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# Predicting User Preference for Innovative Features in Intelligent Connected Vehicles from a Cultural Perspective

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**Abstract:** The increasing level of intelligence in automobiles is driving a shift in the human–machine relationship. Users are paying more attention to the intelligent cabin and showing a tendency toward customization. As culture is considered to be an important factor in guiding user behavior and preference, this study innovatively incorporates cultural and human factors into the model to understand how individual cultural orientation influences user preference for innovative human-machine interaction (HMI) features. Firstly, this study considered five Hofstede cultural dimensions as potential impact factors and constructed a prediction model through the random forest algorithm so as to analyze the influence mechanism of culture. Subsequently, K-means clustering was used to classify the sample into three user groups and then predict their preferences for the innovative features in the intelligent cabin. The results showed that users with a higher power distance index preferred a sense of ceremony and show-off-related features such as ambient lighting and welcome mode, whereas users with high individualism were keen on a more open and personalized in-vehicle information system. Long-term orientation was found to be associated with features that help to improve efficiency, and users with a lower level of uncertainty avoidance and restraint were more likely to be attracted to new features and were also more willing to use entertainment-related features. The methodology developed in this study can be widely applied to people in different countries, thus effectively exploring the personal requirements of different individuals, guiding further user experience design and localization when breaking into a new market.

**Keywords:** intelligent cabin; electric vehicle; intelligent connected vehicle; HMI; random forest; Hofstede cultural dimensions; power distance; user preference prediction

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## 1. Introduction

With the rapid development of autonomous driving (AD) technology, drivers' hands and vision are gradually being liberated. Vehicles are no longer limited to driving alone, and hours on the road previously spent driving could be used to video call a friend, watch a funny movie, or even work [1,2]. Driven by the current trend of electrification, intelligentization and connectivity, original equipment manufacturers (OEMs) have started to make extensive use of new technologies and make their products more differentiated and personalized through the combination of hardware and software [3,4]. So, intelligent connected vehicles (ICVs) emerge as the times require.

The intelligent cabin is the most important touch point between users and ICV, gathering a large number of innovative Internet technologies and intelligent interaction technologies, which has become a key consideration for consumer decision making [4,5]. How to accurately grasp the personalized needs of different users and conduct research and development (R&D) on the cabin has become a key concern for OEMs. OEMs have begun to pay attention to user needs and have suggested various new feature concepts for non-driving-related activities inside the cabin. However, for many on-sale models renowned for their rich innovative human-machine interaction (HMI) features and good user experiences, there is numerous user feedback indicating their disinterest with certain features. It remains questionable whether the new feature concepts proposed by OEMs have correctly considered user needs to make the designs that are suitable for specific user groups [6]. Hence, it is necessary to understand the preference of different users for new features in ICVs to provide users with features they like and offer meaningful user experiences.

In the past two decades, many researchers have tried to find out the mystery of users' consumer decision making from different perspectives, mainly focusing on economic incentives, local policies, product features and brand services [2,7–10]. However, It is still up to the users themselves to make the final consumer decision [11]. Subjective internal causes such as the user's personality, past experience, product preference, etc., are the real decisive factors. For people with different cultural backgrounds, their education, social cognition, emotional tendencies, customs and habits are so different that they have cultivated distinct superficial practical activities and deep values [12–16].

On one hand, users' consumption willingness and product preferences often reflect the differences in cultural orientations [17–19]. For example, in American and European cultures, the relationship between people is more equal, so the automotive intelligent assistant usually appears as a partner role and will directly address the user's name. While in the Confucian cultural circle represented by East Asia, users prefer an assistant with the image of a butler or servant and want them to address themselves as "master". Therefore, human factors must be taken into account in ICVs' HMI function design [20]. Only by fully realizing the needs discrepancy between different people can their user preferences be correctly grasped, thus forming the basis for further personalized function design and user experience improvement [21,22]. Culture is a stable bridge that connects users' changing external performances and unchanging essential needs.

On the other hand, technology adoption can also be seen as a process of innovation diffusion, and cultural background and cross-cultural differences are the main factors influencing whether users accept new technologies and innovations [1,23,24]. According to distributed cognition theory, in the process of innovation diffusion, knowledge does not only exist within an individual but also in the individual's social and physical environments [25,26].

Many scholars have also provided their own insights into this research theme, demonstrating that people's perceptions of social and cultural environments have a significant impact on user consumption and acceptance of new technologies. In the field of transport, scholars have carried out a large number of studies related to acceptance and consumer willingness around automobiles [27–31], confirming that culture has a significant impact on different aspects of automobiles such as autonomous driving and user interface (UI) design and that innovative designs that match the cultural values of the target users are more likely to win the approval of consumers [23,32,33]. However, the current research mainly focuses on the cultural differences between countries and nations and still lacks research on individual cultural orientations at the micro level, ignoring the inconsistencies within the same country or region [34].

Under the trend that OEMs and users focus more and more on the intelligent cabin, the study aims to explore the influential mechanism between an individual's cultural orientation and the preference for innovative HMI functions in the intelligent cabin, which will help R&D to grasp the personal user needs of current user groups from a cultural perspective. Focusing on young Chinese users, the study will collect user preference data through qualitative and quantitative methods, establish a random forest model to quantify the influence of cultural and human factors on preferences for innovative HMI functions and further segment potential consumers into different user groups with similar cultural orientations to predict their user preferences.

## 2. Literature Review

### 2.1. Cultural Models

Culture is the origin of studying the internal logic of user behavior. Psychologists believe that culture affects people's memory, judgment, perception and decision-making, which in turn plays an important role in guiding people's behavior [35]. Differences in cultural backgrounds make consumers value some product attributes more than others, which will affect their use and perception of this product [36]. Therefore, people's tendency to select a product is deeply linked to culture and values.

Given the important role of culture, many scholars have been studying culture for a long time and tried to define culture, an extremely abstract concept, from different perspectives. Johann Gottfried von Herder, a famous German thinker and philosopher in the 18th century, was the first to explore the relationship between human beings, society and culture. He proposed that culture is a living mode universally agreed upon by the whole society, and it represents the spiritual core of a nation or area [37]. Some other scholars consider culture to be the whole way of people's lives, including a society's common sense, technologies and artifacts.

To further study and compare the differences in cultural orientations among different groups, many cultural models have been proposed as a tool. The iceberg cultural model believes that when observing the culture of an area, people can only see 10% of the basic characteristics, while the remaining 90% is as difficult to measure as the part of an iceberg hidden below the surface of the water [36]. The invisible section aspects typically include beliefs, values, opinions, preferences and other intangible drivers that cannot be easily changed by external factors. Richard, an American scholar, has conducted an in-depth and extensive study of the iceberg model and finally evolved the onion model on the basis of the iceberg model. It divided culture into three layers. The core, wrapped in layers like the kernel of an onion, is the cultural values that are the most profound and difficult part to understand [38]. Then the outer layer is the social norms such as rituals and customs, something that most people in a cultural group would do in a certain situation. The outermost layer, like the skin of an onion, can be easily observed and usually is expressed through symbols like languages, works of art and consumption preferences.

