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RESEARCH ARTICLE

An Elderly-Oriented Design of HMI in Autonomous Driving Cars Based on Rough Set Theory and Backpropagation Neural Network

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ABSTRACT As the issues of social sustainability and the aging of population becomes increasingly severe, Autonomous Driving technology is increasingly being seen as an important issue for future travel. At present, the Human Machine Interface (HMI) of Autonomous Driving system has certain difficulties for middle-aged and elderly users, which further affects their perception of cars status and operation experience. Therefore, in order to design an elderly-oriented HMI design of Autonomous Driving cars that meets the Kansei needs of middle-aged and elderly users, a design flow based on Kansei Engineering/ Rough Set Theory/ Backpropagation Neural Network is proposed. The HMI of Autonomous Driving cars is taken as an example in this paper. Under the framework of Kansei Engineering research, Kansei intention analysis is carried out. Factor Analysis is used to reduce dimension and cluster the collected Kansei words. By using the morphological analysis method, the HMI samples are deconstructed into 14 different design features. The attribute reduction algorithm in Rough Set Theory is used to identify the key design features of HMI that have important influence on the elderly-oriented level. Backpropagation Neural Network is used to establish the mapping model between the Kansei intention of middle-aged and elderly users and the key design features of HMI. The mapping model demonstrates good fit as the errors between the predicted and actual values in the 4 types of kansei semantic evaluation tests are all less than 5%. So that it could meet the needs of middle-aged and elderly users and obtain the design combination with the highest Kansei average value. Based on the experimental results, it is found that the optimal emotion of middle-aged and elderly users could be obtained by overall color type three, mode of speed display type three, font display of rotate speed type three, reminding color of turning type four and mode of fuel indicator display one in the morphological deconstruction table. The research results show that the elderly-oriented HMI design constructed by Kansei Engineering/ Rough Set Theory/ Backpropagation Neural Network can meet the sentimental needs of middle-aged and elderly users and can provide a reference example for relevant elderly-oriented design.

INDEX TERMS Elderly-oriented design, kansei engineering, rough set theory, backpropagation neural network, human machine interface, autonomous driving.

I. INTRODUCTION

Long-term driving has a negative impact on human's physical health, driving safety, social and mental health. The

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innovation of science and technology and the development of Autonomous Driving (AD) technology have brought efficient and convenient means of transportation to mankind, and also brought important opportunities and challenges to the sustainable development of human society. Humans begin to think about how AD technology can be combined with sustainable development, working to promote the development of more intelligent, more efficient and safer autonomous driving solutions. The three main principles of sustainable development are: environ-mental sustainability, economic sustainability and social sustainability [1]. With the increasingly serious problem of global population aging, governments and relevant institutions have sought ways to solve the problem of elderly travel. Under such a background, AD technology is considered as a potential solution to the challenges of an aging population. With the in-depth exploration of the perception mechanism, decision making mechanism and cybernetics of autonomous vehicles [2], [3], [4], scholars begin to combine machine learning and computer vision technology to promote the frontier development of interdisciplinary research in autonomous driving [5]. The integration of these technologies and approaches will play a crucial role in advancing the innovation and practical deployment of autonomous vehicle technology. Cars with different levels of automation are expected to play a major role in the future traffic system [6], and its AD system has attracted more and more attention from academic and industrial circles [7], [8]. With the maturity of AD automotive technology. AD technology provides better solutions for the elder's travel, thus meeting their diverse transportation needs and promoting sustainable social development.

With the continuous increase of the world's aging population, middle-ages and elderly customers occupy an important part of the customer group. They pay more attention to product functionality, quality, safety and comfort. An elderly-oriented design promotes the society's attention to the needs of the aging population, which can prompt manufacturers and governments to change the production process and business structure to practice social responsibility. With the United Nations' calling on countries to fully consider the impact and needs of aging in their development policies, the problem of global population aging becomes an important issue of concern to the international community in the 21st century in 1994 [9]. At the same time, previous studies have shown that optimizing the life quality of elderly people can be a solid foundation for the nation's sustainable development [10]. The progress of AD technology has changed the appearance and layout functions of the human-computer interaction interface in the automotive interior, especially the arrival of the era of sentimental consumption, and the communication and interaction between drivers and cars need to adapt to different levels of automation and the needs of user groups. Therefore, AD auto-motive HMI design should meet the sentimental needs of middle-aged and elderly users; meanwhile, expanding middle-aged and elderly customer groups will help promote the development and popularization of AD technology, solve the travel problems of middle-aged and elderly users, and pro-mote the sustainable development of society.

In the study of users' perception, Kansei Engineering (KE) is a translation technology that translate users' perception and intention into products' design specifications [11]. In the past 50 years of development, the practical ap-plication of KE and the production of the first "sentimental products" began in the automotive industry and achieved great success [12]. Since then, Kansei engineering, as an important method of design and development, has been widely used in product de-sign [13], [14] and service design [15], such as automobile [16], mobile phone appearance [17], logistics service [18] and other fields. The sentimental needs of users are expressed in the form of data with varying degrees and imprecision [19]. Therefore, the two main steps of implementing KE are: (1) Determining the key design features of the sample; (2) Establishing a mapping mod-el between users' perception and key design features. Identifying key patterns can re-duce computation time and help de-signers improve design efficiency. Lai et al. [20], Zerti et al. [21], Lin and Wei [22] applied Grey Relation-al Analysis (GRA) to identify the most influential design features in product form. Liu and Yu [23] used Exploratory Factor Analysis (EFA) to identify users' main preferences for smart phones. On the other hand, establishing the functional relationship be-tween customer feelings and design elements through a comprehensive approach is the core of KE. Traditional statistical analysis (such as correlation coefficient analysis, factor analysis, multiple regression analysis, etc.) can only express the length, height and low-level linear relationship and it is difficult to accurately describe the nonlinear relationship of image text curve characteristics, such as beauty or ugliness. Therefore, AI techniques such as Genetic Algorithm (GA) [24], Grey System Theory (GST) [25], Energy-Based Curriculum [26] and Support Vector Regression (SVR) [27] are widely used to build databases and inference mechanisms. With the development of artificial intelligence technology, it repeatedly simulates human thinking with simple computational rules, which has the advantage of fewer errors and faster speed [28]. Rough Set Theory (RST) is a mathematical method for dealing with fuzzy, imprecise and uncertain data problems proposed by Polish scholar, Pawlak in 1982 [29]. Its greatest ad-vantage is that attribute reduction can be performed without relying on any additional knowledge. Backpropagation Neural Network (BPNN) has powerful capabilities to perform efficient classification and regression tasks.

Therefore, a design process in combination of KE, RST and BPNN is proposed in this paper, which is devoted to designing an elderly-oriented HMI design of AD cars in line with the sentimental needs of middle-aged and elderly users. According to the literature survey, there is no literature based on KE's perspective on elderly-oriented HMI design of AD. On the one hand, HIM elderly-oriented design of AD cars can pro-vide theoretical guidance for automobile companies and designers, reduce the development time and risk of suitable for aging products, and help enterprises to expand middle-aged and elderly consumer groups and increase market share. On the other hand, it can maximize the sentimental needs of middle-aged and elderly users, promote the development of autonomous driving technology, solve the travel problems of middle-aged and elderly users, thus achieving the ultimate goal of elderly-oriented design and sustainable social development. The main contributions of this paper can be summarized as follows:

a) In the previous KE research, there is no design study combining RST and BPNN methods.
b) At present, there are few studies on elderly-oriented HMI of AD cars.
c) RST attribute reduction algorithm is used to simplify HMI design features and improve design efficiency.
d) BPNN is used to replace the traditional linear analysis method to establish the mapping relationship between users' perception and key design.

The paper is organized as follows: in the second part, the author briefly reviews the concepts of related methods. In the third part, the author describes the proposed research framework for AD elderly-oriented HMI design. The fourth part is the analysis and discussion of the research results. Finally, in the fifth part, the author summarizes the constructions of this study and puts forward some suggestions for future research.

II. RELATIVE METHODS

A. THE APPLICATION OF KE IN HMI DESIGN

With the continuous improvement of the life quality, customers begin to pursue spiritual values beyond the basic functions of products, emphasizing the sentimental communication between people and things [30]. Kansei engineering and Kansei Ergonomics were founded at Hiroshima University about 30 years ago. Covering a wide range of disciplines from ergonomics to psychology, KE is a theory of engineering techniques to explore the relationship between intangible human perception, sexual needs, mental imagery and tangible products' design norms [31]. In the existing research in academic circle, François et al. [32] and other scholars' framework based on cognitive ergonomics verifies the potential benefits of drivers' participation in automotive HMI design. In addition, Gkouskos and Chen [33] found that sentimental design has not been fully applied to the filed of HMI design through expert interviews. At the same time, with the emergency of applications programs and new features in HMI, the increase of information has a significantly negative impact on drivers' safety [34]. In order to evaluate automotive HMI design, situation awareness [35] and font size tests [36] are also applied into existing studies, but these studies tend to focus on users' preferences or sensory imagery, ignoring the combined effects of the two. Therefore, the AD cars HMI as the study case is chosen in this paper, which takes middle-aged and elderly users as the users group. It is committed to developing a elderly-oriented HMI design of AD cars, promoting the development and popularization of AD technology, strengthening the social attention to middle-aged and elderly users, and thus promoting the sustainable development of society.

