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Impact of Human-Computer Interaction Tasks in Smart Cockpit on User Experience Satisfaction

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ABSTRACT

In order to help automotive interior and exterior decoration and human-computer interaction interface designers effectively avoid the risk of poor interface usability and further enhance the user experience, we quantify the complexity of human-computer interaction behaviors in smart cars, and explore the specific task indicators and weight distributions affecting the complexity of human-computer interaction inside the smart cockpit, as well as propose a methodology for measuring the complexity of human-computer interaction tasks in smart cars. First, by using the questionnaire survey method, an index system composed of eight evaluation indicators: we established the complexity of the logical structure, the complexity of the interface design elements, the complexity of the information channel transmission method, the number of actions, the complexity of the management interface information, the complexity of human-computer interaction input,the level of knowledge and cognition required for human-computer interaction, and the complexity of the layout of the digital interface for human-computer interaction.Secondly, we use the weight calculation method that combines Fuzzy Analytic Hierarchy Process (FAHP) and Entropy Weight Method (EWM) to determine the factors that have the most influence on the complexity of human-computer interaction behaviors of the smart cockpit. Finally, the highly complex human-computer interaction behavior is calculated and suggestions for design optimization are given. The evaluation results show that the complexity of the human-machine interaction digital interface layout in the cockpit (X8), the complexity of the logical structure (X1), the level of knowledge and amount of cognition (X7) required for human-computer interaction have a greater impact on the complexity of human-computer interaction tasks in the car. Meanwhile, navigation operation, video and audio playback and music selection switching are human-computer interaction tasks with higher complexity and also need to be explored by designers focusing on them. The method can help designers avoid the risk of excessive design complexity and high user learning costs, and can assist designers to intervene in advance of design problems related to the above indicators.

Keywords: Complexity test, Human-computer interaction, Entropy weight method, Smart cockpit

INTRODUCTION

With the development of a new generation of information technology such as 5G and AI, the traditional automotive industry is developing in the direction of intelligence on the basis of the deep integration of informationization and industrialization, and the modern automobile has developed into a comprehensive mobile space covering the personal, public, and social spheres (Zhu et al., 2023). This trend is not only a natural product, but also an inevitable result of the rapid development of artificial intelligence, Internet technology, communication technology in the environment, and bringing unprecedented changes to the traditional automotive industry (Xu et al., 2023). With the help of the latest information technology, smart technology is developing rapidly, and simple, ordinary cars are being transformed into smart cars (Kim, 2014). Traditional mechanized construction is being replaced by smarter solutions, vehicles are becoming smarter, and Intelligent technologies are widely used in the design and manufacture of automobiles. This change is not just about revolutionizing the technology, but also disrupting the entire industry model and service experience. In this evolution, the car is no longer simply a means of transportation, but an integrated mobility space that incorporates advanced technologies to provide new experiences in the personal, public and social spheres.

In this context, the relationship between intelligent systems and people, and people and information in smart car cockpits has become increasingly complex, leading to a diversified trend in human-computer interaction behaviors in the car, which directly affects the user experience in the vehicle. As a result, in terms of improving driving safety, reasonable human-computer interaction technology can help drivers better communicate with the vehicle, provide important information and receive instructions from the driver, thus reducing the risk of accidents. At the same time, in terms of improving driving comfort, human-computer interaction tasks can enhance driver and passenger comfort and make driving more enjoyable. This includes more intuitive control interfaces, automated driving functions and personalized cockpit settings to meet the needs of different drivers. Therefore, in the process of intelligent cockpit research, the complexity of human-computer interaction tasks is an important indicator for evaluating the in-vehicle interaction experience and cockpit layout design, and this complexity directly affects the driver's cognitive load when accomplishing a specific task, which in turn has a direct impact on the safety and efficiency of the intelligent vehicle driving process. In view of this, in-depth research on the complexity of human-computer interaction tasks and its rational application are the key factors to improve the user experience of intelligent vehicle driving. In this study, we will investigate the users' real feelings about the indicators through scale assessment, obtain the subjective and objective weight values of the indicators, and calculate the integrated values of the two weights through the subjective and objective weight combination method. Meanwhile, on this basis, the complexity of the 7 human-computer interaction behaviors will be calculated and the human-computer interaction behavior with the highest complexity will be identified. Therefore, this study aims to provide a research basis for the design improvement and optimization of the HMI interface of the future smart cockpit, which can make the enterprises and designers more targeted in the development process of the smart cockpit.