According to various cultural models, cultural values internally guide people's outward behavior in all areas. That is also true in the transport and automobile fields. Although there are not many studies that systematically discuss the influences of culture, in fact, there are still some scholars indirectly demonstrating the significant role of it. For example, most of the results for the same topic are limited by the differences in user samples, which leads to the fact that they can only be applied in a certain area or research scenarios, and the degree of explanation is much poorer when they are applied in other regions. User samples from different regions tend to carry different cultural characteristics, so the variability of factors such as gross domestic product (GDP) and region can partly expose the role of cultural background, so it is extremely necessary to regard culture as an important human factor in the research of user preferences.

### 2.2. Hofstede's Cultural Dimensions Theory

Geert Hofstede, a Dutch psychologist professor, has conducted large-scale research on cultural values in the famous multinational company IBM. After analyzing the data, he defined culture as "the software of the mind that distinguishes members of one ethnic group from members of other groups" [39]. He also regarded culture as a broad and collective model of perceptions, emotions and actions and as having a significant impact on the operation pattern of the whole society, groups within the society and individuals of those groups. Fascinated by the consequences of cultural differences, Hofstede has developed a six-dimensional framework to help people identify, quantify and understand the invisible cultural forces. According to Hofstede's cultural dimension theory, power distance, uncertainty avoidance, individualism versus collectivism, masculinity versus femininity, long-term versus short-term orientation and indulgence versus restraint are used to transform abstract culture into measurable variables [39,40]. The definition, characteristics and typical countries of each dimension are shown in Table 1. Subsequently, many sociologists and anthropologists have also put forward their own ideas, such as the seven cultural dimensions theory proposed by the Dutch psychologist Fonts Trompenaars and the four cultural dimensions proposed by Edward Twitchell Hall Jr.

**Table 1.** Hofstede's six cultural dimensions.

| Dimension | Definition | Characteristics | Typical Countries |
| --- | --- | --- | --- |
| Power Distance | This constitutes the extent to which the less powerful members of an organization or institution—such as a family—accept and expect that power is distributed unequally [39]. | High Power Distance:<br>• Privileges and status symbols are normal and popular. Superiors and subordinates are unlikely to see each other as equals in the workplace.<br>Low Power Distance:<br>• There tends to be more equality between different people, and status symbols are frowned upon. Employers and managers are more likely to ask employees for input. | PDI Index:<br>- China (80)<br>- Japan (54)<br>- USA (40)<br>- Germany (35)<br>- Norway (31)<br>- Denmark (18) |
| Uncertainty Avoidance | This dimension reflects the extent to which members of a society attempt to cope with their anxiety by minimizing uncertainty. It refers to how threatening change is to a culture [39]. | High Uncertainty Avoidance:<br>• Institutions and individuals within these societies seek to minimize the unknown through strict rules, regulations and so forth. There is a hesitancy toward new products and technologies.<br>Low Uncertainty Avoidance:<br>• The unknown is more openly accepted, and less strict rules and regulations may ensue. There is a fast acceptance of new features such as mobile phones and the Internet. | UAI Index:<br>- Japan (92)<br>- Germany (65)<br>- Norway (50)<br>- USA (46)<br>- China (30)<br>- Denmark (23) |
| Individualism versus Collectivism | This involves the integration of individuals into groups. Individualism is focused on the rights and concerns of each person, while collectivism stresses the importance of the community [39]. | High Individualism:<br>• People may feel that their own well-being and goals carry greater weight. And, there is individual ownership of resources, even for children.<br>High Collectivism:<br>• People may strive to sacrifice their own happiness for the greater good of the group, and they believe resources should be shared with relatives. | IDV Index:<br>- USA (91)<br>- Denmark (74)<br>- Norway (69)<br>- Germany (67)<br>- Japan (46)<br>- China (20) |
| Masculinity versus Femininity | This dimension looks at how much a society values traditional masculine and feminine roles. A masculine society values assertiveness, courage, strength and competition, while a feminine society values cooperation, nurturing and quality of life [39]. | High Masculinity:<br>• A masculine society values assertiveness, courage, strength and competition. People live in order to work, and careers are compulsory for men and optional for women.<br>High Femininity:<br>• A feminine society values cooperation, nurturing and quality of life. There is a higher share of working women in professional jobs. | MAS Index:<br>- Japan (95)<br>- China (66)<br>- Germany (66)<br>- USA (62)<br>- Denmark (16)<br>- Norway (8) |

**Table 1.** *Cont.*

| Dimension | Definition | Characteristics | Typical Countries |
|---|---|---|---|
| Long-Term versus Short-Term Orientation | This constitutes the degree to which cultures encourage delaying gratification or the material, social and emotional needs of their members. A society with long-term orientation tends to focus on the future in a way, while a short-term orientation society places a stronger emphasis on the present rather than the future [4]. | Long-Term Orientation:<br>• People emphasize traits such as persistence, perseverance, thrift, saving, long-term growth and the capacity for adaptation.<br>Short-Term Orientation:<br>• People believe that efforts should produce quick results. This culture may result in unrestrained spending. | LTO Index:<br>- Japan (88)<br>- China (87)<br>- Germany (83)<br>- Denmark (35)<br>- Germany (31)<br>- Norway (35)<br>- USA (26) |
| Indulgence versus Restraint | This is the extent and tendency of a society to fulfill its desires. A highly indulgent society allows relatively free gratification and high levels of bon de vivre. But, a high-restraint society tends to suppress the gratification of needs and regulate them through social norms [39]. | High Indulgence:<br>• People may tend to spend more money on luxuries and enjoy more freedom when it comes to leisure time activities. Maintaining order in the nation is not given a high priority.<br>High Restraint:<br>• People are more likely to save money and focus on practical needs. Maintaining order in the nation is considered a high priority. | IVR Index:<br>- Denmark (70)<br>- USA (68)<br>- Norway (55)<br>- Japan (42)<br>- Germany (40)<br>- China (24) |

Compared with other cultural theories, Hofstede's cultural dimensions theory is still the most authoritative and widely recognized theory in the field of cultural studies. As an effective tool to compare different cultures, it has been widely applied in different cross-cultural research like finance, insurance, consumption, advertising, global marketing and international negotiations [19]. Hofstede's methodology can intuitively explain the cultural differences of different areas, helping people to understand and win insights into national cultures. What is more, Hofstede's cultural framework is more systematic than other theories. It has also been verified and supplemented by many other scholars in the past thirty years, still having strong vitality and credibility.

Previous studies have shown that Hofstede's theory plays an important role in the study of consumption and product preferences [12,19,41]. For example, according to an empirical study with data from sixty countries, power distance, long-term orientation and masculinity were positively associated with the demand for life insurance, while individualism and uncertainty avoidance were negatively related to it. In the field of automobiles, cultural background leads to differences in a user's ability to cope with uncertainty and the willingness to accept innovative technologies. A study among 21 countries has shown that ethnic culture was an important factor in affecting the market share and acceptance of electric vehicles (EVs) [17]. Uncertainty avoidance, individualism, masculinity and indulgence had an obvious negative impact on sales, while long-term orientation could be effective in facilitating EVs' market expansion. At the same time, for complex automotive HMI interactions, there is a correlation between culture and automotive HMI usability factors especially in the area of "Ease of Learning" [36], and Chinese users are likely to prefer shallow (flat) information hierarchies that are less structured [22]. Although other scholars have introduced new models to measure culture's consequences, they have not been as effective as Hofstede's six dimensions. Some studies have also proved that the influence of basic human factors such as gender and age cannot be ignored while researching culture [23,42].

