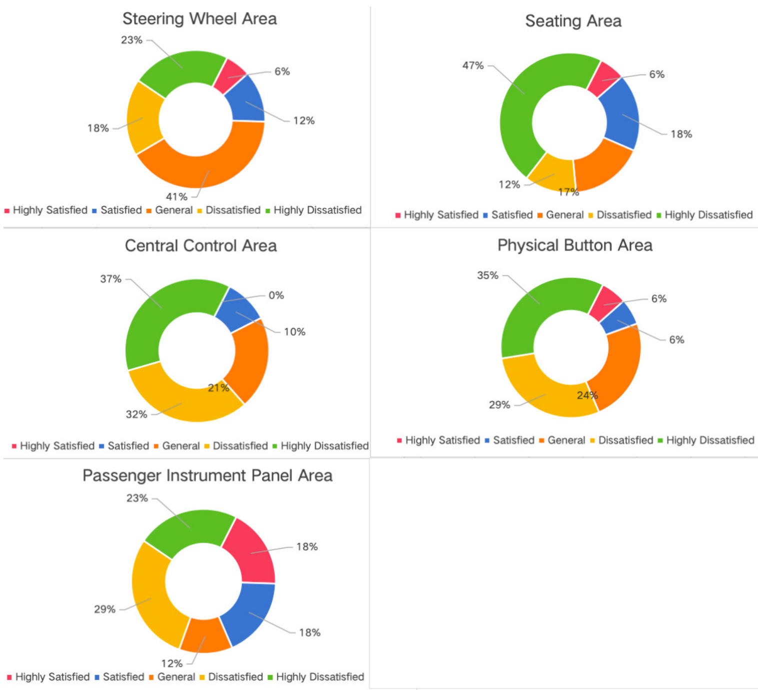

Figure 8: Distribution of satisfaction levels for different layout areas

the most satisfactory among all areas. Therefore, in the sedan's design, the steering wheel and seat areas should be prioritized for styling adjustments.

In the perception of information layout and form, subjective data evaluation is primarily used. The distribution of satisfaction levels for various areas is shown in Figure 10.

As shown in Figure 10, users have similar and satisfactory experiences with both the central control and the instrument panel.

5 Discussion

In recent years, the advancement of intelligent connected vehicles has led to a fundamental shift in in-car interaction behaviors and methods, from large screens to multiple screens, and from traditional dashboards and central consoles to virtual reality technologies. Traditional human-machine interfaces no longer meet industry needs. The development of autonomous vehicles will significantly increase drivers' HMI time and internet access, driving investment from the internet industry into the automotive sector. Therefore, the design of intelligent car cabins is crucial for user experience.

The fuzzy comprehensive evaluation model proposed in this paper for assessing user satisfaction in intelligent car cabins has three main characteristics. First, it is objective and authentic. Unlike traditional methods, the results of the new method are less influenced by participants' experience and expression abilities. Second, it provides quantitative data. Unlike interviews and questionnaires, which yield mostly descriptive text, this method produces quantitative data that can be generalized to the entire user population. Third, it captures rich dimensions, offering high-dimensional, quantifiable data that can reveal potential user insights.

This user satisfaction testing and evaluation method for intelligent car cabin design can be applied throughout the design process, such as in design method selection and improvement. Traditionally, design evaluations rely on expert reviews, but the target users are not necessarily experts. Experts represent only a subset of user opinions and their reviews remain subjective, potentially leading to choices that do not align with user preferences. User feedback during design improvements is usually gathered through questionnaires and interviews, which have limitations. Questionnaires often yield mediocre responses, and the effectiveness of interviews heavily depends on the moderator's experience.