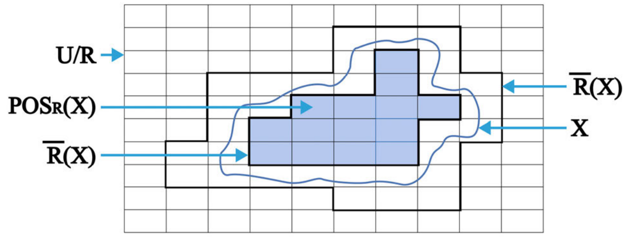

FIGURE 1. Fundamental concepts of RST.

B. ROUGH SET THEORY

Feature selection based on RST belongs to filtering method [37], which was firstly proposed by Polish scientist, Pawlak in 1982 [38]. RST is a new mathematical tool for dealing with uncertain [39], inconsistent and incomplete data to identify a reduced set of all attribute sets in a decision system [40]. RST is capable of processing data of any linear or non-linear feature type, which can cope with imprecise, non-linear human perception [41]. RST can effectively deal with the uncertain and fuzzy data of sentimental needs and it is used to study the interaction between consumers' sentimental needs and products' features in product design [42], thus discovering the rules and knowledge hidden in the data and deducing the decision or classification rules of the problem through knowledge reduction. Zhai et al. [43] built a KE system based on RST that can extract sentimental knowledge from imprecise design information and integrate it into a product development system. Shieh et al. [44] combined KE and PST in the visual design of tooth-brushes to explore the relationship between products' shape and color. Li et al. [45] used variable precision rough set and KE to reduce the knowledge database, thus forming a condensed and high-frequency rule base. Kang [46] combines RST with KE to reduce nine design features to five key design features for 60 study objects so as to improve computational efficiency and predict the hybrid cars' body styling in the future.

At the same time, RST attribute reduction algorithm can effectively extract the key design features that have important influences on the elderly-oriented level when facing the multi-attribute decision making problem composed of morphological analysis table. Therefore, based on this method, the redundant design features are reduced in this paper and the key design features that have an important impact on the HMI elderly-oriented level of AD cars design are retained so as to save the time and cost of products' development. In the RST attribute reduction algorithm, the weight of the conditional attribute index is 0, indicating that the conditional attribute does not play a role in the reduction process or has no ability to distinguish the decision attribute. From the perspective of reduction, the conditional attribute with a weight of 0 can be removed from the decision table to simplify the decision table and reduce the complexity of the calculation, thus improving the efficiency and accuracy of the algorithm. The following contents briefly explain the fundamentals of RST (Figure 1) and the attribute reduction algorithm:

Definition 1: $S = (U, A, V, f)$ is an information system in which U represents non-airspace of all evaluation records; A is nonempty finite attribute set and $A = C \cup D, A = C \cap D \neq \emptyset$; C is a set of conditional attributes (design features); D is the decision attribute set (elderly-oriented degree); V indicates the value range of the attribute; f is a relation set of U and A, which is also known as a set of information functions. If $D \neq \emptyset$, the information system S is called a data table and conversely, it is called a decision information system, or a decision table for short.

Definition 2: Let R be the equivalence relation on U, which is shown in formula (1); therefore, conditional attributes (design features) equivalence classes, namely $U/IND(C)$;decision attribute (elderly-oriented satisfaction) equivalence class, namely $U/IND(D)$; without considering specific conditional attributes or fields, equivalence classes are divided according to the original feature set as follows: $U/IND(C\text{-}\{c_e\})$.

$$IND(R) = \{(x, y) \in U \times U \,|\, \forall a \in A, f(x, a) = f(y, a)\} \quad (1)$$

Definition 3: In RST feature selection and data analysis, in order to define the approximation degree of knowledge, RST refers to two exact set concepts: lower approximate set and upper approximate set. $\underline{R}(X)$ is the approximate set under R, which is shown in formula (2); $\overline{R}(X)$ is the upper approximation set of R, which is shown in formula (3) and is also know as the positive field of X indicated as $POS_R(X)$. X is exact set of R; when $\underline{R}(X) \neq \overline{R}(X)$, X is R rough set; therefore, the positive field of the set of conditional attributes (design features) is represented as $pos(D)$, $pos_{c-|c_e|}(D)$.The cardinality of the conditional attribute set is expressed as $card[pos_c(D)]$, $card[pos_{c-|c_e|}(D)]$.

$$\underline{R}(X) = \{x \in U \,|\, IND(R) \subseteq X\} \quad (2)$$

$$\overline{R}(X) = \{x \in U \,|\, IND(R) \subseteq X\} \quad (3)$$

Definition 4: If $IND(B) = IND(B\text{-}\{r\})$, then r is called a knowledge that can be approximated in B. If $K = B\text{-}\{r\}$ is independent, then K is a knowledge reduction of B.

Definition 5: The degree of dependence of decision attribute D (elderly-oriented satisfaction) on conditional attribute (design feature) is namely $r_c(D)$; the dependence degree of decision attribute D on knowledge $C\text{-}\{c_e\}$ is namely $r_{c-|c_e|}(D)$; the importance of conditional attributes to decision attributes is namely $\sigma(c_e)$, which is shown in formula (4).

$$\sigma(c_e) = r_c(D) - r_{c-|c_e|}(D) \quad (4)$$

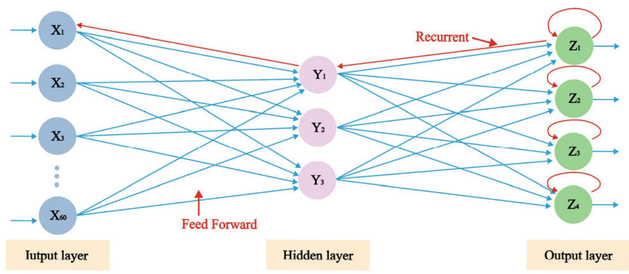

FIGURE 2. BPNN model structure.

Definition 6: The conditional attribute indicator weight is namely w_e, which is shown in formula (5).

$$w_e = \frac{\sigma(c_e)}{\sum_{\lambda=1}^{n} \sigma(c_\lambda)} \quad (5)$$

C. BACKPROPAGATION NEURAL NETWORK

Artificial neural network model is the most typical in non-linear regression analysis, and BPNN is widely used in product optimization design because it can learn and store a large number of input and output mapping relationships [47]. BPNN is a multilayer feedforward neural network trained by error backpropagation algorithm. The structure of BPNN model is shown in figure 2. It is very suitable for establishing the mapping relationship between users' sentimental needs and products design. Fan et al. [48] applied KE and BPNN methods to know consumers' preferences for 3D printing cloud service platforms. Guo et al. [49] built a BPNN model between mobile phone de-sign variables and users' prefer-ences to optimize mobile phone design. Hsiao and Huang [50] used BPNN to analyze the relationship between configuration parameters and image perception. Chen and Cheng [51] built a mapping relationship image between users' perception and pattern design elements through BPNN, thus providing a more scientific and intelligent pattern design method; Misaka and Aoyama [52] applied NN to develop a cup's crack pattern design system based on KE. Therefore, BPNN is used in this paper to construct the mapping relationship between the Kansei intention of middle-aged and elderly users and the HMI design features of AD system. The training process includes two forms: forward propagation and back propagation.

The following contents briefly describes the basic principles and calculation methods of BPNN.