### *2.3. Individual Cultural Orientation*

However, the concept of culture is often associated with national and ethnic identities. Since the cultural characteristics of a country are not closely related to each individual, regarding culture only at the macro level cannot explain the diversity of human beings [11,40,43,44]. Especially in China, a mixed multi-ethnic country that has a vast territory and a long history, people show great differences in perspectives of customs, language, symbols, ceremonies, religious beliefs, etc. In addition, economic globalization and the fast development of internet technology have enhanced exchanges among countries. Influenced by a combination of traditional values, Western thoughts and new concepts formed in the process of reform and opening-up, the ideologies of contemporary Chinese people have undergone significant changes. Furthermore, the socialist market economy has spawned a variety of stakeholders, which in turn has produced diversified cultural backgrounds. Under such circumstances, it is inaccurate to uniformly adopt the national character in the macro sense to generalize each individual's traits [17].

With ICVs gradually becoming more personalized, it is essential to accurately identify the traits of each potential consumer to gain an advantage in product feature design and positioning. Therefore, it is obviously more meaningful to pay attention to the influence of individual cultural orientations when considering user preferences. In previous studies, Hofstede's cultural dimensions theory has been widely applied to measure individual cultural orientations in many fields [19,45,46]. In the field of transport, scholars have begun to explore the effect of potential consumers' cultural orientations on residents' consumption desire for electric vehicles in India [43]. The research has shown that collectivism and long-term orientation are important factors influencing their consumption decisions.

### *2.4. Summary*

To sum up, although research has demonstrated the significant influence of culture in various aspects of transport and automobiles, such a kind of influence is often expressed indirectly regarding country and region and lacks a systematic analysis of the role of culture. In addition, Hofstede's theory has been shown to affect human–vehicle interaction behaviors and HMI UI design, but there is still a lack of study on how it affects users' preferences for innovative features for ICVs. Last but not least, current cultural research focuses more on macro-level national or ethnic characters, ignoring the inconsistencies within the same cultural circle.

Firstly, culture is treated as a direct influencing factor in this study. Theories from the field of cultural studies are applied to the research of ICVs on the basis of previous studies. Secondly, this study, for the first time, takes users' preferences for innovative HMI features in intelligent cabins as the main research object, aligning with the current trend that OEMs vigorously apply emerging technologies and develop new features for the cabin. Currently, there is a lack of research specifically targeting innovative HMI features in ICVs, representing a new research direction. Thirdly, this study focuses on the cultural orientation of individuals rather than the macro-national character of a country, which will help OEMs make domestic market segmentation and product positioning.

Therefore, referring to the Hofstede theory, this study divides diversified individuals into several user groups with similar values and consumption views through individual cultural orientation. This study not only fills the research gap but also enhances the realistic practical value.

## 3. Materials and Methods

### *3.1. Control Variables*

#### 3.1.1. Demographic Information

Past studies have shown that Chinese people's behaviors are largely influenced by people in their interpersonal circle because China is a society with high collectivism culture, so demographic variables are closely related to user preferences [23,25,42,47]. In addition, users' past experience of using ICVs will help form their own attitude toward preferences of innovative HMI features in the subsequent use process [3,22].

Due to the above reasons, this study adopted gender, age and city as three variables to reflect the basic demographic information. Car brand, average weekly mileage and average weekly usage count of the in-vehicle information system (IVIS) were also taken into account to comprehensively show users' past experiences of innovative HMI features and provide a reference for the subsequent division of the user groups.

#### 3.1.2. Cultural Dimensions and Individual Cultural Orientations

The study selected appropriate cultural dimensions for subsequent analysis based on the following three principles:

1. These cultural dimensions are able to effectively show cultural diversity among different countries and nations;
2. These cultural dimensions can clearly explain users' different performances in automotive human–vehicle interaction and user experience;
3. These cultural dimensions have been validated by multiple authoritative experts in the cultural field and are independent of each other across different dimensions.

Hofstede's cultural dimensions are the most generally applicable model in the field of cultural research at present [22,34]. Its mature system and high credibility make it the core variable to measure individual cultural orientations in this study. Since Chinese traditional values tend to cultivate more stereotypical behaviors and concepts between men and women, the dimension of masculinity/femininity can be reflected to a certain extent through people's gender. So, this dimension was removed from the variables under comprehensive consideration.

Therefore, power distance, uncertainty avoidance, individualism versus collectivism, long-term versus short-term orientation and indulgence versus restraint [2] in Hofstede's cultural dimensions theory were selected to measure individual cultural orientations in this study. An individual's orientation to a particular cultural dimension is represented by a total score of five related questions taken from the Hofstede standardized questionnaire (Values Survey Module 2013 questionnaire).

#### 3.1.3. User Preferences for Innovative HMI features

Thanks to the rapid development of new energy vehicles in China, the new EV brands led by NIO, Xpeng and Leading Ideal have developed many innovative new HMI features, taking the concept of intelligent cabin to the extreme [4]. Through qualitative interviews with 30 users and 5 experts in the automotive field, this study gained an in-depth understanding of ICV potential users' psychological conditions, daily needs and behavioral characteristics. Not only did the qualitative study preliminarily identify the fact that there exists a large influence of culture on user needs, but it also helped to filter out 18 innovative HMI features that are currently widely used in ICVs and highly rated by users. These 18 innovative HMI features are listed in Table 2.

**Table 2.** Innovative HMI features in intelligent cabin.

| Feature | Description |
|---|---|
| Ambient lighting | Ambient lighting is a function that decorates the car and sets the mood in the interior. It can interact with passengers and conduct some information through the rhythm of colors, bringing a strong sense of ceremony and creating a relaxing and pleasant atmosphere. |
| Welcome mode | When the user approaches the vehicle, the courtesy lighting comes on and projects a personalized pattern, the screen displays welcome words and the seat automatically adjusts itself to a suitable position for easy entry, bringing the user ingress and egress ceremony. |
| Diverse UI themes | The theme of the in-vehicle information system (IVIS) switches with different usage scenarios, seasons and festivals, bring users a more interesting experience (e.g., Tesla's vehicle model on the instrument central screen (ICS) will be replaced by Santa's sleigh car during Christmas Day). |
| Birthday surprises | On the user's birthday and special anniversaries, the vehicle will play a birthday song, offer well wishes on the screen, give a surprise gift or make hidden surprises in the IVIS. |
| Over-the-air technology (OTA) | Vehicles are able to remotely manage and upgrade software through a mobile communications interface. Similar to upgrading a mobile phone system, each OTA is aimed to improve vehicle performance, fix bugs, gain more new features, etc. |