Our method collects objective user data and employs scientific and objective data processing and analysis, resulting in more accurate outcomes. With a sufficient sample size, user profiles can be

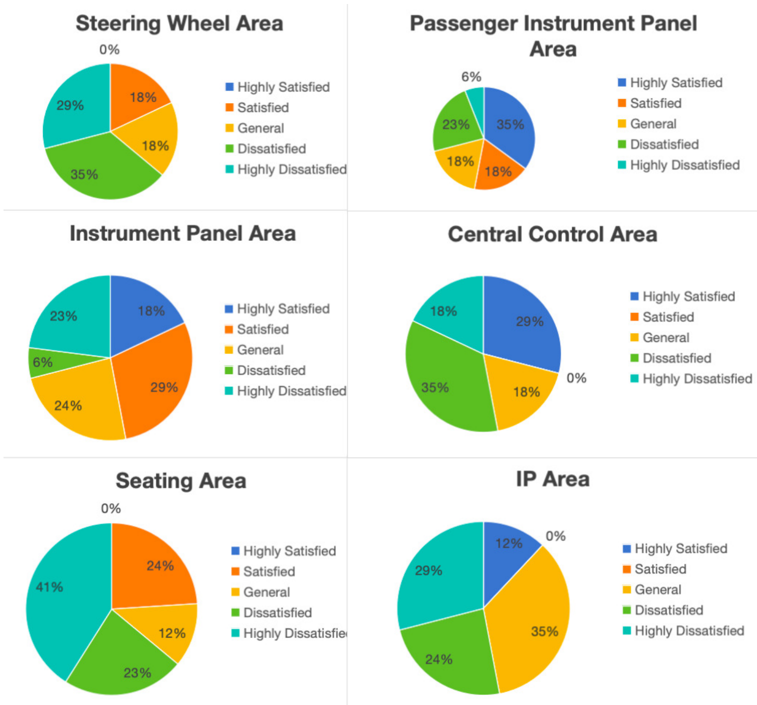

Figure 9: The distribution of satisfaction levels for various styling areas

created to gauge preferences and identify strengths and weaknesses of the car cabin design. This method can also compare different brands' intelligent car cabin designs using the same user group, providing comparative user experience ratings. This information can guide design improvements and offer purchasing insights based on user experience scores.

However, the study also reveals critical limitations requiring deeper reflection. A notable discrepancy emerged between subjective and objective evaluations in specific design areas. For instance, the physical button area received high subjective scores (average: 6/7) despite poor objective ratings (e.g., 68.6% 'extremely unsatisfactory' in Participant 1's case). This divergence suggests that users may overlook functional inefficiencies once tasks are completed, highlighting the need for real-time task difficulty metrics to complement post-task surveys. Similarly, styling evaluations showed inconsistencies: participants struggled to articulate aesthetic preferences, leading to moderate subjective scores that poorly correlated with objective data (e.g., seat design dissatisfaction in Figure 9). Such gaps underscore the challenge of aligning user self-reports with behavioral/physiological indicators, particularly for abstract or unfamiliar design elements.

Despite these limitations, the FCE model offers a scalable foundation for cockpit design optimization. Its hybrid weighting mechanism (AHP-entropy) balances expert knowledge with data-driven insights, mitigating biases inherent in standalone methods. For automotive manufacturers, adopting this framework could reduce design iteration costs by prioritizing high-impact areas while flagging latent issues (e.g., unintuitive button layouts). Future work should focus on real-world validation across diverse vehicle models and user groups to refine the model's robustness and address the identified limitations.