Definition 7: BPNN includes input layer, output layer and hidden layer. N is the number of nodes in the input layer (number of design features), K is the number of nodes in the output layer (number of Kansei terms), and M is the number of nodes in the hidden layer, as shown in formula (6).

$$M = \frac{N + K}{2} \quad (6)$$

Definition 8: BPNN is trained by Trainlm gradient descent algorithm. The output parameters are limited to [0,1], and the

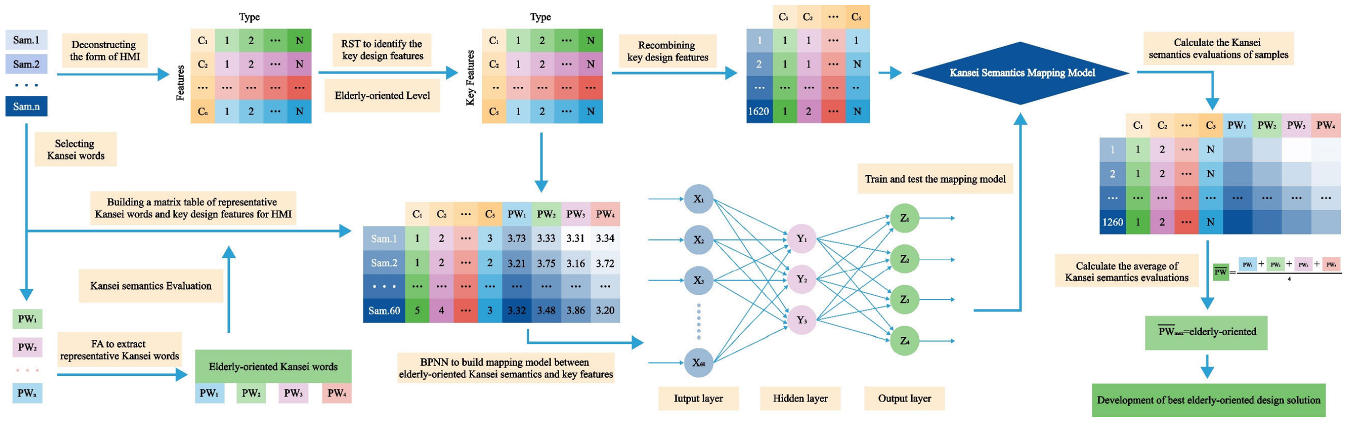

FIGURE 3. The proposed research framework.

Kansei evaluation needs to be normalized. In this study, minimax method is used to normalize input and output variables so that x_{max} is the maximum value, and x_{min} is the minimum value; X_α is the data after the normalization of input and output variables, which is shown in formula (7).

$$X_\alpha = \frac{x_\alpha - x_{min}}{x_{max} - x_{min}} \tag{7}$$

The output parameters can be input into the BPNN model for training.

Definition 9: The activation function of the hidden layer is expressed as follows using the logarithmic sigmoid transfer function, as shown in formula (8).

$$f(x) = \frac{1}{1+e^{-x}} (0 < f(x) < 1)] \tag{8}$$

Definition 10: The output layer uses the linear function purelin. By testing the predicted value and the true value of the root mean square error (RMSE), the method of calculating standard deviation is used to evaluate the performance of the model. The common-used RMSE is expressed as follows, which is shown in equation (9).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (x_i - x_0)^2}{n}} \tag{9}$$

In this equation, x_i is the output value of No i; x_0 is the expected value assessed by the subjects in the experiment. If there is no difference or error between the output value and the expected value, the RMSE is 0. When the RMSE of the neural network is small, it means that the neural network architecture can be used for prediction, judgment and reasoning.

III. THE PROPOSED RESEARCH FRAMEWORK

The purpose of this paper is to develop a HMI elderly-oriented design of AD cars with the combination of artificial intelligence technology under the background of global population aging. The research method is qualitative and quantitative modeling. On the basis of HMI questionnaire, 22 Kansei words are obtained by using Python natural language processing tools, and 4 Kansei words which represent elderly-oriented are identified by FA reduction and clustering. The 14 design features obtained by morphological analysis are reduced by RST, and 5 key design features are obtained. BPNN is used to build a mapping model between the sentimental intention of middle-aged and elderly users and the key design features of HMI, thus obtaining the HMI elderly-oriented design of AD cars. Based on the experimental results, the de-sign practice is completed, and 200 middle-aged and elderly subjects evaluate the satisfaction of the elderly-oriented design results to verify the feasibility of design process. Specific research steps are as follows:

Firstly, FA are used to cluster the representative Kansei words of middle-aged and elderly users for HMI design. Secondly, morphological analysis method is used to deconstruct the design features of HMI. Thirdly, the RST attribute reduction algorithm is used to obtain the key features that have important influences on the elderly-oriented level. Finally, the Kansei evaluations of middle-aged and elderly users are collected through questionnaires, thus establishing the matrix of Kansei evaluation value and key design features. Moreover, BPNN is used to establish the best mapping model corresponding to different Kansei words. The specific research framework is shown in figure 3.

A. DETERMINATION OF REPRESENTATIVE PRODUCTS

The front view of AD cars HMI design is chosen as the sample angle in this paper. 100 interface samples that fit the research scope are extensively collected through automotive magazines and design websites in this paper. In order to avoid the bias of the final result caused by the users' fixed preference for automobile brands affecting their Kansei evaluation, the fuzzy, occlusions and highly familiar images are eliminated through focus group discussion to reduce the impact on the visual sense of the subjects. A total of 60 representative HMIs are screened out and the AD cars' HMI database is established (figure 4) for further analysis.

FIGURE 4. 60 representative HMIs.

TABLE 1. Nine representative elderly-oriented Kansei words.

Intelligence	Simplicity	Intuition	Clarity	Comfort	Innovation	Focus	Beauty	Friendliness

B. FA TO CLUSTER ELDERLY-ORIENTED KANSEI WORDS IN HMI

Focus groups are used to evaluate the Kansei words of the mass-produced auto-motive HMI design samples in the sample bank. Meanwhile, the sentimental intention evaluation questionnaire for conceptual HMI design samples is released, and a total of 817 Kansei words are obtained. Through Python web scraping technology, 9 Kansei words are initially selected (Table 1). Then, a questionnaire survey is conducted on 25 graduate students and 25 designers. For 60 samples, 9 kinds of Kansei intention evaluation are carried out on each sample (scoring method is 5-scale Likert scale, 5 sores refers to "very suitable", 3 scores refers to "suitable", 1 score refers to unsuitable). A total of 50 valid questionnaires are collected and the mean value of the collected results is calculated, as shown in table 2.

TABLE 2. Kansei semantic evaluation matrix data.

No.	Intelligence	Simplicity	Intuition	Clarity	Comfort	Innovation	Focus	Beauty	Friendliness
1	4.52	3.04	3.84	3.84	3.72	3.84	3.60	3.92	3.76
2	4.00	4.00	4.16	4.04	3.76	3.16	3.88	3.52	3.76
3	4.12	4.56	4.20	4.04	3.92	3.88	3.88	4.08	3.88
4	4.20	3.48	3.84	3.68	3.80	3.76	3.32	3.72	4.00
5	4.08	3.60	4.16	4.04	3.64	3.60	3.92	3.76	4.00
6	4.08	3.84	4.04	3.76	3.88	3.96	3.76	3.96	3.68
7	3.76	3.96	3.92	4.00	3.64	3.28	3.68	3.52	3.64
8	4.04	4.56	4.40	4.28	4.08	3.80	4.16	3.80	4.12
9	4.16	3.56	3.88	3.68	3.80	3.64	3.92	3.76	3.84
10	3.88	3.92	4.00	3.96	3.72	3.84	3.72	3.76	3.96
11	4.00	4.08	4.00	3.92	3.92	3.80	3.92	3.68	3.84
12	3.88	3.92	4.12	3.68	3.76	3.56	3.72	3.68	3.72
13	4.24	3.12	3.80	4.12	3.56	3.72	3.40	3.76	3.96
14	3.88	3.24	3.96	3.80	3.40	3.76	3.28	3.20	3.52
15	4.08	4.00	4.00	4.20	3.80	3.92	3.92	3.84	4.00
16	3.84	4.00	3.96	4.12	3.88	3.72	3.92	3.72	3.72
17	4.04	3.96	4.16	3.84	3.64	3.80	3.76	3.56	3.52
18	4.00	4.24	4.08	4.04	4.04	3.64	4.04	3.96	3.92
19	4.00	4.36	3.68	4.00	3.72	3.56	3.92	3.60	3.72
20	4.20	4.16	4.16	4.12	3.96	4.16	3.92	3.96	3.88
21	3.68	2.96	3.28	3.52	3.20	3.36	3.32	3.16	3.44
22	3.72	3.12	3.56	3.72	3.32	3.24	3.48	3.12	3.44
23	4.16	3.12	3.24	3.36	3.64	3.76	3.28	3.44	3.60
24	4.32	4.08	4.04	3.64	3.96	3.80	3.76	4.04	3.84
25	3.80	3.00	3.44	3.60	3.52	3.36	3.56	3.28	3.68
26	3.88	3.16	3.64	3.48	3.48	3.64	3.48	3.52	3.96
27	3.80	3.84	4.16	4.12	4.08	3.68	4.00	4.04	3.84
28	3.80	3.76	3.64	3.76	3.76	3.32	3.52	3.68	3.76
29	3.68	3.40	3.76	3.60	3.52	3.12	3.64	3.36	3.64
30	4.04	3.72	4.16	4.00	4.08	3.72	3.80	3.92	4.08
31	3.84	4.12	4.04	4.12	3.80	3.64	3.80	3.64	3.68
32	3.80	3.48	3.96	3.64	3.64	3.60	3.64	3.60	3.80
33	4.32	3.68	3.84	3.84	3.88	4.08	3.80	3.96	3.96
34	4.16	3.72	3.8	3.76	3.80	3.76	3.64	3.64	3.80
35	3.64	3.48	3.32	3.80	3.48	3.52	3.48	3.48	3.64
36	3.92	3.72	3.80	3.76	3.84	3.80	3.72	3.72	3.56
37	3.88	3.72	4.12	3.80	3.72	3.68	3.56	3.40	3.68
38	4.04	3.60	3.80	3.92	3.80	3.88	3.56	3.96	3.72
39	3.92	3.68	3.96	3.76	3.68	3.80	3.68	3.60	3.72
40	3.92	4.12	4.04	3.96	3.72	3.48	3.84	3.76	3.84
41	4.44	3.64	4.00	3.92	4.00	4.04	3.72	3.88	3.72
42	3.68	4.00	4.00	3.72	3.64	3.92	3.76	3.52	3.72
43	3.96	4.28	4.04	3.80	3.84	3.88	3.80	3.80	3.88
44	4.04	3.56	3.92	3.64	3.68	3.84	3.88	4.00	3.92
45	3.92	3.72	3.84	3.68	3.76	4.04	3.60	3.48	3.64
46	3.84	3.80	3.92	4.00	3.92	3.88	3.64	3.80	3.96
47	3.92	4.12	3.88	3.88	3.60	3.48	3.88	3.64	3.60
48	4.00	4.20	4.04	3.76	3.76	3.76	3.76	3.84	3.64
49	3.8	3.64	3.92	3.64	3.76	3.48	3.88	3.64	3.76
50	3.88	3.56	3.76	3.68	3.68	3.80	3.64	3.68	3.76
51	3.88	4.00	4.28	3.88	3.56	3.52	3.68	3.60	3.76
52	4.00	3.92	4.04	4.04	3.84	3.64	3.84	3.80	4.00
53	3.68	3.76	3.76	3.76	3.72	3.48	3.52	3.64	3.48
54	3.84	3.60	3.52	3.72	3.52	3.68	3.56	3.40	3.48
55	4.12	4.08	3.96	3.96	4.08	4.00	3.84	3.80	3.80
56	3.84	4.00	4.04	3.92	4.04	3.68	3.88	3.84	3.92
57	3.92	3.72	3.92	3.80	3.80	4.04	3.44	3.84	3.80
58	3.72	3.84	3.84	3.80	3.48	3.56	3.48	3.40	3.60
59	3.96	3.32	3.60	3.72	3.60	3.84	3.36	3.48	3.76
60	3.84	4.20	4.08	3.88	3.64	3.80	3.72	3.72	3.76