REVIEW

The emergence of smart cockpit improves the level of automobile user experience, breakthrough interaction mode change makes the car become a key node of the Internet of everything, giving rise to a new concept of automobile service and the corresponding industry ecology, and it is an important carrier for the construction of the future smart city. The development history of intelligent cockpit can be divided into three stages: electronic cockpit, intelligent assistant and mobile space (Shreyas et al., 2020). The current intelligent cockpit is still only at the primary level of intelligent assistant, and the functions of the future intelligent cockpit will be more diversified, further replacing the traditional physical buttons through the use of large screens, multi-screen displays and voice recognition systems.

The core medium of human-computer interaction in automotive intelligent cockpit is the human-computer interface, which is usually divided into physical interface (i.e., buttons, knobs, paddles, etc.), touch screen interface (i.e., the user can issue commands to the vehicle through the action of pointing, pulling and dragging on the screen), voice interface (i.e., recognizing and responding to the human's voice commands), and action interface (i.e., recognizing and responding to the human's action commands), and so on. The interactive interfaces and cockpit arrangements of the center control and instrumentation of different smart cockpits are different, which leads to a large difference in the complexity of human-computer interaction between humans and different components of the vehicle in the smart cockpit, and therefore affects the safety and efficiency of the driving process of smart vehicles. In fact, multi-screen information displays increase the cognitive load of drivers. Grahn and Kujala (2020) pointed out that the user interface design has a relatively large impact on the visual demand and visual interference potential compared to the screen size. Different types of interaction modes can be used to reduce the impact of distracted driving in tasks of varying complexity and difficulty (Ma et al., 2022; Graichen et al., 2022).

Foreign scholars have studied the contextual cognition and attentional mechanism of in-vehicle driving through experiments, and categorized high-frequency in-vehicle scenarios such as navigation, communication, entertainment, in-vehicle APP, and temperature adjustment (Bach et al., 2009). Based on the previous research, this study selects 7 main human-computer interaction tasks in the cockpit (answering and calling cell phones, music selection and switching, in-vehicle APP interaction, navigation operation, video and audio playback, voice wake-up and center control screen interaction), and performs the complex quantification and analysis of 8 latitudes, and the indexes' contents and meanings are as follows:

Table 1. Complexity metric content and meaning.

No.	Serial number	Elements	Source
Complexity of the logical structure	X1	The complexity of the logical structure of the task will directly affect the driver's cognitive performance and the smoothness of cockpit user experience	(Jianan and Abas, 2020)
Complexity of interface design elements	X2	In the HMI interface design, various graphics, text and interactive elements used are intuitive and user-friendly in order to give the user a level of complexity conveyed during the interaction.	(Ebel et al., 2023)
Complexity of information channel delivery methods	X3	The ease of information exchange between the driver and the vehicle system.	(Detjen et al., 2020; Detjen et al., 2019)
Number of actions	X4	The number of actions required for a single human-computer interaction task in a smart cockpit.	(Spyridakos et al., 2020)
Complexity of management interface information	X5	Complexity of management interfaces information in smart cockpit HMI	(Zhao et al., 2023)
Complexity of human-computer interactio inputs	X6	Complexity of human-computer interaction inputs for smart cockpits	(Ma et al., 2023)
The level of knowledge required for human-computer interaction and cognitive capacity	X7	The level of knowledge and amount of cognition required for human-computer interaction in smart cockpits	(Faas et al., 2020; Rittger et al., 2022)
Complexity of human-computer interaction digital interface layout	X8	Complexity of digital interface layouts for human-computer interaction in smart cockpits	(Ma et al., 2023; Li et al., 2017)

METHOD

Using the Entropy Method to Recognize the Complexity of Human-Computer Interaction Tasks

In 1948, Shannon (Shi et al., 2020) first introduced the concept of entropy into information theory. The entropy method is a way for mainly measuring the degree of system disorder. The lower the entropy, the greater the amount of effective information, and the greater the entropy, the smaller the amount of effective information. The entropy method can visualize the degree of data disorder or uncertainty, so as to making the algorithm easy to understand and interpret.