6 Limitations of the Study

Although this study has achieved certain results, there are still some limitations. this research still has several limitations. Such as follow ones:

The scope of participants and sample size are restricted. The satisfaction tests for intelligent car cockpit layout and design only involved drivers. However, the cockpit experience varies among different seating positions like the passenger seat and rear seats. With a sample size of merely 20 participants, it is relatively small. A larger and more diverse sample, including passengers and individuals with

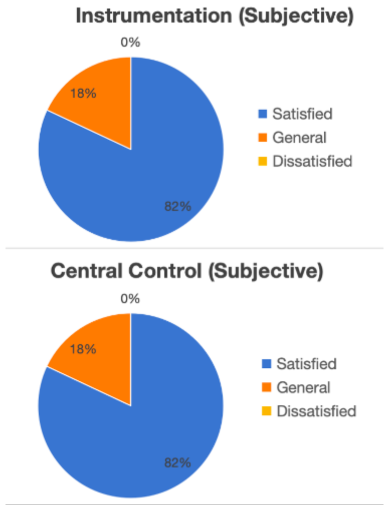

Figure 10: The Distribution Chart of Satisfaction Levels Among 20 Subjects Regarding the Cockpit User Interface Experience

different driving habits and vehicle usage patterns, is essential for drawing more generalizable conclusions. The limited scope and sample size may lead to an incomplete understanding of user satisfaction across the entire user group, potentially overlooking crucial aspects of the cockpit experience from non - driver perspectives.

Some cockpit elements were not included in the study. Elements such as lighting or ambient lighting, which significantly impact user experience in terms of comfort, mood, and even safety, were not considered. Future evaluations should incorporate assessments of these additional elements to comprehensively understand user satisfaction in intelligent car cockpits.

Expanding the evaluation scope is crucial. Future research directions identified in this study, such as evaluating different seating positions and more cockpit functions, can guide automotive manufacturers to conduct more comprehensive assessments. By considering factors like lighting and passenger experiences, manufacturers can create a more inclusive and comfortable cockpit environment. This not only enhances user satisfaction but also gives companies a competitive edge in the market. Addressing these limitations will contribute to more in - depth research and better - designed intelligent car cockpits.

7 Conclusion

This paper primarily investigates the testing and evaluation methods for user satisfaction in intelligent car cabins. Initially, it explores the theoretical framework for user satisfaction assessment, encompassing research classification and user experience channels. Based on relevant research indicators, a user satisfaction evaluation system for intelligent car cabin experiences is proposed, utilizing a fuzzy comprehensive evaluation model. This model integrates the Analytic Hierarchy Process (AHP), entropy weight method, and fuzzy comprehensive evaluation method, leveraging their strengths to provide a more accurate and objective assessment of user experience.

Ultimately, subjective data from participants and various objective behavioral indicators were collected through real vehicle testing to evaluate the intelligent car cabins. This validated the feasibility and effectiveness of the proposed fuzzy comprehensive evaluation model. The research provides robust data support for the design of intelligent car cabins by enterprises and offers an objective basis for improvements in intelligent car cabin design.

Although this study has achieved certain results, there are several aspects of the user satisfaction testing and evaluation methods for automotive cabin design that require further research:

(1) The satisfaction testing for the layout and design of intelligent car cabins has been conducted solely with drivers as participants. However, the cabin experience is not limited to drivers; it varies across different seating positions within the vehicle. Additionally, the sample size of this study is

relatively small. Future research should include evaluations from different seating positions within the cabin. The design of the cabin should also encompass elements such as lighting or ambient lighting, which were not included in this study. Future evaluations should incorporate assessments of these additional equipment experiences.

(2) This study explored the multidimensional standard parameters of user experience, with heart rate data providing supplementary information for a more comprehensive cognitive analysis. However, in the test design, external factors affecting tasks should be minimized. When collecting EEG data during observation and tactile activities, participants should be instructed to minimize other movements to ensure data accuracy.

(3) The fuzzy comprehensive evaluation model is established based on the Analytic Hierarchy Process (AHP), entropy weight method, and fuzzy comprehensive evaluation method. The indicator weights are determined by combining expert scoring with the entropy weight method, integrating both subjective and objective approaches. However, some indicators possess specific attributes that necessitate the inclusion of more effective measures to calculate and retain those that best represent the dimensional characteristics. In the comprehensive evaluation, discrepancies between subjective and objective data were observed. This phenomenon requires further investigation and analysis of data methodologies to address inconsistencies.

Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

References

[1] Ansari,S.; Naghdy,F.; Du,H. (2022). Human-machine shared driving: Challenges and future directions, *IEEE Transactions on Intelligent Vehicles*, DOI: http://doi.org/10.1109/TIV.2022.3154426,7(3), 499–519, 2022.

[2] Chen, L., Li, Z., Deng, X. (2020). Emergency alternative evaluation under group decision makers: a new method based on entropy weight and DEMATEL, In *International Journal of Computers Communications* & *Control*, DOI: https://doi.org/10.1080/00207721.2020.1723731,51(3), 570-583, 2020.

[3] Darko, A.; Chan, A. P. C.; Ameyaw, E.E.; Owusu, E.K.; Pärn, E.; Edwards, D. J. (2019). Review of application of analytic hierarchy process (AHP) in construction, *International journal of construction management*, DOI: https://doi.org/10.1080/15623599.2018.1452098,19(5), 436–452, 2019.

[4] Jolliffe, I.T.; Cadima, J. (2016). Principal component analysis: a review and recent developments, *Philosophical transactions of the royal society A: Mathematical, Physical and Engineering Sciences*, DOI: https://doi.org/10.1098/rsta.2015.0202,374(2065), 20150202, 2016

[5] Lee, J.; See, K.A. (2021). Trust in automation: designing for appropriate reliance, In *Human Factors*, DOI: https://doi.org/10.1518/hfes.46.1.50_30392,46(1), 50–80, 2021.

[6] Li, W.; Cao, D.; Tan, R.; Shi, T.; Gao, Z.; Ma, J.; Wang, L. (2023). Intelligent cockpit for intelligent connected vehicles: definition, *IEEE Transactions on Intelligent Vehicles*, DOI: http://doi.org/10.1109/TIV.2023.3339798,9(2), 2023.

[7] Li, Y.; Qian, Y.; Li, Q.; Li.L. (2023). Evaluation of Smart City Construction and Optimization of City Brand Model under Neural Networks, *Computer Science and Information Systems*, DOI: https://doi.org/10.2298/CSIS220715010L,20(2),573-593, 2023.

[8] Lin, C.; Jhang, J.; Chuang, C. (2024). Navigation Control of an Autonomous Ackerman Robot in Unknown Environments by Using a Lidar-Sensing-Based Fuzzy Controller, *Computer Science and Information Systems*, DOI: https://doi.org/10.2298/CSIS220826008L,21(2), 473–490, 2024.

[9] Liu, S.; Wei, G.; Wu, S.; Sun, Y. (2023). An Ensemble Learning Based Strategy for Customer subdivision and Credit Risk Characterization, *Tehnički vjesnik*, DOI: https://doi.org/10.17559/TV-20221220085239,30(2), 426-433, 2023.

[10] Meng, F.; Zhu, X. (2022). Application and development of AI technology in automobile intelligent cockpit, *In 2022 3rd International Conference on Electronic Communication and Artificial Intelligence (IWECAI)*, DOI: http://dx.doi.org/10.1109/IWECAI55315.2022.00059,2022.

[11] Meschtscherjakov, A.; Wilfinger, D.; Tscheligi, M. (2021). How human factors affect operators' task evolution in Logistics 4.0, *Human Factors and Ergonomics in Manufacturing & Service Industries*, DOI: http://dx.doi.org/10.1002/hfm.20872,29(4), 307-320, 2021.

[12] Osório, A.; Pinto, A. (2022). Information, uncertainty, and the manipulability of artificial intelligence autonomous vehicles systems, *International Journal of Human-Computer Studies*, DOI: https://doi.org/10.1016/j.ijhcs.2019.07.004,130,40–46, 2022.