In this paper, FA is used for dimensionality reduction of Kansei words, and the data results are imported into the Statistical Package for the Social Sciences (SPSS) software for dimensionality reduction analysis. KMO and Bartlett tests are required for factor analysis. In this way, the structural validity and interrelationship of factor analysis are verified.

TABLE 3. KMO and bartlett's test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.863
Bartlett's Test of Sphericity	Appro. Chi-Square	317.567
	df	36
	Sig.	0.000

TABLE 4. Total variance explained.

IE	Sum of Squared Loadings						Sum of Squared Rotated Loadings		
	Sum	Var./%	Cum./%	Sum	Var./%	Cum./%	Sum	Var./%	Cum./%
1	4.857	53.965	53.965	4.857	53.965	53.965	2.845	31.615	31.615
2	1.588	17.647	71.611	1.588	17.647	71.611	1.903	21.140	52.755
3	0.667	7.411	79.022	0.667	7.411	79.022	1.649	18.327	71.082
4	0.488	5.418	84.440	0.488	5.418	84.440	1.202	13.358	84.440
5	0.436	4.840	89.281						
6	0.360	4.000	93.281						
7	0.232	2.583	95.864						
8	0.195	2.164	98.027						
9	0.178	1.973	100.000						

TABLE 5. Rotated component matrix.

Kansei word	Component			
	1	2	3	4
Intelligence		0.726		
Simplicity	0.884			
Intuition	0.65			0.506
Clarity				0.843
Comfort	0.678			
Innovation		0.926		
Focus	0.819			
Beauty	0.532	0.516	0.556	
Friendliness			0.846	

TABLE 6. Component score coefficient matrix.

Kansei word	Component			
	1	2	3	4
Intelligence	-0.28	0.372	0.207	0.13
Simplicity	0.481	0.036	-0.383	-0.045
Intuition	0.108	0.034	-0.128	0.368
Clarity	-0.307	0.007	-0.084	1.07
Comfort	0.328	0.073	0.14	-0.384
Innovation	-0.015	0.725	-0.463	0.094
Focus	0.406	-0.244	0.161	-0.248
Beauty	0.19	0.105	0.27	-0.333
Friendliness	-0.215	-0.251	0.795	0.074

The experimental results are shown in table 3. KMO value is 0.863 (when KMO value>0.8, the experimental data is suitable for factor analysis); the ap-proximate value is 317.567; the degree of freedom is 36, and the Bartlett spherical experimental disinfection paper is 0.000<0.05, showing significant differences. In summary, KMO and Bartlett sphericity tests prove that this data is suitable for factor analysis. In the total variance interpretation of the users' perception measurement scale, the cumulative contribution rate of the first four indicators is 84.440, close to 85%, which proves that the nine terms can be reduced into four main factors. The results are shown in table 4.

The sensibility factors in the users' sensibility image measurement scale are orthogonally rotated by using the

TABLE 7. Interview content.

(1) What emotion do you most often experience when observing HMI while driving in your daily life?	(2) Are there any specific words or adjectives that describe the emotions you most often feel when observing HMI while driving a car?
(3) When you observe an automotive HMI, you will think of a particular emotion or state; what words or expressions come to your mind?	(4) For you, what words or expressions can best express and trigger your emotions when you observe HMI while driving a car?

TABLE 8. Bivariate correlation analysis parameter results.

The four factors	Pearson correlation	Sig.
Simplicity	0.885	0
Intelligence	0.928	0
Affinity	0.922	0
Clarity	0.709	0

Caesar normalized maximum variance method. The component matrix after rotation is shown in table 5. In order to reduce visual interference, the factors whose absolute value is less than 0.5 are represented by blank space.

Principal component analysis is used to obtain the component score coefficient matrix, as shown in table 6. A total of 4 factors are extracted from the users' sensibility vocabulary of the elderly-oriented HMI for AD cars. The naming and index selection of the factors are all based on the comprehensive consideration and understanding of the elderly-oriented sentimental needs and characteristics. The first factor is composed of four indicators: simplicity, intuition, comfort and focus, which is named as the simplicity factor. The second factor is composed of intelligence and innovation, which is named intelligence factor. The third factor, which is composed of two indexes of beauty and friendliness, is named the affinity factor. The fourth factor is named as the clarity factor.

In order to verify that the four factors after clustering meet the Kansei needs and characteristics of elderly users,

Design Features	Type1/8	Type2/9	Type3/10	Type4/11	Type5	Type6	Type7
The overall color	Black	White	Gray	Blue	High contrast	Gradient	
The speed display mode	Numeric	Semi-circle scale + Numeric	Circular scale + Numeric	Graphic + Numeric	Bar scale + Numeric		
The color of speed icon	None	Black + Red	Black + Blue	Black + Green	Black + White	Black + Purple	Black + Orange
The font of speed display	Large	Medium	Small				
The mode of displaying rotate speed	Numeric	Semi-circle scale + Numeric	Circular scale + Numeric	Bar scale + Numeric	Graphic + Numeric		
The font of displaying rotate speed	Large	Medium	Small				
The display color of rotate speed icon	None	Black + Red	Black + Blue	Black + Green	Black + White	Black + Purple	Black + Orange
The color of turning prompt	None	Black + White	Black + Blue	Blue + White	Black + Orange	Black + Green	
The dynamic display of auxiliary driving	None	Car	Car + Road + Environment	Car + Road	Arrow + Road		
The display mode of fuel indicator	Icon	Icon + Numeric	Icon + Number + Scale				
The display color of fuel indicator.	Blue	Green	White	Red			
The overall layout style	NAV ANAS RPM	RPM ANAS V	NAV ANAS	ANAS RPM	ANAS	RPM ANAS	V ANAS RPM
	V ANAS	NAV V RPM	RPM NAV V	RPM ANAS NAV			
The position of displaying speed number	00	00	00	00	00	00	00
The position of displaying rotate speed	00	00	00	00	00	None	

FIGURE 5. From deconstruction table.

we conduct face-to-face interviews with 20 elderly users over 45 years old (interview contents are shown in the table 7). Variable A: through interview results, the occurrence frequency of words highly correlated with the four after clustering in the interview is counted respectively. Variable B: elderly users evaluate the emotional needs of four factors in line with the HMI elderly-oriented design (using a 7-order Likert scale). The above two variables are imported into the software of SPSS26 for bivariate correlation analysis. The Pearson coefficient between each factor and the emotional needs of elderly users is greater than 0.7, and the significance is 0. The results are shown in Table 8. The above results indicate that the four representative elderly-oriented Kansei words after clustering have a strong correlation with the elderly users' emotional needs for HMI, which can be used to establish a deep emotional connection between HMI and elderly users.