**Table 2.** *Cont.*

| Feature | Description |
|---|---|
| Virtual assistant | A voice-activated virtual assistant with a unique image that provides vehicle control on user's command. The equipped emotion engine allows it to communicate with users like a human being and respond to the user's words in an interesting way. |
| Personal relaxing space | The cabin acts as a private, comfortable, cocoon-like hideaway and a personal space where customers can relax, spend quality time and even work. |
| Personalized mode | The vehicle gives users more control in the form of personalized modes, customized buttons, etc. Users can set up the vehicle according to their own usage habits. |
| Intelligent recommendation | Through big data and recommendation algorithms, the vehicle actively predicts the user's interests and needs in order to automatically push the required information for the user, improving the user's search efficiency. |
| Calendars | Through data sharing between the vehicle and mobile phone calendars, the user's travel information is automatically synchronized to the IVIS, so the users can achieve one-click navigation to the destination and arrange their working schedules during the daily commute. |
| Unconscious pay | It is a fast payment service for scenarios like parking, charging and car wash. The vehicle is bound to the mobile payment account so as to achieve rapid payment by license plate recognition, without stopping to scan the code and pay. |
| Occupant monitoring system (OMS) | The vehicle will monitor the status of passengers through in-cabin sensors and cameras, combined with facial recognition and posture tracking, to provide timely warnings and interventions in the event of risky driving behavior by the driver or abnormal status of the passenger. |
| Safeguard | It is a safety guard function based on the original hardware of the vehicle. The vehicle can record images and send alarms to the mobile phone so that the owner can always pay attention to safety when away from the vehicle. |
| Remote control | Users are able to remotely control the vehicle's locking/unlocking, seats, doors and windows when away from the vehicle via the mobile app and can also remotely authorize the vehicle for family members and friends to use. |
| Entertainment system | Users can watch films or play games through the screen, sound system, steering wheel and other hardware in the cabin under the premise of not affecting driving safety. The IVIS supports the connection of gaming peripherals, giving users a more enjoyable entertainment experience. |
| Multi-screen collaboration | In the cabin, users can share information with the ICS, co-driver screen and rear-row screens to communicate with other passengers easily. The vehicle can also connect with user's mobile phones and smart home devices to share files, information and control commands. |
| Vlogging | Users are able to take photos or videos via in-cabin and outside cameras. The software on ICS enables users to quickly edit the videos, add filters to them and then share with one click. |
| Application ecosystem | Through co-operation with internet vendors, the IVIS can access lots of third-party applications covering all aspects of life, providing users with a more convenient, efficient and continuous car experience. |

### *3.2. Samples and Data Collection*

This study collected first-hand data through a structured quantitative questionnaire. The samples focused on young car users, who have gradually become the main consumer groups after the consumption upgrade and have a certain ability and willingness to consume as well as stable cultural orientations. What is more, these people have a higher acceptance of ICVs and also have a certain degree of understanding of the intelligent cabin and new features [22].

The questionnaire was distributed through the online platform in Beijing, Shanghai, Hangzhou and Chengdu, which are the first-tier cities with a high level of acceptance of electric vehicles. A total of 509 samples were collected, the overall response rate of the questionnaire was 100% and the number of valid questionnaires was 507, with an effective rate of 99.6%. The sample size of this questionnaire is greater than five times the number of valid questions, which meets the basic requirements of the sample size. Concerning the demographic profile of the samples, female (143) and male (366) representation was 28% and 72%; 163 (32%) were in the 20–25 years age group, whereas 223 (40%) and 143 (28%) were, respectively, in the 26–30 and 31–35 age group; and 457 (90%) had already owned a car and were in the habit of using it, while 52 (10%) had no recent intention of purchasing a car. The details are shown in Table 3.

**Table 3.** Characteristics of sample ($n$ = 507).

| Item | Category | Number | Percentage |
|---|---|---|---|
| Age | 20~25 years old | 163 | 32% |
| | 26~30 years old | 203 | 40% |
| | 31~35 years old | 143 | 28% |
| Gender | Male | 366 | 72% |
| | Female | 143 | 28% |
| City | Beijing | 128 | 25% |
| | Shanghai | 255 | 52% |
| | Hangzhou | 54 | 11% |
| | Chengdu | 68 | 13% |
| Car brand | Luxury brand | 252 | 50% |
| | Mainstream joint venture brand | 81 | 16% |
| | Domestic brand | 81 | 16% |
| | New energy brand | 43 | 8% |
| | Have no car | 52 | 10% |
| Average weekly mileage | 200~300 km | 302 | 59% |
| | 300~500 km | 192 | 38% |
| | More than 500 km | 15 | 3% |
| Average weekly usage count of IVIS | Under 3 per week | 34 | 7% |
| | 3~6 per week | 441 | 87% |
| | At least once a day | 32 | 6% |

### *3.3. Measures and Procedure*

The independent variables of the questionnaire consisted of two parts: basic demographic information and individual cultural orientation score, and the dependent variable was users' preferences for the 18 innovative HMI features. The basic demographic information included gender, age, city, car brand, average weekly mileage and average weekly usage count of in-vehicle information system (IVIS). The part of individual cultural orientation was scored in the form of the Likert scale, with 1 being the lowest degree and 5 being the highest degree. The specific formulation of the options varied with the questions. To ensure high standardization and validity, the questions in this part were selected from the standard questionnaire used by Hofstede and adapted with reference to previous studies to fit well with the present study [34]. A total of 15 questions were selected from this study, and each user's orientation toward each cultural dimension was assessed by scores on three related questions. User preferences were measured by a two-part question. Firstly, two ranking questions about the main factors and features that users pay the most attention to when using the car provide the reference for the final ranking and weighting comparison of the features preferred by each user group. Secondly, people would make binary classification choices (like/dislike) for 18 features to obtain user preference data that could be used for subsequent analysis.

The data were initially processed by SPSS 25 after the questionnaires were collected. Since the basic information of users is in the form of character strings, the study used the numbers 1–5 to refer to different options for the subsequent data processing. Moreover, to avoid interference in the process, nominal variables and ordered categorical variables with unequal distance between different levels were treated as dummy variables so that each variable referred to at most 2 meanings. The answers in the cultural dimension part were converted into a score of 1–5 points, and the total score (0–15 points) of 3 questions about a specific cultural dimension was also calculated to represent individual cultural orientation. The score of each cultural dimension was converted to 5 grades (1–5 scales from low to high, respectively) according to a 3-point gap to balance the weights among all the variables, avoiding the data bias generated by too large a difference in scores. This study adopted 0 or 1 as a binary classification variable in the part of user preferences assessment to indicate that users do not want or want the car to have a certain feature.

Common machine learning algorithms for binary classification problems include logistic regression, support vector machine (SVM) and random forest [48].

Random forest is a machine learning algorithm that adopts the concept of ensemble learning. It combines multiple CART decision trees and achieves better predictive performance by outputting the mode of the predicted results from decision trees [49]. Random forest can not only effectively assess the role of different features in the classification problem with high accuracy [50–52], but it also handles a large number of input variables with high-dimensional features without dimensionality reduction. What is more, the random forest algorithm is highly inclusive of default values and unbalanced datasets; thus, it is suitable for this study. Taking the "ambient lighting" as an example, the predictive accuracy obtained with the random forest algorithm is 93.521%, indicating a satisfactory overall performance.

Logistic regression is a simple, efficient and commonly used classification model. Its advantage lies in its ability to obtain a classification probability and robustness to small noise in the data [53]. However, it may not handle categorical variables with many levels well. In this study, there exist some categorical variables such as gender, age group and usage frequency, making logistic regression unsuitable. Moreover, categorical probability from logistic regression is not the main focus of this study, thus not bringing out its strengths. Taking the data of ambient lighting into the logistic regression model yields a classification accuracy of 86.982%, which is just a moderate performance. Therefore, logistic regression is not considered in this study.

The SVM algorithm excels in handling large feature spaces and interactions among nonlinear features. However, its efficiency decreases with large sample sizes, and it performs poorly on imbalanced datasets. Through the SVM algorithm, the accuracy of classifying user preferences for "ambient lighting" is 91.765%, which is slightly weaker than the random forest model. Unlike decision trees, SVM cannot provide feature importance values, meaning that its interpretability is significantly weaker than random forest. Moreover, the data obtained in this study are an unbalanced sample set. The SVM algorithm is not considered for use in this study.