As an objective empowerment method, the entropy method can determine the weight of the indicators according to the relative change degree of each complexity indicator on the impact of the system as a whole, and the indicators with a large degree of relative change have a larger weight, which can be determined according to the effective information of each indicator, and the larger the effective information is, the larger the weight will be. This study proposes an entropy-based method to quantify the complexity of human-computer interaction tasks in intelligent cockpits, and to introduce the entropy method into the analysis of human-computer interaction task complexity in intelligent cockpits, so as to obtain the result of the objective importance degree.

Using the FAHP to Analyze the Complexity of Human-Computer Interaction Tasks

The analytic hierarchy process (AHP) (Saaty, 1980) is a multi-criteria context-based decision-making methodology that is widely used as a decision-making tool in various fields. The AHP most notably provides an effective mechanism to check the consistency of the assessment measures and enables decision makers to incorporate subjectivity, experience, and knowledge into the decision-making process in an intuitive and natural way. The AHP could first identify the main factors that influence decision making and then arranges these factors into different levels to reduce the complexity of the decision-making problem (Saaty, 1977; Saaty, 1986).

In fact, the traditional AHP cannot accurately capture the fuzzy and uncertain perceptual demands of users, its assessment scale cannot fully cover the subjectivity of human cognition of things. For this reason, to combine fuzzy mathematics with AHP can effectively solve the problem of user cognitive complexity, so as to the fuzzy analytic hierarchy process (FAHP) (van and Pedrycz, 1983) was proposed to make the decision-making results will be more accurate (Kubler et al., 2016). Thus, the FAHP is very suitable for the user to express subjective preference related to affective responses (Shieh et al., 2017). In recent years, the FAHP has been widely used by scholars in product and decision making research (Batwara et al., 2022; Zhu et al., 2022; Chai and Wang, 2022), and its specific study process can be found in the literature (Wang and Zhou, 2020). This study focuses on calculating the subjective weight values of human-computer interaction complexity indicators based on the FAHP.

Combining Weights

In this study, the complexity weights are calculated based on the FAHP method and entropy method, where FAHP is the result of subjective weight calculation and entropy is the result of objective weight assignment, so as to arrive at the result of the objective importance degree, and the weight calculation formula for the combination of the two is shown below:

$$W_i = \frac{W_{\mathrm{AHP}}\, W_{\mathrm{Entropy}}}{\sum_{i=1}^{n} W_{\mathrm{AHP}}\, W_{\mathrm{Entropy}}} \tag{1}$$

Since the formula considers both subjective and objective weight combination algorithms, it is highly adaptable in the process of determining the weights, which can further lead to the value of the integrated weights of the factors in the target program layer.

Questionnaire Design

In this study, based on the specifics of the research problem, a panel of 30 experts (associate professors in automotive human-computer interaction and design and UX practitioners with more than 5 years of experience in the field) and 20 real users of smart cars were selected, and then 8 complexity metrics under the 7 main interaction tasks of the smart car cockpit were scored in the form of a Likert scale. Specifically, the 7 levels of the 8 complexity indicators corresponded to the complexity scales 1, 2, 3, 4, 5, 6, and 7, respectively, and 50 panelists scored the 8 complexity indicators under the 7 main interaction tasks, and the questionnaire survey was conducted through the Questionnaire Star online platform.

RESULTS

Reliability Analysis

Reliability validity is used to measure the accuracy and stability of the results of a questionnaire. Reliability is used to measure whether the results of a questionnaire are reliable or not, and is generally verified by Cronbach's α. When the value of Cronbach's α is greater than or equal to 0.7 it means that the data has high reliability (Wang et al., 2023; Wang et al., 2023). The questionnaire data were imported into the SPSS statistical software for the reliability test, and the results of the software showed that the value of Cronbach's α is 0.843, which was higher than 0.8, indicating that the data of the study has a high level of credibility.

Descriptive Statistics

We surveyed respondents about their commuting patterns based on their age and driving experience. In terms of commuting, the majority of participants (80%) reported driving more than 40 minutes per day in a single trip. Additionally, 71% of those who chose to travel by cab or online car reported commuting more than 40 minutes per day. Our research results show that those who primarily drive to and from work spend more time in the car each day.