C. RST TO IDENTIFY THE KEY DESIGN FEATURES OF HMI

The appearance forms of 60 AD cars' HMI samples in the sample database are decomposed; the corresponding relationship between HMI design and the elderly-oriented degree is explored; the key features that have an important impact on the elderly-oriented degree are extracted. Morphological analysis decomposes the HMI into 14 design features, which are respectively the overall color, the overall layout style, the position of displaying speed number, the speed display mode, the color of speed icon, the font of speed display, the position of displaying rotate speed, the mode of displaying rotate speed, the font of displaying rotate speed, the display color of rotate speed icon, the color of turning prompt, the dynamic display of auxiliary driving, the display mode of fuel indicator and the display color of fuel indicator. Each design feature is further subdivided into multiple design types with a total number of 78, as shown in figure 5.

Due to the different importance of each design feature of HMI to the elderly-oriented degree, design features that have no effect on the elderly-oriented degree of HMI may lead to inaccurate conclusions. Therefore, RST attribute reduction algorithm is used to reduce the data dimension to obtain high precision recognition. Firstly, the focus group evaluates the elderly-oriented satisfaction of 78 design types subdivided by 14 design features (1 score is defined as the low elderly-oriented satisfaction, 3 scores is defined as high elderly-oriented satisfaction), and an evaluation matrix of design types' elderly-oriented satisfaction degree is formed; the results are shown in table 9. Secondly, 60 AD cars' HMI design samples are mapped to the design features in the morphological analysis table; 100 subjects (half of them are male and half of them are female, with more than three years' driving experience) are selected to evaluate the

TABLE 9. Elderly-oriented levels evaluation matrix of HMI design types.

Design Features	Type1	Type2	Type3	Type4	Type5	Type6	Type7	Type8	Type9	Type10	Type11
1	3	3	2	2	3	1					
2	2	3	1	1	1	1	3	2	3	3	2
3	3	3	1	1	3	1	3				
4	3	2	3	1	1						
5	2	1	2	3	3	1	1				
6	3	2	1								
7	3	3	2	2	2	1					
8	3	2	2	1	1						
9	2	2	1								
10	2	1	2	3	3	1	1				
11	1	3	3	3	1	2					
12	1	2	2	3	3						
13	1	1	3								
14	3	3	2	1							

TABLE 10. Elderly-oriented levels evaluation matrix of 60 representative HMIs.

No.	Lvl	No.	Lvl	No.	Lvl	No.	Lvl	No.	Lvl	No.	Lvl	No.	Lvl	No.	Lvl	No.	Lvl	No.	Lvl
1	2.44	7	3.67	13	2.41	19	3.5	25	3.7	31	2.32	37	3.65	43	3.53	49	3.45	55	2.37
2	3.61	8	3.64	14	3.62	20	3.61	26	3.52	32	3.55	38	3.57	44	3.74	50	3.62	56	3.64
3	2.18	9	3.72	15	2.21	21	2.5	27	3.73	33	2.46	39	3.55	45	2.5	51	3.58	57	3.59
4	3.61	10	3.63	16	3.71	22	3.53	28	3.65	34	3.64	40	3.69	46	3.57	52	3.56	58	3.55
5	3.6	11	3.76	17	3.64	23	2.31	29	3.57	35	3.61	41	3.67	47	3.72	53	2.29	59	3.51
6	3.59	12	3.72	18	3.74	24	2.42	30	3.61	36	3.64	42	3.65	48	3.71	54	3.54	60	3.59

elderly-oriented satisfaction of 60 AD cars HMI and make a score on the results, as shown in table 10. Due to the strong continuity of the original data, the author uses the expert evaluation method to convert the original data of AD automotive HMI 's elderly-oriented satisfaction score into type data. After making score on the elderly-oriented satisfaction and comprehensive consideration, the expert group carries ou t the discretization to the original data (defined as discrete value 1 for low elderly-oriented satisfaction; discrete value 2 for middle-level elderly-oriented satisfaction and discrete value 3 for high elderly-oriented satisfaction). RST condition attribute the overall color, the overall layout style, the position of displaying speed number, the speed display mode, the color of speed icon, the font of speed display, the position of displaying rotate speed, the mode of displaying rotate speed, the font of displaying rotate speed, the display color of rotate speed icon, the color of turning prompt, the dynamic display of auxiliary driving, the display mode of fuel indicator and the display color of fuel indicator is set as the set C. The elderly-oriented degree of AD cars HMI is set as decision attribute D; the converted discrete values are shown in table 11.

Matlab2023b software is applied to RST attribute reduction algorithm to identify the key design features that have an important impact on uses' elderly-oriented satisfaction. The results are as follows:

Firstly, the data in the table are divided into equivalence classes according to conditional attributes (design characteristics) and decision attributes (elderly-oriented satisfaction).

$U/IND(D)$ = {(1, 3, 13, 15, 19, 21, 23, 24, 31, 33, 39, 43, 45, 49, 53, 54, 55, 58, 59), (2, 4, 5, 6, 8, 10, 14, 17, 20, 22, 26, 28, 29, 30, 32, 34, 35, 36, 37, 38, 42, 46, 50, 51, 52, 56, 57), (7, 9, 11, 12, 16, 18, 25, 27, 40, 41, 44, 47, 48)}

$U/IND(C)$ = {(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

Remove the conditional attributes (design features) respectively, and the equivalence classes of the fields are divided as follows:

$U/IND(C\text{-}\{c_1\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16, 34), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_2\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_3\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_4\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16, 17), (18), (19), (20), (21),

TABLE 11. Discrete decision table.

U	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}	D
1	3	2	3	3	2	2	3	3	1	2	3	2	3	3	1
2	3	2	3	3	2	2	3	3	1	2	3	3	1	3	2
3	3	3	3	1	2	2	3	1	2	2	1	3	3	3	1
4	3	1	3	3	2	2	2	1	1	3	3	2	3	3	2
5	3	2	3	3	2	3	2	1	1	3	3	3	3	3	2
6	2	1	3	3	2	2	3	2	1	1	1	3	3	3	2
7	2	1	3	3	2	2	3	2	1	3	3	3	3	3	3
8	1	1	3	3	2	2	3	1	2	3	1	3	1	2	2
9	3	2	3	3	2	2	2	1	2	3	3	3	3	3	3
10	3	3	3	2	2	3	3	2	2	2	1	3	1	1	2
11	3	3	3	1	2	2	3	1	2	2	1	3	1	3	3
12	1	3	3	3	2	2	2	3	1	2	1	3	3	3	3
13	3	3	1	3	3	1	2	3	1	2	3	2	1	3	1
14	3	3	1	3	2	3	2	3	2	2	1	2	1	2	2
15	3	1	3	3	2	2	3	1	1	2	1	2	3	3	1
16	3	3	3	3	2	2	3	2	2	2	1	3	3	3	3
17	3	3	3	2	2	2	3	2	2	2	1	3	3	3	2
18	3	3	1	3	3	1	3	2	2	3	1	2	1	2	3
19	3	1	3	2	1	2	3	2	1	1	1	2	1	2	1
20	3	1	3	1	3	3	2	1	1	3	3	2	1	3	2
21	3	3	3	3	2	2	2	2	1	1	1	3	1	2	1
22	3	3	3	3	1	2	3	1	1	3	1	3	3	2	2
23	3	3	3	3	2	2	3	1	1	2	1	3	3	3	1
24	3	2	3	1	2	3	3	1	1	1	1	3	3	2	1
25	3	3	3	2	2	3	3	2	1	2	1	3	1	3	3
26	3	3	3	2	1	2	3	2	1	1	1	3	1	2	2
27	3	2	3	3	2	3	3	1	1	3	3	3	3	2	3
28	1	3	1	3	2	2	2	1	2	2	1	3	1	3	2
29	3	3	3	3	3	2	3	2	2	3	1	1	1	3	2
30	3	1	3	3	2	2	1	3	1	3	3	2	3	3	2
31	1	3	3	3	3	2	3	1	2	1	1	3	1	2	1
32	3	3	3	2	3	3	3	2	2	3	1	2	1	3	2
33	3	3	3	1	3	3	3	1	2	3	3	2	3	3	1
34	2	3	3	3	2	2	3	2	2	2	1	3	3	3	2
35	3	3	3	3	3	1	3	2	1	3	3	3	3	2	2
36	3	2	3	3	2	2	3	2	1	3	3	3	3	3	2
37	3	3	3	3	1	3	3	1	2	1	1	3	1	2	2
38	3	3	1	2	2	3	2	2	2	2	3	2	1	2	2
39	3	3	3	1	3	3	3	1	2	3	3	3	1	2	1
40	3	3	1	2	2	3	2	2	2	2	3	3	1	3	3
41	1	3	3	1	1	2	3	1	2	1	1	3	1	2	3
42	1	1	3	1	1	3	3	1	2	1	1	3	1	2	2
43	2	3	3	3	3	2	3	3	2	3	1	3	1	2	1
44	2	3	3	2	2	3	3	2	2	2	3	3	3	3	3
45	3	3	1	1	1	2	3	1	2	1	1	3	1	2	1
46	3	3	3	1	3	3	3	1	2	3	1	2	3	3	2
47	3	3	3	2	2	3	3	2	2	2	3	2	3	3	3
48	3	3	3	1	1	1	3	1	2	1	3	3	1	2	3
49	3	3	3	3	1	3	3	2	2	1	3	3	1	2	1
50	2	2	3	3	2	3	3	2	2	3	3	3	3	2	2
51	1	3	3	3	2	3	3	3	2	2	1	3	3	3	2
52	3	3	1	2	3	2	3	1	2	2	1	3	3	2	2
53	3	3	3	1	2	3	2	3	1	2	3	3	3	2	1
54	3	3	3	3	1	1	3	2	2	1	3	3	1	2	1
55	3	3	3	1	3	2	3	1	2	3	2	3	1	2	1
56	3	2	3	3	2	2	3	3	2	2	3	2	3	3	2
57	1	3	3	1	2	3	3	1	2	2	1	3	3	3	2
58	2	3	3	1	2	3	3	1	1	2	3	3	1	2	1
59	1	2	3	3	2	2	1	3	1	2	3	2	3	3	1
60	3	3	3	1	3	3	3	1	2	3	1	3	3	3	2