Through comparing different algorithms [54,55], it was found that the random forest algorithm achieved the highest predictive accuracy and demonstrated strong interpretability. Therefore, the model is built by the random forest algorithm to find out the human factors that have an influential role in the user preference for innovative HMI features and to deeply analyze the influence mechanism of individual cultural orientation.

After multiple features enter the model, decision trees commonly employ the *Gini* index to determine the selected features. The *Gini* index is a parameter used to measure the ability of a decision tree to distinguish sample data and select attributes for classification. A lower *Gini* index indicates higher dataset purity. The *Gini* index is defined as follows:

$$Gini(D) = \sum_{k=1}^{K}\left(\frac{|C_k|}{|D|}\right)^2 \tag{1}$$

where $D$ represents the dataset to be distinguished, and $C_k$ represents the subset of samples belonging to the $k$th class in $D$.

CART calculates the *Gini* index for all feature nodes, starting from the root node of the decision tree. When attribute $A$ divides the training sample set $D$ into $D_1$ and $D_2$, then the *Gini* index formula of E after separation is (taking the example of determining whether feature $A = a$ is true)

$$Gini(D, A = a) = \frac{|D_1|}{|D|}Gini(D_1) + \frac{|D_2|}{|D|}Gini(D_2) \tag{2}$$

Among them, $|D_k|/|D|$ is the probability of a subset of $k$ ($k = 1, 2$).

Subsequently, the calculation results of all features are compared, and the feature with the smallest Gini index is selected as the best classification attribute. Following this principle, the data in the set are classified accordingly. In random forests, $n$ samples are randomly selected from the dataset, and $k$ features are randomly selected from all features. Then, this process is repeated m times (building m decision trees). Finally, the classification result is decided by the voting results of m decision trees. The results are shown in the following equation [49] where $y$ is the output variable, and $x$ are the input variables.

$$H(x) = \mathrm{argmax} \sum_{ik} I(h_i(x) = y) \quad (3)$$

In this study, the random forest model was constructed by calling the sklearn module through Python, setting the training set and test set as 75% and 25% and the number of decision trees as 100. The rest parameters in the model were kept at default values. The influences affecting each dependent variable are explored through loops.

At last, the young potential customers in China were divided into several user groups with different cultural orientations by the clustering algorithm so that the characteristics of each group were brought into the random forest algorithm to respectively predict user preferences, helping enterprises to make R&D plans and marketing programs [56].

## 4. Results

### 4.1. Assessment of Measurement Models

In this study, the reliability and validity were tested by SPSS 25, and the results obtained are shown in Table 4 below. The questionnaire's alpha coefficient for the 34 items is 0.823, suggesting that the items have relatively high internal consistency [2]. (Note that a reliability coefficient of 0.70 or higher is considered "acceptable" in most social science research situations.) As shown in Table 5, the Kaiser–Meyer–Olkin (KMO) value is 0.791, which shows that the validity of the questionnaire is quite good. (In general, when the KMO test coefficient is more than 0.6 and the significance probability $p$-value of the Bartlett sphere test statistical value is less than 0.05, the questionnaire is said to have structural validity). The communality analysis in Table 6 shows that the extracted common factors of all indicators are greater than 0.6, which means that the extracted common factor can explain the data of the questionnaire relatively well.

**Table 4.** Reliability statistics.

| Cronbach's Alpha [a] | N of Items |
| --- | --- |
| 0.823 | 34 |

[a] The value is negative due to a negative average covariance among items. This violates reliability model assumptions. You may want to check item codings.

**Table 5.** KMO and Bartlett test.

| Kaiser–Meyer–Olkin Measure of Sampling Adequacy | | 0.791 |
| --- | --- | --- |
| Bartlett's Test of Sphericity | Approx. Chi-Squared | 438.534 |
| | df | 55 |
| | Sig. | 0.000 |

Common evaluation metrics for classification problems include accuracy, the receiver operating characteristic curve (ROC curve), the area under the curve (AUC value) and metrics such as precision and recall obtained through a confusion matrix. ROC curves are plotted with false-positive rates on the horizontal axis and true-positive rates on the vertical axis. The performance of the model is generally evaluated by AUC, with a value closer to 1 indicating better model performance. Besides ROC and AUC, the F1-score is also a common evaluation metric. It is the weighted average of precision and recall. The closer it is to 1, the better the model is. In this study, the prediction accuracy, AUC and F1-score of 18 functions were obtained by the random forest algorithm, as detailed in Table 7.

**Table 6.** Communalities.

| | Initial | Extraction |
|---|---|---|
| Age | 1 | 0.677 |
| Gender | 1 | 0.731 |
| City | 1 | 0.594 |
| Car brand | 1 | 0.671 |
| Average weekly mileage | 1 | 0.614 |
| Average weekly usage count of IVIS | 1 | 0.576 |
| Power distance score | 1 | 0.844 |
| Collectivism/individualism score | 1 | 0.751 |
| Long-term/short-term orientation score | 1 | 0.741 |
| Uncertainty avoidance score | 1 | 0.793 |
| Restraint/indulgence score | 1 | 0.686 |

Extraction method: principal component analysis.

**Table 7.** Indicators for model evaluation.

| Feature | Accuracy | AUC | Weighted Avg F1-Score |
|---|---|---|---|
| Ambient lighting | 0.93521 | 0.73349 | 0.88 |
| Welcome mode | 0.86247 | 0.76555 | 0.87 |
| Diverse UI themes | 0.69548 | 0.69144 | 0.79 |
| Birthday surprises | 0.75442 | 0.72975 | 0.84 |
| OTA | 0.81925 | 0.71396 | 0.86 |
| Virtual assistant | 0.88212 | 0.75877 | 0.92 |
| Personal relaxing space | 0.69745 | 0.69716 | 0.81 |
| Personalized mode | 0.81729 | 0.77963 | 0.91 |
| Intelligent recommendation | 0.78782 | 0.63882 | 0.83 |
| Calendars | 0.89784 | 0.87044 | 0.88 |
| Unconscious Pay | 0.73674 | 0.78627 | 0.79 |
| OMS | 0.83104 | 0.82094 | 0.91 |
| Safeguard | 0.88016 | 0.88971 | 0.93 |
| Remote control | 0.75442 | 0.71584 | 0.72 |
| Entertainment system | 0.86444 | 0.75943 | 0.83 |
| Multi-screen collaboration | 0.75539 | 0.78866 | 0.83 |
| Vlogging | 0.80353 | 0.83765 | 0.89 |
| Application ecosystem | 0.73281 | 0.71568 | 0.85 |

The results show that the prediction accuracy of most of the features is above 70%, which is of high value. Additionally, the AUC values are mostly above 0.7, while F1-scores range from 0.72 to 0.93, indicating a relatively good quality of the model. Yet, the accuracy of "Diverse UI themes" and "Personal relaxing space" is lower than 70%, which still needs to be improved by adding new potential independent variables into the model.

*4.2. Influence Mechanism*

The input independent variables were age, gender, City_Beijing, City_Shanghai, City_Hangzhou, City_Chengdu, Brand_Luxury brand, Brand_Mainstream joint venture brand, Brand_Domestic brand, Brand_New energy brand, Brand_Have no car, average weekly mileage, average weekly usage count of IVIS, power distance score, collectivism/individualism score, long-term/short-term orientation score, uncertainty avoidance score and restraint/indulgence score.