[13] Ostrom, A.L.; Fotheringham, D.; Bitner, M.J. (2022). Customer acceptance of AI in service encounters: understanding antecedents and consequences, *Handbook of Service Science, II*, DOI: http://dx.doi.org/10.1007/978-3-030-42472-1-22, 2022.

[14] Pavlou, P.A. (2021). Consumer acceptance of electronic commerce: integrating trust and risk with the technology acceptance model, *International Journal of Electronic Commerce*, DOI: http://dx.doi.org/10.1080/10864415.2003.11044275,7(3), 101–134, 2021.

[15] Sáenz-Royo C.; Chiclana F.; Herrera-Viedma E. (2024). Ordering vs. AHP. Does the intensity used in the decision support techniques compensate?, *Expert Systems with Applications*, DOI:https://doi.org/10.1016/j.eswa.2023.121922, 238: 121922,2024.

[16] Shannon, C.E.(1948). A mathematical theory of communication, *The Bell system technical journal*, DOI: https://doi.org/10.1002/j.1538-7305.1948.tb01338.x, 27(3), 379-423, 1948.

[17] Shi, Y.; Ong, H.R.; Yang, S.; Fan, Y. (2024). Deep Multimodal Fusion of Visual and Auditory Features for Robust Material Recognition, *International Journal of Computers Communications & Control*, DOI: https://doi.org/10.15837/ijccc.2024.5.6457,19(5), 379-423, 2024.

[18] Wang, Y.; Hung, J. C.; Huan, C.; Hussain, S.; Yen, N.; Jin, Q. (2024). Design of TAM-based Framework for Credibility and Trend Analysis in Sharing Economy: Behavioral Intention and User Experience on Airbnb as an Instance, *Computer Science and Information Systems*, DOI: https://doi.org/10.2298/CSIS230323010W, 21(2), 547–568, 2024.

[19] Wu, L.; Xue, J.; Li, W.; Wang, K.; Zhang, X.; Guo, G. (2022). Toward decreasing the driving risk: speech-based driver's anger regulation in smart cockpit, *IEEE Journal of Radio Frequency Identification*, DOI: http://dx.doi.org/10.1109/JRFID.2022.3208199, 6, 764–768, 2022.

[20] Xia, B.; Qian, G.; Sun, Y.; Wu, X.; Lu, Z.; Hu, M. (2022). The implementation of automotive Ethernet-based general inter-process communication of smart cockpit, *SAE Technical Paper*, DOI: http://dx.doi.org/10.4271/2022-01-7067, 01–7067, 2022.

[21] Xuan, W.; Deng, M. (2023). Logistics Service Quality Sentiment Analysis with Deeper Attention LSTM Model with Aspect Embedding, *Tehnički vjesnik*, DOI: https://doi.org/10.17559/TV-20221018031450,30 (2), 634-641, 2023.

[22] Yang, J.; Xing, S.; Chen, Y.; Qiu, R.; Hua, C.; Dong, D. (2022). A comprehensive evaluation model for the intelligent automobile cockpit comfort, *Scientific Reports*, DOI: https://doi.org/10.1038/s41598-022-19261-x, 12(1), 15014, 2022.

[23] Yan, Z.; Hongle, D.; Lin, Z.; Jianhua, Z. (2023). Personalization Exercise Recommendation Framework based on Knowledge Concept Graph, *Computer Science and Information Systems*, DOI: https://doi.org/10.2298/CSIS220706024Y, 20(2), 857–878, 2023.

[24] Zadeh, L. A. (1978). Fuzzy sets as a basis for a theory of possibility, *Fuzzy sets and systems*, DOI: https://doi.org/10.1016/0165-0114(78)90029-5, 1(1), 3-28, 1978.

Cite this paper as:

Yao, M.; Li, Z. (2026). Evaluating User Satisfaction in Automotive Cockpits Using a Fuzzy Evaluation Model, *International Journal of Computers Communications & Control*, 21(1), 7067, 2026. https://doi.org/10.15837/ijccc.2026.1.7067