(22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_5\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_6\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20),

TABLE 12. Kansei semantic evaluation matrix.

No.	c_1	c_4	c_9	c_{11}	c_{13}	Simplicity	Intelligence	Affinity	Clarity
1	1	1	3	2	3	3.73	3.33	3.31	3.34
2	1	1	3	4	2	3.21	3.75	3.16	3.72
3	1	4	2	1	3	3.82	3.8	3.87	3.24
4	2	1	3	2	3	3.76	3.28	3.21	3.75
5	1	1	3	4	3	3.27	3.81	3.31	3.32
6	3	1	3	1	3	3.82	3.7	3.31	3.71
7	3	1	3	4	3	3.29	3.77	3.73	3.36
8	6	1	2	1	2	3.26	3.72	3.29	3.77
9	1	1	1	2	3	3.88	3.25	3.34	3.79
10	5	2	1	1	1	3.74	3.33	3.3	3.75
11	5	4	2	1	1	3.75	3.8	3.85	3.72
12	6	1	3	1	3	3.33	3.29	3.88	3.83
13	5	1	3	4	2	3.31	3.67	3.72	3.2
14	1	1	1	1	2	3.36	3.85	3.82	3.73
15	1	1	3	1	3	3.68	3.76	3.22	3.25
16	5	3	2	1	3	3.24	3.24	3.18	3.75
17	5	2	2	1	3	3.21	3.71	3.78	3.86
18	1	3	1	1	2	3.31	3.78	3.19	3.84
19	1	2	3	1	2	3.81	3.28	3.28	3.77
20	1	5	3	2	2	3.2	3.83	3.81	3.18
21	1	3	3	1	2	3.79	3.82	3.19	3.84
22	5	3	3	1	3	3.68	3.15	3.18	3.75
23	5	3	3	1	3	3.26	3.78	3.17	3.82
24	1	1	3	5	3	3.82	3.39	3.24	3.3
25	5	2	3	1	2	3.6	3.77	3.75	3.33
26	5	2	3	1	2	3.82	3.3	3.77	3.35
27	1	1	3	2	3	3.33	3.75	3.28	3.82
28	6	1	1	1	2	3.16	3.2	3.77	3.64
29	1	3	2	1	2	3.74	3.25	3.32	3.29
30	2	1	3	2	3	3.16	3.7	3.85	3.65
31	6	3	1	1	2	3.29	3.34	3.85	3.78
32	5	2	1	1	2	3.78	3.31	3.34	3.77
33	5	4	1	2	3	3.17	3.26	3.72	3.3
34	4	3	1	1	3	3.24	3.27	3.8	3.91
35	1	3	3	2	3	3.24	3.77	3.81	3.19
36	1	1	3	2	3	3.17	3.77	3.78	3.37
37	5	3	1	1	1	3.3	3.74	3.85	3.26
38	1	2	1	3	2	3.24	3.74	3.81	3.3
39	5	4	1	2	2	3.78	3.33	3.29	3.79
40	1	2	1	3	2	3.84	3.18	3.7	3.83
41	6	4	2	1	2	3.76	3.21	3.32	3.73
42	6	4	2	1	2	3.8	3.3	3.75	3.2
43	4	1	2	1	2	3.41	3.72	3.63	3.27
44	4	2	1	3	3	3.74	3.31	3.7	3.17
45	5	4	2	1	2	3.26	3.61	3.27	3.63
46	5	4	1	1	3	3.38	3.75	3.31	3.78
47	5	2	1	2	3	3.77	3.21	3.23	3.76
48	1	4	2	2	2	3.83	3.14	3.29	3.81
49	5	3	1	2	2	3.67	3.09	3.15	3.83
50	4	1	2	2	3	3.26	3.28	3.75	3.77
51	6	1	1	1	3	3.18	3.23	3.15	3.79
52	1	2	1	1	3	3.79	3.71	3.27	3.76
53	5	4	3	3	3	3.15	3.72	3.89	3.25
54	1	3	2	1	2	3.29	3.82	3.74	3.25
55	5	4	1	6	2	3.76	3.19	3.27	3.78
56	2	1	2	4	3	3.76	3.32	3.86	3.84
57	6	4	1	1	3	3.26	3.92	3.26	3.74
58	4	4	3	4	2	3.71	3.26	3.39	3.86
59	1	1	3	2	3	3.77	3.19	3.74	3.83
60	5	4	1	1	3	3.32	3.48	3.86	3.2

(21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49, 54), (50), (51), (52), (53), (55), (56), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_7\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_8\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20),

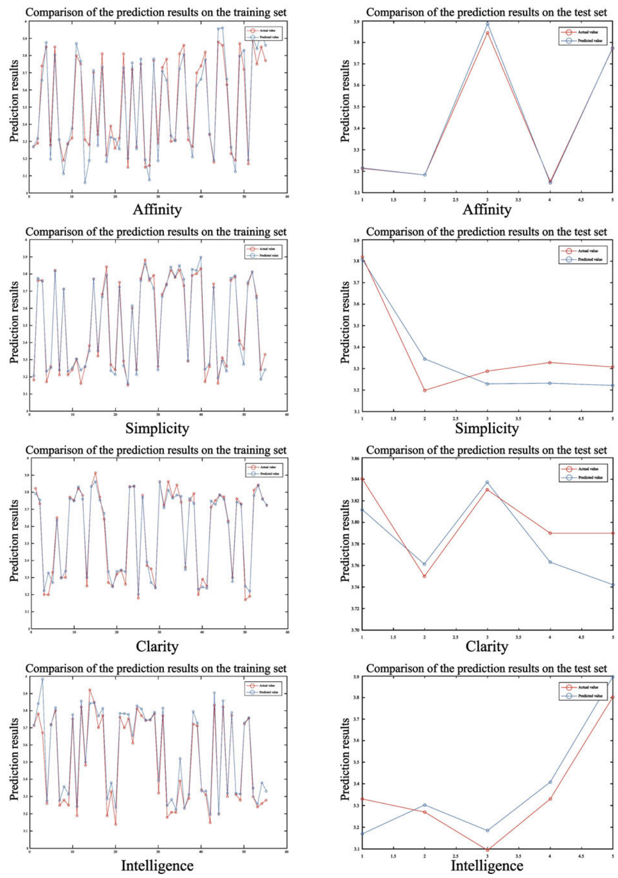

FIGURE 6. Fitting graph of training set and test set.

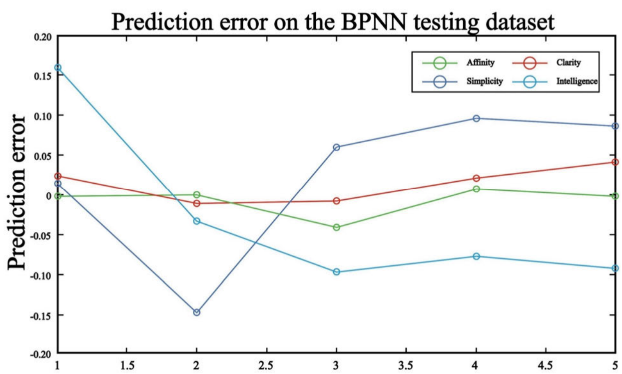

FIGURE 7. The error in the test set.