The 18 binary classification variables were ambient lighting, welcome mode, diverse UI themes, birthday surprises, Over-the-air technology (OTA), virtual assistant, personal relaxing space, personalized mode, intelligent recommendation, calendars, unconscious pay, Occupant monitoring system (OMS), safeguard, remote control, entertainment system, multi-screen collaboration, vlogging and application ecosystem.

Taking ambient lighting as an example, after training on a large amount of data in the training set, the model predicted the results of the test set with an accuracy of 93.521%, which is at a superior level. The importance of each variable is shown in Figure 1.

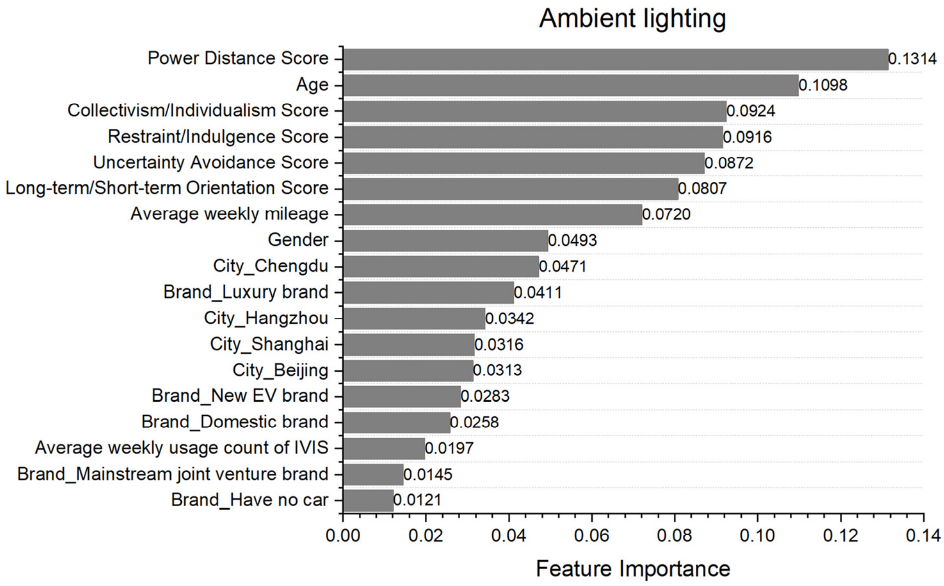


**Figure 1.** Feature importance of ambient lighting from random forest.

It shows that the grade of the power distance accounts for the largest proportion of 13.14%. The second most significant factor is age, accounting for 10.98%. Overall, indicators related to individual cultural orientations make a significant contribution, with five of them ranking in the top six. The importance of factors related to gender and city falls between 3% and 5%, representing a moderate contribution. In terms of past usage experiences, the importance of average weekly mileage is 7.20%, while the importance of average usage weekly count of IVIS is only 1.97%. This may be because ambient lighting is not a new feature exclusive to ICVs; it is also available in many luxury cars. Therefore, owners of luxury cars may have already developed a preference and habit for using ambient lighting. From Figure 1, "Brand_Luxury brand" accounts for a proportion of 4.11%, making it the most significant contributor among all brands, which is consistent with the previous conclusion discussion.

The prediction result and impact factors of user preferences for all 18 innovative HMI features were obtained in the same way and presented in Appendix A as Figures A1–A17. The top five factors for each feature are shown in Table 8.

**Table 8.** Top five factors of each feature.

| Features | Top Five Factors | | | | |
|---|---|---|---|---|---|
| Ambient Lighting | Power Distance—High | Age—Young | Collectivism | Restraint | Uncertainty Avoidance—High |
| Welcome Mode | Power Distance—High | Long-Term Orientation | Restraint | Age—Old | Collectivism |
| Diverse UI Themes | Power Distance—High | Uncertainty Avoidance—Low | Indulgence | Short-Term Orientation | Age—Young |
| Birthday Surprises | Uncertainty Avoidance—Low | Power Distance—High | Age—Young | Indulgence | Short-Term Orientation |
| OTA | Short-Term Orientation | Indulgence | Uncertainty Avoidance—Low | City—Shanghai | Luxury Brand |

**Table 8.** *Cont.*

| Features | Top Five Factors | | | | |
|---|---|---|---|---|---|
| Virtual Assistant | Power Distance—High | Age—Young | Average Weekly Mileage—More | Indulgence | Uncertainty Avoidance—Low |
| Personal Relaxing Space | Long-Term Orientation | Age—Old | Individualism | Luxury Brand | Indulgence |
| Personalized Mode | Uncertainty Avoidance—Low | Age—Young | Short-Term Orientation | Individualism | Gender—Female |
| Intelligent Recommendation | Uncertainty Avoidance—Low | Indulgence | Age—Young | Long-Term Orientation | New Energy Brand |
| Calendars | Power Distance—High | Long-Term Orientation | Age—Old | Uncertainty Avoidance—High | City—Beijing |
| Unconscious Pay | Long-Term Orientation | Age—Young | Indulgence | Average Weekly Mileage—More | City—Shanghai |
| OMS | Indulgence | Age—Old | Power Distance—Low | Long-Term Orientation | Uncertainty Avoidance—High |
| Safeguard | Long-Term Orientation | Uncertainty Avoidance—High | Power Distance—High | Average Weekly Mileage—More | Age—Old |
| Remote Control | Uncertainty Avoidance—Low | Indulgence | Long-Term Orientation | Age—Young | New Energy Brand |
| Entertainment System | Indulgence | Age—Young | Collectivism | Average Weekly Usage Count of IVIS—More | Short-Term Orientation |
| Multi-Screen Collaboration | Power Distance—Low | Indulgence | Long-Term Orientation | Uncertainty Avoidance—High | Average Weekly Mileage—More |
| Vlogging | Uncertainty Avoidance—Low | Indulgence | City—Chengdu | Collectivism | Age—Young |
| Application Ecosystem | Average Weekly Mileage—More | Uncertainty Avoidance—High | Collectivism | Power Distance—High | Indulgence |

### *4.3. Clustering and Preferences Prediction*

To accurately identify the user groups with similar cultural orientations, systematic clustering was adopted to make an initial analysis of samples, obtaining an appropriate number of clusters. In this study, all 507 samples were clustered by Wald's method, which measures the similarity between data points by squared Euclidean distance. The pedigree chart was obtained as shown in Figure 2. In the figure, the horizontal axis represents the sample number, while the vertical axis represents the squared Euclidean distance. A good clustering result would have larger distances between each cluster, which means that it is more appropriate to divide the users into three–five categories. Considering that there should be a clearer distinction between different user groups, it was chosen to be divided into three categories with the distances between 10 to 20.

The results of systematic clustering were then substituted into the K-means clustering algorithm to segment the accurate user groups. Based on the following analysis of variance (ANOVA) in Table 9, the *p*-value of all the variables was less than 0.05, which means each variable can be considered to have contributed significantly to the clustering. So, it can be proved that the clustering analysis works well. The three user groups and the main characteristics of each group are shown in Table 10.

The characteristics of the three user groups were inputted into the trained random forest model as independent variables, and the preferences for 18 innovative HMI features of each user group were obtained as Table 11 shows. Moreover, 1 indicates that the users like and want to use the feature, while 0 indicates that they do not want to use the feature.