The Entropy-FAHP Method Was Applied to Calculate the Weights

The basic idea of FAHP is to first establish a hierarchical describing system functions or characteristics according to the evaluation requirements, and then make a secondary comparison of the relative importance of the design elements and give the corresponding scale to form a judgment matrix between an upper-level factor and a lower-level related factor, in order to give a sequence of the relative importance of the related factors.

The entropy weighting method determines the weight of indicators based on the size of each indicator's information load. According to information theory, in order to examine the role of each factors in the indicator system, it is necessary to study the variability of the indicators. The greater the variability of the indicator, the higher the information content of the indicator and the greater the "differentiating power" of the indicator. This means that the weight of each indicator should be determined by the change in the values of the attributes of the options under that indicator; the greater the change, the greater the weight of the indicator; conversely, the smaller the weight.

Apply Entropy Weight Method to Determine Indicator Weights

The EWM is applied to determine the objective weight of indicators. First, the evaluation data of experts are collected, and then the initial weight matrix is obtained based on the EWM. Finally, the importance of the eight complexity indicators is obtained. The results are shown in Table 2.

Table 2. Weight scores of 8 complexity indicators based on EWM.

X1	X2	X3	X4	X5	X6	X7	X8
0.120	0.112	0.110	0.131	0.143	0.113	0.106	0.165

Determining the Weight of Indicators Through FAHP

The fuzzy analytic hierarchy process is used to determine the subjective weight of the indicator. By constructing a judgment matrix, and then using the 9-scale method to conduct pairwise comparisons, the calculation of the subjective weight is completed. On this basis, it is necessary to pass the consistency test. If the value of CI is less than 0.1, the judgment matrix passes the consistency test. Otherwise, the judgment matrix needs further adjustment. Finally, the results of this study are shown in Table 3.

Table 3. Weight calculation of 8 complexity indicators based on FAHP.

Project description	Item number	Weighting Values	CI value
The complexity of the logical structure	X1	0.1845	0.08
The complexity of interface design elements	X2	0.0749	0.07
The complexity of the information channel transmission method	X3	0.0612	0.01
Number of actions	X4	0.0931	0.06
The complexity of management interface information	X5	0.0771	0.06
The complexity of human-computer interaction input	X6	0.0621	0.04
The level of knowledge and amount of cognition required for human-computer interaction	X7	0.1247	0.03
The complexity of human-computer interaction digital interface layout	X8	0.1951	0.01

Subjective and Objective Methods Combined to Improve Weights

The weight is calculated through the EWM and the FAHP method. The result obtained by the entropy method is the objective weight, and the result obtained by the FAHP method is the subjective weight. The combined calculation of the weight is completed through formula (1), and the results are shown in Table 4. According to the calculation results, the weights and ranking results of the eight complexity indicators are shown in Table 5.

Table 4. Numerical calculation of weights combining subjective and objective methods.

Project description	Item number	Entropy Weights method	FAHP Weighting	Combined Weighting value
The complexity of the logical structure	X1	0.120	0.1845	0.196
The complexity of interface design elements	X2	0.112	0.0749	0.074
The complexity of the information channel transmission method	X3	0.110	0.0612	0.060
Number of actions	X4	0.131	0.0931	0.108
The complexity of management interface information	X5	0.143	0.0771	0.098
The complexity of human-computer interaction input	X6	0.113	0.0621	0.062
The level of knowledge and amount of cognition required for human-computer interaction	X7	0.106	0.1247	0.117
The complexity of human-computer interaction digital interface layout	X8	0.165	0.1951	0.285

Table 5. Indicator weight sorting.

Index	X1	X2	X3	X4	X5	X6	X7	X8
Weight	0.196	0.074	0.06	0.108	0.098	0.062	0.117	0.285
Rank	2	6	8	4	5	7	3	1

Interaction Complexity Analysis

Perform weighted calculations on the weight results and user evaluation results to explore the 7 main human-computer interaction tasks in the smart cockpit. For example, the complexity of making and receiving calls on a mobile phone S1, the complexity of music selection and switching S2, the complexity of vehicle APP interaction S3, the complexity of navigation operation S4, the complexity of video and audio playback S5, the complexity of voice wake-up S6 and the complexity of central control screen interaction S7, the comprehensive complexity values of different indicators of the seven human-computer interaction tasks were further calculated, and the results are shown in Table 6. It can be seen from Table 6 that the most complex human-computer interaction behaviors in the smart cockpit are further proposed to further improve strategies.