(21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_9\})$={(1, 56), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_{10}\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_{11}\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33, 46), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_{12}\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46, 60), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59)}

$U/IND(C\text{-}\{c_{13}\})$={(1), (2), (3, 11), (4), (5), (6), (7), (8), (9), (10), (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

$U/IND(C\text{-}\{c_{14}\})$={(1), (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16), (17), (18), (19), (20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32), (33), (34), (35), (36), (37), (38), (39), (40), (41), (42), (43), (44), (45), (46), (47), (48), (49), (50), (51), (52), (53), (54), (55), (56), (57), (58), (59), (60)}

Calculate the cardinality of each attribute set:

$$
\begin{aligned}
&card[pos_c(D)] = 60, card[pos_{c-|c_1|}(D)] = 58,\\
&card[pos_{c-|c_2|}(D)] = 60,\\
&card[pos_{c-|c_3|}(D)] = 60, card[pos_{c-|c_4|}(D)] = 58,\\
&card[pos_{c-|c_5|}(D)]60,\\
&card[pos_{c-|c_6|}(D)]60, card[pos_{c-|c_7|}(D)]60,\\
&card[pos_{c-|c_8|}(D)] = 60,\\
&card[pos_{c-|c_9|}(D)] = 58, card[pos_{c-|c_{10}|}(D)] = 60,\\
&card[pos_{c-|c_{11}|}(D)] = 58,\\
&card[pos_{c-|c_{12}|}(D)] = 60, card[pos_{c-|c_{13}|}(D)] = 58,\\
&card[pos_{c-|c_{14}|}(D)] = 60
\end{aligned}
$$

Therefore:

$$
\begin{aligned}
&r_C(D) = 60/60, r_{C-c_1}(D) = 58/60, r_{C-c_2}(D) = 60/60,\\
&r_{C-c_3}(D) = 60/60,\\
&r_{C-c_4}(D) = 58/60, r_{C-c_5}(D) = 60/60, r_{C-c_6}(D) = 60/60,\\
&r_{C-c_7}(D) = 60/60,\\
&r_{C-c_8}(D) = 60/60, r_{C-c_9}(D) = 58/60, r_{C-c_{10}}(D) = 60/60,\\
&r_{C-c_{11}}(D) = 58/60,\\
&r_{C-c_{12}}(D) = 60/60, r_{C-c_{13}}(D) = 58/60, r_{C-c_{14}}(D) = 60/60
\end{aligned}
$$

According to the formula (4):

$$\sigma(c_1) = 2/60, \sigma(c_2) = 0, \sigma(c_3) = 60/60,$$

TABLE 13. BPNN training parameters.

Parameter name	Parameter name
Training function	Trainlm
Hidden layer activation function	logsig
Output layer activation function	purelin
Training set samples	No.1~55
Test set samples	No.56~60
Number of iterations or learning epochs	500

TABLE 14. System configuration.

System components	Detailed system information
Processor	13th Gen Intel Core i9-13900HX
Memory	32GB（SAMSUNG DDR5 4800MHz 16GB x 2）
Graphics Card	NVIDIA GeForce RTX 4080 Laptop GPU (12 GB/ Quanta)
Motherboard	THUNDEROBOT NLZD(LPC Controller/eSPI Controller-7A0C)
Primary Hard Drive	SSSTCCL5-8D1024(1024GB/ Solid State Drive)
Analysis Software	MATLAB R2023b

TABLE 15. The parameter results.

Kansei word	The predicted results on the training set.		The result of the actual value and the predicted value.		Error between predicted values and actual values in the test set
	R^2	RMSE	R^2	RMSE	e
Simplicity	0.98314	0.033993	0.83451	0.091358	(0.10, -0.15)
Intelligence	0.93476	0.06506	0.85845	0.10006	(0.01, -0.03)
Affinity	0.94017	0.070103	0.9966	0.018064	(0.20, -0.10)
Clarity	0.97688	0.036603	0.47758	0.028404	(0.05, -0.02)

$$\sigma(c_4) = 2/60, \sigma(c_5) = 0, \sigma(c_6) = 0,$$
$$\sigma(c_7) = 0, \sigma(c_8) = 0, \sigma(c_9) = 2/60,$$
$$\sigma(c_{10}) = 0, \sigma(c_{11}) = 2/60, \sigma(c_{12}) = 0,$$
$$\sigma(c_{13}) = 2/60, \sigma(c_{14}) = 0$$

Calculate the weight coefficient according to the formula (5):

$$w_1 = 0.2, w_2 = 0, w_3 = 0, w_4 = 0.2, w_5 = 0,$$
$$w_6 = 0, w_7 = 0,$$
$$w_8 = 0, w_9 = 0.2, w_{10} = 0, w_{11} = 0.2, w_{12} = 0,$$
$$w_{13} = 0.2, w_{14} = 0$$

Therefore, through the reduction of RST attributes, the key design features that have an important impact on the elderly-oriented satisfaction of cars' HMI are identified, namely the overall color, the mode of speed display, the display font of rotate speed, the reminding color of turning and the display mode of fuel indicator.

D. BPNN TO BUILD MAPPING MODEL BETWEEN KANSEI SEMANTICS AND KEY FEATURES OF HMI

After the first-stage of clustering, the four most representative elderly-oriented Kansei words are combined with 60 HMI samples, constructing a 5-order Likert scale. A total of 100 subjects with half of males and half of females, aged between 25 and 55, are invited to participate in the Kansei evaluation experiment. The subjects include a small number of interaction designers and a large number of middle-aged and older users. The matrix between design features of Kansei words samples and Kansei evaluation value is constructed, as shown in table 12.

Based on Matlab2023b software platform, BPNN is used to learn the matrix data in table 12. The BPNN model training parameters are shown in Table 13. All data analysis work in this study is completed on a high-performance workstation. The specific configuration is shown in Table 14. The Kansei word "affinity" is taken as an example. In this study, the number of nodes in the input layer is 5 key design features after reduction, and the number of nodes in the output layer is 1 from the selected representative Kansei term "affinity". Therefore, the number of nodes in the hidden layer is 3 according to the formula. The first 55 samples are input into the network as a training set and the learning times are set to be 500 times with a learning rate of 0.01. The functions of logsig and purelin are used for the hidden layer and output layer respectively. The model is trained by Trainlm gradient descent function. After many times' training, convergence

FIGURE 8. Elderly-oriented HMI Design for AD Cars.

FIGURE 9. The design effect of elderly-oriented HMI Design for AD Cars.

turns to be a better prediction result of training set. The Kansei word "affinity" is taken as an example, which converges to a good parameter result (RMSE=0.070103, $R^2 = 0.94017$, MSE=0.0049144, PRD=3.8917) indicating that the model in this study has good prediction ability, high degree of fitting and little difference between the predicted result and the true value. The curve graph is shown as figure 6. The last five samples in table 12 are used to verify the reliability of the trained network, and the comparison between the actual perceived evaluation value of the test set and the perceived evaluation value predicted by the network is shown in figure 6. The parameter result ($R^2 = 0.9966$) is shown in table 15. The results show that the evaluation effect of this model is good and the accuracy is high. The error (e∈0.01, −0.03) between the predicted value and the actual value of the test set is in line with the experimental expectation, as shown in table 15. The experimental results show that the constructed BPNN has high prediction accuracy and can be used to establish the mapping relationship between users' Kansei semantics and elderly-oriented HMI design features. Similarly, the prediction results' comparison of the training set (figure 6), the error between the predicted value and the actual value of the test set (figure 7) and the parameter results (table 15) for the remaining three Kansei words can be obtained.

Finally, in order to obtain the HMI design features' combination with the highest elderly-oriented degree, namely the AD cars HMI design features' combinations with the highest average value of Kansei words evaluation, there are 5 key features reduced by rough set attributes and each design feature has 6,4,3,6 and 4 categories respectively. Therefore, there are a total of $6 \times 5 \times 3 \times 6 \times 3 = 1620$ combined design schemes. Through computer coding all combinations and taking them as input layer parameters of BPNN model, the perceived value corresponding to each combination design scheme is calculated. For each sample, the evaluation value of four Kansei words is averaged and the maximum value is selected as the basis for evaluating the elderly-oriented degree. The maximum mean value of perception evaluation is 4.28175, and the corresponding design features' combination is the optimal combination of AD cars HMI elderly-oriented design. The number of corresponding design groups us 3,3,3,4,1. This method will take the evaluation value of each Kansei words with a balanced way. It is believed that only when all aspects reach a relatively high elderly-oriented level will the overall design be more suitable for middle-aged and elderly users.