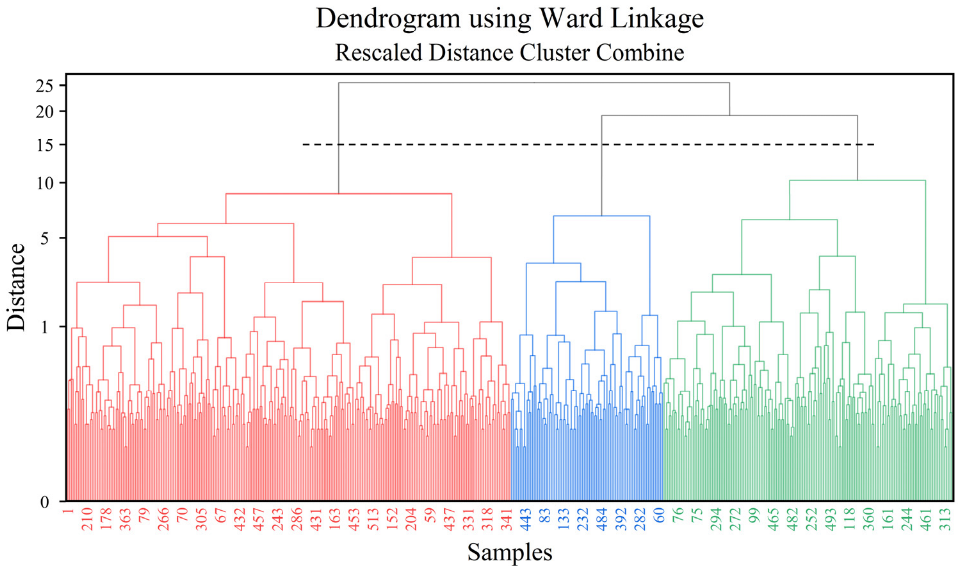


**Figure 2.** Results of systematic clustering.

**Table 9.** ANOVA.

| | Cluster Mean Square | df | Error Mean Square | df | F | Sig |
|---|---|---|---|---|---|---|
| Age | 12.38 | 2 | 0.553 | 504 | 122.395 | 0.000 |
| Gender | 4.483 | 2 | 0.186 | 504 | 24.113 | 0.000 |
| City | 205.499 | 2 | 0.44 | 504 | 367.146 | 0.000 |
| Car brand | 338.365 | 2 | 0.536 | 504 | 231.763 | 0.000 |
| Average weekly mileage | 1.77 | 2 | 0.296 | 504 | 5.984 | 0.003 |
| Average weekly usage count of IVIS | 4.326 | 2 | 0.11 | 504 | 39.394 | 0.000 |

**Table 10.** Cluster.

| | Group 1 | Group 2 | Group 3 |
|---|---|---|---|
| Age | 20–25 years old | 31–35 years old | 26–30 years old |
| Gender | Female | Male | Male |
| City | Shanghai | Beijing | Chengdu |
| Car brand | New energy brand | Luxury brand | Luxury brand |
| Average weekly mileage | 200~300 km | 300~500 km | More than 500 km |
| Average weekly usage count of IVIS | three~six per week | Under three per week | At least once a day |
| Power distance score | 9 | 12 | 7 |
| Collectivism/individualism score | 12 | 10 | 9 |
| Long-term/short-term orientation score | 7 | 12 | 9 |
| Uncertainty avoidance score | 10 | 11 | 7 |
| Restraint/indulgence score | 6 | 10 | 8 |

**Table 11.** Results of user preference prediction.

| Feature | Group 1 | Group 2 | Group 3 |
|---|---|---|---|
| Ambient lighting | 1 | 1 | 1 |
| Welcome mode | 0 | 1 | 0 |
| Diverse UI themes | 1 | 0 | 1 |
| Birthday surprises | 1 | 0 | 1 |
| OTA | 0 | 0 | 1 |
| Virtual assistant | 1 | 0 | 1 |
| Personal relaxing space | 1 | 0 | 0 |
| Personalized mode | 1 | 0 | 1 |

**Table 11.** *Cont.*

| Feature | Group 1 | Group 2 | Group 3 |
|---|---|---|---|
| Intelligent recommendation | 1 | 0 | 0 |
| Calendars | 1 | 1 | 0 |
| Unconscious pay | 1 | 1 | 1 |
| OMS | 1 | 1 | 1 |
| Safeguard | 1 | 1 | 0 |
| Remote control | 0 | 1 | 1 |
| Entertainment system | 1 | 0 | 1 |
| Multi-screen collaboration | 0 | 0 | 1 |
| Vlogging | 1 | 0 | 1 |
| Application ecosystem | 1 | 0 | 0 |

1 = like, 0 = dislike.

## 5. Discussion

### *5.1. User Groups Classification and Definition*

The impact of each cultural dimension on users' preferences can be derived from the results of the random forest model. It can be seen that young Chinese consumers are more influenced by the dimensions of power distance, uncertainty avoidance and long-term orientation. This is generally consistent with the results of previous research [24,34,57,58].

According to Hofstede's theory, values are an important part of culture and stable outward expressions of culture. He regarded values as the evaluative dimension of a person's orientation system that guides human behavior. Thus, individual cultural orientation has an effect on people's behavior and consumption decisions through values. There can be a great gap in values for different individuals.

The result shows that power distance is more closely associated with some features related to atmosphere and luxury, which may be caused by the values of "a sense of ceremony" and "show-off". China is a country with high collectivism culture, so young consumers tend to focus on their interpersonal circle and intimate relationships, which has a great positive effect on vlog recording and sharing, open application ecosystems and other features related to social sharing. Moreover, the increased individualistic orientation of the young people in China has also given rise to the need for personal space. Long-term orientation was found to be more related to efficiency-related features, which may be influenced by China's traditional values of saving resources and time. Those with high long-term orientations are more concerned about safety, health and future development. People with a lower level of uncertainty avoidance have a more positive attitude toward accepting and trying new innovative features and are more likely to be attracted to features that are full of changes, unknowns and a sense of freshness [24]. Restraint/indulgence is associated with the extent to which individuals control their primal desires and instincts. Users with a high level of restraint tend to believe that they only need mild entertainment, such as listening to music or radio, and are not willing to pay for features related to relaxation or self-pleasure. However, for users with a high level of indulgence, comfort and entertainment on intelligent devices are as important as the traditional driving experience in ICVs. In the Chinese consumer market, this is also why models of Leading Ideal, which are renowned for comfortable seats and smart large screens, rank among the top sellers.

### *5.2. User Groups Classification and Definition*

In addition to the study of the influencing mechanism of cultural orientations, it can also obtain three groups of typical young Chinese consumers through cluster analysis, which will help to more comprehensively understand the individual characteristics and various needs of potential users.

Group A can be characterized as women born post 1995 in Shanghai, who tend to have high collectivism, moderate uncertainty avoidance and low restraint orientations. They prefer new EVs and have a low weekly mileage probably caused by daily urban commutes.

Group B are men born post 1985 in Beijing with a high power distance index, high long-term orientation and high tendency of restraint. Most of them used to have luxury brands like BBA with a moderate weekly mileage but less frequent use of the car's IVIS and entertainment system. According to the previous one-on-one interview, people in group B tend to pay more attention to their career and social etiquette, seeking high efficiency and future rewards. What is more, they score highest in uncertainty avoidance, which means that they are less receptive to novelty and new technologies and are more focused on quality and safety.