Table 6. Human-computer interaction behavior complexity entropy value.

Index	S1	S2	S3	S4	S5	S6	S7
X1	2.833	3.699	2.833	4.500	3.976	2.167	3.333
X2	3.167	3.887	3.500	3.667	3.500	1.833	3.500
X3	3.773	3.333	3.500	4.211	3.333	2.121	3.667
X4	3.167	3.121	3.167	4.598	3.500	2.167	3.833
X5	3.967	3.367	3.500	3.833	3.167	2.667	3.500
X6	3.532	3.667	3.862	3.431	3.333	2.477	3.833
X7	3.391	3.573	4.833	3.833	3.763	1.500	3.833
X8	3.667	3.882	3.540	4.970	3.775	1.833	3.333
Overall complexity	3.407	3.632	3.523	4.356	3.650	2.034	3.525

DISCUSSION

This study first discussed the importance of 8 complexity indicators, calculated them using a combination of subjective and objective methods, and obtained the complexity factors of human-computer interaction behavior in smart cockpits. Among them, the complexity of human-computer interaction digital interface layout (X8), the complexity of the logical structure (X1), the level of knowledge and the amount of cognition required for human-computer interaction (X7) rank in the top three in importance respectively. On this basis, with reference to the weight values of 8 indicators, calculate the complexity of 7 driving interaction behaviors and obtain the relative complexity of different human-computer interaction tasks.The results show that the most complex human-computer interaction behavior is navigation operation, with a score of 4.356, followed by video and audio playback, with a complexity of 3.650, and music selection and switching, with a complexity of 3.632.

The complexity of the human-computer interaction task of making and receiving calls on a mobile phone is moderate at 3.407, mainly because this interaction involves multiple aspects, including Bluetooth connection, incoming call management, call control, etc. Complexity may come from factors such as handling multiple phone models and Bluetooth protocols, as well as communication stability when the vehicle is in motion. At the same time, there are fewer misoperations, but during the process of making and receiving calls, the user still needs to look at the phone interface in the central control screen to complete the task of answering and making calls.

The human-computer interaction task complexity of music selection and switching is relatively high, at 3.632. The complexity of this behavior may be affected by factors such as the diversity of audio formats, the size of the song library, and the processing of users' personalized music preferences. At the same time, a good user experience also requires intelligent design of behavioral operations such as switching songs and adjusting volume. When users cannot effectively obtain their favorite music through multiple operations, the perceived human-computer interaction complexity value will be high. In addition, the interface design of the vehicle system is critical. The navigation, content layout and window switching of the music interface are all key factors in the human-computer interaction task of music selection and switching.

The complexity of the vehicle APP interaction task is relatively high, which is 3.523. The complexity of vehicle APP interaction may be due to the increase in application types, for example, navigation, entertainment and information tasks have high complexity, switching between different applications, data transmission, and user configuration may lead to increased system complexity. In addition, experts and users generally believe that the information provided by vehicle APPs needs to be different from the content presented on mobile phones, tablets, computers, etc., and the presentation methods should also be different.

The navigation operation interaction task has the highest complexity, which is 4.356. On the one hand, the navigation operation process requires the user to complete information input through multi-modal interaction and through the input field in the central control screen, and finally complete the navigation operation task. Sometimes during the interaction process, due to the uncertainty of the destination, the user needs to further confirm the information, which results in a higher number of required actions and makes the human-computer interaction task itself more complex. On the other hand, due to the update of real-time traffic information, path planning and other aspects, the highly intelligent navigation system also requires users to constantly adjust according to the actual situation, and inevitably produces a certain degree of behavioral complexity.

The complexity of the interactive task of video and audio playback is 3.650. This is mainly because the user requires a large number of actions during the selection and switching process, and constantly adjusts his or her choices during the execution process, resulting in a certain degree of behavioral complexity. Contemporary, due to users' personalized needs for subtitles, image quality, etc., this indirectly increases the complexity of the system.