In order to verify the effectiveness of the proposed method more clearly and truly, the author takes the experimental results as a reference. Namely, in the morphological analysis table, the overall color (3), the mode of speed display(3) and the font display of rotate speed (3), the reminding color of turning(4) and the mode of fuel indicator display(1) are selected. For other design features, the design categories with higher elderly-oriented degree are selected in table 7. By using graphic design software such as Figma and AI and in combination with designers' subjective beauty and creativity, the elderly-oriented HMI design of AD cars is obtained, as shown in figure 8. The usage scene is built by using Cinema 4D, as shown in figure 9. A total of 210 subjects (113 persons are from 35 to 45 years old; 97 persons are over 45 years old, with 3 years or more than 3 years' driving experience) make a score on the HMI design of AD cars in figure 6 by using a 7-step Likert scale; the average score is 5.68, which is significantly higher than the average score of 3.5, fully proving the effectiveness and feasibility of the proposed combination method. Designers can use this important reference to guide the early stages of elderly-oriented design development, thus meeting the sentimental needs of middle-ages and elder users.

IV. RESULT ANALYSIS AND DISCUSSION

A. DESIGN RESULTS

With the global aging problem becoming more and more prominent, elderly-oriented design has become an important issue in the design field. Various industries are striving to provide more convenient, comfortable and safe products and services for the elderly. However, most of the previous literatures used qualitative analysis to evaluate the elderly-oriented design, which lacks a complete quantitative analysis method. The key of elderly-oriented design is to meet the needs of elderly while adjusting the design parameters to meet their sentimental needs. Therefore, factors such as the physiological characteristics and cognitive ability of the elderly should be fully considered in the design process to ensure the perfection and applicability of HMI function and realize the sustainable development of society. At present, there is no systematic researches on the combination of design features for elderly-oriented HMI. In view of this, in the early stage, combining KE/RST/BPNN is used in this paper to determine the optimal combination of AD cars' HMI elderly-oriented design. AD cars' HMI is taken as the research object; four representative elderly-oriented Kansei words are obtained through Python and FA dimensionality reduction, which are respectively simplicity, wisdom, affinity and intuition. Through morphological analysis, 14 design features and 78 corresponding types of HMI are obtained. Due to its wide variety, it is easy to increase the burden of subjects and designers. The RST attribute reduction algorithm is used to obtain the key design features that have an important influence on the elderly-oriented degree, namely the overall color, the model of speed display, the display font of rotate speed, the reminding color of turning and the model of fuel indicator display. The results show that middle-aged and elderly users are very concerned about the color, font and display mode of key design features when viewing HMI. Finally, the four Kansei words are brought into BPNN respectively and the design combination with the highest Kansei average is predicted to obtain the best HMI elderly-oriented design combination. It is found that in the morphological analysis table, the overall color, display mode of speed, display font of rotate speed, reminding color of turning and display mode of fuel indicator are selected as type 3,3,3,4,1, which can meet the sentimental experience of middle-aged and elderly users to the maximum extent. Based on the experimental data obtained, I optimize the HMI design of AD cars specially for the group of elderly users, focusing on the simplicity of interface and the emotional needs of elderly users so as to better meet the specific usage habits and needs of elderly users. In addition, I believe that the simple and intuitive elderly- oriented design principles also have good adaptability for young users who use the vehicle interaction system for the first time. To test this hypothesis, I recruit a group of young car owners who just purchased this car to evaluate their satisfaction with the elderly-oriented design of HMI in AD cars in this research. A total of 112 subjects make a score on the HMI design of AD cars in figure 6 by using a 7-step Likert scale; the average score is 5.24, which is significantly higher than the average score of 3.5. The test results show that the interface I design can not only meet the needs of elderly users, but also be welcomed by young users, which proves that the wide applicability of the elderly-oriented interface I designed in different groups of people. Furthermore, the evaluation

TABLE 16. Comparison of different sentimental mapping algorithms.

Algorithms	Data processing	Fuzzy expression	Reasoning complexity	Adaptability	Loss rate	Decision result
BPNN	High	Moderate	Moderate	High	Low	High
SVM	Moderate	Low	Moderate	Low	Moderate	Moderate
GA	Non	High	Moderate	Moderate	High	Low
DCNN	High	Moderate	Moderate	High	Low	High
QT-I	High	Low	Low	Non	Low	Non
PCA	Low	Low	Low	Non	Moderate	Non

results show that the design method proposed in the paper can effectively meet the different needs of different users. And the HMI design of AD cars by me is the fuzzy front end of the product, and the subsequent optimization design will be continued. At present, we are conducting preliminary negotiations and cooperation with BYD auto company to consider applying this interface design and design method to vehicles' interactive interface design in BYD brand's autonomous vehicle models in the future. In this paper, RST and BPNN in artificial intelligence technology are used to accurately calculate the mapping function of sentimental intention and design features of middle-aged and elder users in KE. Therefore, designers can directly refer to these optimal combinations to help enterprises expand middle-aged and elderly consumer groups, obtain middle-aged and elderly users' satisfaction and significantly improve product sales and market value of enterprises.

B. BPNN AND ARTIFICIAL INTELLIGENCE TECHNOLOGY IN KANSEI MAPPING PROCESS

In KE, the weight of Kansei index and the weight of design feature index need to be determined first so as to provide data references for the subsequent design process. In previous studies, Xue et al. [53] obtained the partial correlation coefficient of product elements through quantitative theory type I to get the priority ranking of product design elements that affect Kansei images. Hartono [54]discovered the performance of each service attribute based on customers' perception through Kano model and screened out the most critical service attribute. Michele STAIANO and other scholars analyzed the results of all evaluators through AHP to get their preference direction for the most attractive Seat Concept. Gan et al. [55] used social robots as carriers to determine the key features of their appearance aesthetics and emotional preferences through linear regression analysis. The above methods have disadvantages such as subjectivity, computational complexity and lack of data support. Therefore, in order to distinguish the design features' influence degree on Kansei factors, previous method is replaced by artificial intelligence technology RST attribute reduction algorithm. The core of KE is to build a mapping model between users' sentimental intentions and design features. The linear statistical methods used in the past, such as quantitative theory type I (QT-I) and principal component analysis (PCA), cannot directly measure and quantify the subjective and uncertain information of users' emotions. With the development of artificial intelligence technology, such as Support Vector Machine (SVM) [56], Genetic Algorithm (GA) [57], Deep Convolutional Neural Network (DCNN) [58] and others have been applied to construct the mapping relationship between products' design features and users' emotions [59]. To compare, the computational complexity of SVM is high and the processing ability of high-dimensional data is weak; while DCNN has high requirements on image size and input data is relatively weak in non-image data processing. GA has been widely and successfully used in engineering optimization problems, but it can only calculate a small number of optimal solutions. Compared with the traditional parameter statistics and NN method, BPNN has strong data adaptability and model fitting ability. BPNN can directly learn from known data and make accurate predictions, and it is more suit-able for various types of data when constructing mapping models. Table 16 shows the comparison between BPNN and other methods in terms of Kansei mapping. In combination with the HMI design of this study case, there are multiple types of data such as images and texts. Therefore, an elderly-oriented HMI design process based on KE/RST/BPNN is proposed in this paper. Compared with the traditional KE method, the combination of RST and BPNN can deal with a large scale of Kansei data, which uses RST attribute reduction algorithm to exact key design features and uses BPNN to establish nonlinear mapping structure between key design features and Kansei data. This design process solves the problems of computational complexity and lack of linear model fitting ability, which can quickly provide effective and accurate Kansei analysis results.

V. CONCLUSION

Based on KE, RST and BPNN in artificial intelligence technology are combined in this study to develop AD cars' HMI elderly-oriented design. Under the framework of KE research, the Kansei intention evaluation of middle-aged and elderly users on HMI design is obtained, and the factor analysis method is used to extract 4 representative elderly-oriented Kansei words. After obtaining the HMI form deconstruction table, RET selects the key design features that have an important impact on the elderly-oriented degree and uses BPNN to build a mapping model between the users' representative sentimental preference and the key design features, thus obtaining the optimal combination of AD cars' HMI elderly-oriented design that meets the sentimental preference of middle-aged and elderly people. The main contributions of this paper include:

a) Under the framework of KE research, a design process based on the combination of KE/RST/BPNN is proposed.
b) The RST attribute reduction algorithm is used to identity the key design features of HMI that have important influences on the elderly-oriented degree.
c) Instead of the traditional linear analysis method, BPNN establishes the mapping relationship between the Kansei of middle-aged and elderly users and the key design features of HMI, thus obtaining the optimal combination of AD cars HMI elderly-oriented design that meets the sentimental preferences of middle-aged and elderly people.

This paper still has several limitations that need to be improved:

a) Taking the strong uncertainty and variability of emotion into account, I consider introducing physiological signal recognition and combining dynamic feedback in future research to improve the accuracy and reliability of emotion recognition.
b) The Elderly-oriented HMI design should not only consider the appearance of HMI design. Further improvements can be made in terms of functionality, navigation, error handling, feedback and validation, tutorials and other aspects.
c) In this paper, only BPNN is used to construct Kansei mapping model. In the future, a variety of methods can be used to construct Kansei mapping models.

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