The complexity of the interactive task of voice arousal is 2.034, which is a lower score compared to other interactive behaviors. The reason is that as the development of intelligent technology becomes increasingly mature, the design of the voice interaction system is relatively stable, and many instructions can be easily implemented through human-computer dialogue, thus improving the convenience of the user. However, in addition to the semantic logic of voice interaction, there are certain problems in the recognition of the environment inside and outside the car and the recognition of interactive objects, which can easily lead to misoperation problems in random voice interaction.

The complexity of the interactive task of central control screen is 3.525, which is more complex than other interactive behaviors. Since the user fully considers the operating logic factors of the central control screen and the usability factors of interactive behavior during the operation process, the behavior will inevitably have a certain complexity. To improve user experience, four strategies can be adopted: (1) Simplify the interface design, place the most commonly used functions and control options in places that are easy to access and understand, adopt a flat design, and avoid too many icons and buttons to reduce user learning costs. (2) Use contextual navigation to provide relevant options based on the user's current context to avoid frequent switching between different tasks. (3) Intelligent algorithms predict user operations, use intelligent algorithms to predict the user's possible next operations, and provide relevant shortcuts to improve operating efficiency. (4) Provide intuitive feedback, through visual feedback methods such as animation, lighting and color changes, to enhance the user's perception of interaction and let the user clearly know the effect of their operation. By comprehensively applying these strategies, the complexity of interactive tasks on the smart cockpit central control screen can be effectively reduced and the user experience improved.

CONCLUSION

This paper conducts research on the user experience complexity of human-computer interaction tasks in smart cockpits, and evaluates the main human-computer interaction behaviors. The purpose of this study is to use the analytic hierarchy process and the entropy value method to comprehensively evaluate the influencing factors of user experience complexity.The results show that: (1) The complexity of the human-computer interaction digital interface layout (X8), the complexity of the logical structure (X1), and the knowledge level and cognitive amount required for human-computer interaction (X7) are important evaluation indicators that significantly affect the complexity of operating behaviors. (2) From the perspective of human-computer interaction behavior, the most complex human-computer interaction behavior is navigation operation, followed by video and audio playback, and finally music selection and switching. In the future design improvement process, it should be considered that the operation logic in the navigation operation interface design should be simplified and the interface layout should be more reasonable.By accurately capturing users' needs for navigation operations, video and audio playback, and music selection switching, a friendly and simple smart cockpit user interface is designed.

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REFERENCES

A. Batwara, V. Sharma, M. Makkar, and A. Giallanza, An Empirical Investigation of Green Product Design and Development Strategies for Eco Industries Using Kano Model and Fuzzy AHP. Sustainability 14 (2022) 8735.

G.-N. Zhu, J. Ma, and J. Hu, A fuzzy rough number extended AHP and VIKOR for failure mode and effects analysis under uncertainty. Adv. Eng. Inf. 51 (2022).

H. Detjen, S. Faltaous, S. Geisler, and S. Schneegass, User-defined voice and mid-air gesture commands for maneuver-based interventions in automated vehicles, Proceedings of Mensch und Computer 2019, 2019, pp. 341–348.

H. Detjen, S. Geisler, and S. Schneegass, Maneuver-based control interventions during automated driving: Comparing touch, voice, and mid-air gestures as input modalities, 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC), IEEE, 2020, pp. 3268–3274.

H. Grahn, and T. Kujala, Impacts of touch screen size, user interface design, and subtask boundaries on in-car task's visual demand and driver distraction. International Journal of Human-Computer Studies 142 (2020) 102467.

J. Ma, J. Li, and Z. Gong, Evaluation of driver distraction from in-vehicle information systems: A simulator study of interaction modes and secondary tasks classes on eight production cars. International Journal of Industrial Ergonomics 92 (2022) 103380.

J. Ma, W. Wang, J. Li, and W. Xu, Usability Evaluation of Co-Pilot Screen Based on Fuzzy Comprehensive Evaluation Method. World Electric Vehicle Journal 14 (2023) 219.

K. M. Bach, M. G. Jæger, M. B. Skov, and N. G. Thomassen, Interacting with in-vehicle systems: Understanding, measuring, and evaluating attention. People and Computers XXIII Celebrating People and Technology (2009) 453–462.

L. Graichen, M. Graichen, and J. F. Krems, Effects of gesture-based interaction on driving behavior: A driving simulator study using the projection-based vehicle-in-the-loop. Human factors 64 (2022) 324–342.

L. Jianan, and A. Abas, Development of human-computer interactive interface for intelligent automotive. International Journal of Artificial Intelligence 7 (2020) 13–21.

L. Rittger, D. Engelhardt, and R. Schwartz, Adaptive user experience in the car—Levels of adaptivity and adaptive HMI design. IEEE Trans. Intell. Transp. Syst. 23 (2022) 4866–4876.

L. P. J. M. van, and W. Pedrycz, A fuzzy extension of Saaty's priority theory. Fuzzy Sets Syst. 11 (1983) 229–241.

M.-D. Shieh, Y. Li, and C.-C. Yang, Product Form Design Model Based on Multiobjective Optimization and Multicriteria Decision-Making. Mathematical Problems in Engineering 2017 (2017) 1–15.

P. Ebel, C. Lingenfelder, and A. Vogelsang, Multitasking While Driving: How Drivers Self-Regulate Their Interaction with In-Vehicle Touchscreens in Automated Driving. International Journal of Human–Computer Interaction (2023) 1–18.

P. D. Spyridakos, N. Merat, E. R. Boer, and G. M. Markkula, Behavioural validity of driving simulators for prototype HMI evaluation. IET Intelligent Transport Systems 14 (2020) 601–610.

R. Li, Y. V. Chen, C. Sha, and Z. Lu, Effects of interface layout on the usability of in-vehicle information systems and driving safety. Displays 49 (2017) 124–132.

S. Chai, and Z. Wang, Product design evaluation based on FAHP and cloud model. J. Intell. Fuzzy Syst. (2022) 1–21.

S. Kim, A study on the frequency allocation of WAVE for smart vehicle industry. Journal of The Institute of Electronics and Information Engineers 51 (2014) 183–189.

S. Kubler, J. Robert, W. Derigent, A. Voisin, and Y. Le Traon, A state-of the-art survey & testbed of fuzzy AHP (FAHP) applications. Expert Syst. Appl. 65 (2016) 398–422.

S. M. Faas, L.-A. Mathis, and M. Baumann, External HMI for self-driving vehicles: Which information shall be displayed? Transportation research part F: Traffic psychology and behaviour 68 (2020) 171–186.

T. Wang, and M. Zhou, A method for product form design of integrating interactive genetic algorithm with the interval hesitation time and user satisfaction. Int. J. Ind. Ergon. 76 (2020).

T. Wang, Z. Ma, and L. Yang, Creativity and Sustainable Design of Wickerwork Handicraft Patterns Based on Artificial Intelligence. Sustainability 15 (2023) 1574.

T. Wang, Z. Ma, F. Zhang, and L. Yang, Research on Wickerwork Patterns Creative Design and Development Based on Style Transfer Technology. Applied Sciences 13 (2023) 1553.

T. L. Saaty, A note on the AHP and expected value theory. Socio-Economic Planning Sciences 20 (1986) 397–398.

T. L. Saaty, A scaling method for priorities in hierarchical structures. Journal of mathematical psychology 15 (1977) 234–281.

T. L. Saaty, The Analytic Hierarchy Process, McGraw-Hill, New York, 1980.

V. Shreyas, S. N. Bharadwaj, S. Srinidhi, K. Ankith, and A. Rajendra, Self-driving cars: An overview of various autonomous driving systems. Advances in Data and Information Sciences: Proceedings of ICDIS 2019 (2020) 361–371.

W. Xu, M. J. Dainoff, L. Ge, and Z. Gao, Transitioning to human interaction with AI systems: New challenges and opportunities for HCI professionals to enable human-centered AI. International Journal of Human–Computer Interaction 39 (2023) 494–518.

X. Zhao, Z. Li, C. Zhao, C. Wang, and R. Fu, Distraction pattern classification and comparisons under different conditions in the full-touch HMI mode. Displays 78 (2023) 102413.

Y. Shi, Q. Peng, and J. Zhang, An Objective Weighting Method of Function Requirements for Product Design Using Information Entropy. Comput.-Aided Des. Applic. 17 (2020) 966–978.

Y. Zhu, Y. Geng, R. Huang, X. Zhang, L. Wang, and W. Liu, Driving Towards the Future: Exploring Human-Centered Design and Experiment of Glazing Projection Display Systems for Autonomous Vehicles. International Journal of Human–Computer Interaction (2023) 1–16.