Group C are young men born post 1990 in Chengdu. They have an obvious individualist orientation, the lowest uncertainty avoidance and low restraint culture, so they have a high acceptance of changes and new things. People in group C prefer luxury brands and often explore the interesting new features in ICS, so it is presumed that most of them love driving or have a certain interest in ICVs.

According to the results of user preference prediction, the product combinations desired by these three typical user groups are shown in Table 12, which is of some reference significance for automotive enterprises. The findings are not only applicable to the four sampled cities but can also be regarded as a clustering of potential young consumers of ICVs in China. This is because the influence of cities on culture and values can already be represented through the individual cultural orientation in the input metrics. Hence, the obtained results are equally valid in other first-tier, new first-tier and second-tier cities with a high acceptance of electric vehicles, such as Suzhou and Shenzhen.

**Table 12.** Results of user preference prediction for each group.

| Group 1 | Group 2 | Group 3 |
|---|---|---|
| OMS | OMS | Entertainment system |
| Safeguard | Calendars | Remote control |
| Entertainment system | Welcome mode | Vlogging |
| Vlogging | Ambient lighting | OMS |
| Personal relaxing space | Safeguard | OTA |
| Intelligent recommendation | Remote control | Personalized mode |
| Unconscious pay | Unconscious pay | Unconscious pay |
| Virtual assistant | Personal relaxing space | Ambient lighting |
| Calendars | | Diverse UI themes |
| Application ecosystem | | Multi-screen collaboration |
| Personalized mode | | Virtual assistant |
| Birthday surprises | | Birthday surprises |
| Diverse UI themes | | |
| Ambient lighting | | |

### 5.3. Comparison with Previous Studies

Lee, Pfleging and Stevens et al. conducted studies on user needs and design requirements during fully autonomous driving and explored future directions of UI/UX in ICVs [6,59,60]. These researches show that people expect to sleep, eat, work, monitor vehicle status, make phone calls, watch movies and use social media in ICVs. And, people with different cultural backgrounds have varying perspectives on it. The background of previous research is similar to that of this study, aiming to explore users' non-driving needs. It is gratifying that the 18 innovative HMI features selected in this study align well with the findings of previous research. For example, the feature of 'Personal relaxing space' meets people's need for sleep, while the feature of 'Remote control' fulfills the requirement for monitoring vehicle status. However, previous studies only focused on users' needs and did not implement them on specific features. Additionally, although previous research indicated the influence of culture on the results, it did not delve into the influencing mechanisms and effects. This study can be considered as a follow-up to previous research, supplementing the parts not covered by previous studies.

On the question of how to quantify the abstract concept of culture, this study refers to the approach of Ray and Sahney [43], measuring individual cultural orientations through Hofstede's cultural dimensions. Furthermore, this study adopts more comprehensive indicators compared to previous research. Not only does it introduce restraint/indulgence into the model, but it also considers the influence of past usage experience. The findings indicate that, although the newly added indicator of restraint/indulgence has less impact compared to power distance, uncertainty avoidance and long-term orientation, it still often ranks among the top five in terms of feature importance and should not be overlooked. The influence of uncertainty avoidance and long-term orientation appears to be indeed affirmed in many studies [24,43,61], and the results obtained in this study also confirm it. However, many studies indicate that collectivism/individualism has a strong influence on user decision making and preferences, especially in high-collectivist societies such as China, South Korea and India [43,62]. In contrast, the influence of collectivism/individualism in this study seems less significant. This may be because this study focused on smaller features rather than high-value purchases like buying a car, so users may not need to consider the opinions of friends and family as much when expressing their feature preferences. In this study, the influence of collectivism is more reflected in the close connection to family and community, while individualism is more reflected in the emphasis on individual feelings.

## 6. Conclusions

Based on Hofstede's cultural dimensions theory, the study investigated whether individual cultural orientations have an impact on users' preferences and willingness to use innovative features in the intelligent cabin of ICVs. The data from 507 valid samples collected by the quantitative questionnaire were input into a random forest model to identify the cultural and human factors that have the greatest influence on the user preference for each feature. Subsequently, the young Chinese potential consumers were subdivided into three categories, and the targeted prediction was conducted to gain the preferences of these three typical user groups.

Based on the above study, this paper draws the following conclusions:

1. This study selected 18 innovative HMI features widely applied in ICVs and with high user ratings and predicted user preferences from the perspectives of culture and values. It was found that users with a high power distance tend to favor features related to the sense of ceremony and show-off, while those with strong individualism culture are inclined toward more open and personalized IVIS. Users with long-term orientation prefer features that can improve efficiency, while those with low uncertainty avoidance are more attracted to new features. Users with a high level of indulgence are more willing to use entertainment-related features.
2. This study categorized China's young consumers into three user groups based on demographic information, individual cultural orientations and past usage experiences. All three groups show good acceptance of innovative HMI features inside the intelligent cabin. Users in group A appear to prioritize leisure and entertainment as well as personalized features prominently. Users in group B show a greater emphasis on efficiency and safety. Users in group C prefer an open and real-time updated software ecosystem. This clustering result is applicable to Chinese young consumers (under 35 years old) with a high acceptance of ICVs.

In terms of topic selection, most current human factors research on ICVs primarily centers on user trust and acceptance, consumer decision making, driving safety and distraction, as well as user interface design. Researchers always take the entire vehicle as the main object, with scant attention paid to the features in the intelligent cabin. As consumers increasingly emphasize the intelligence and entertainment aspect of automobiles, this study innovatively focuses on user preferences for innovative HMI features inside the ICV's intelligent cabin, thereby enriching research in this area. In terms of indicator selection, previous research on user preferences has often focused on factors such as price, brand, product reputation and policy incentives. Although indicators such as country and region indirectly express the influence of cultural background, culture has not been the primary focus of these studies. Nowadays people's consumer attitudes are rapidly changing, emerging technologies and new concepts are abundant and automotive brands target global markets. In such a contemporary context, this study adopts individual cultural orientations based on Hofstede's cultural dimensions as a measurement indicator. It provides a new method for dividing user groups and predicting the preferences of each group with different values in a cross-cultural context. In terms of the conclusion, studies on the integration of culture and automobiles often explain the influence of culture through usability and ease of use, but they typically focus on what kinds of people favor what kinds of outcomes, without delving into deeper influencing mechanisms. This study systematically investigates cultural models and explains the results through a framework of culture values–preferences, thus delving deeper into the essence of culture.

The main theoretical contribution of this study is to explore the influence on the user preferences of ICVs from the perspective of cultural and human factors. Through introducing the concept of individual cultural orientation, a new prediction model is constructed that aims to predict the needs and preferences of individuals with different cultural values by five cultural dimensions, basic demographic information and past usage experience. It provides insights for automotive developers, designers and marketing personnel responsible for the cross-cultural promotion of automotive products, helping to accurately grasp the needs of different users and promote the innovation diffusion of new technologies and design philosophies. This study also holds significant practical value. This study investigated 507 valid samples and identified three user groups of potential young ICVs consumers in China. In fact, the method to classify user groups proposed by this study can be applied to any country or cultural group. Moreover, it can effectively assist OEMs in rapidly classifying large-scale populations by simple indicators. The targeted product development effectively circumvents the high costs associated with the extensive development of unpopular innovative features in the intelligent cabin. Moreover, it also facilitates the localization of products with foreign user's special needs and cultural values when entering new markets.

However, this study still has few limitations.

Since ICVs are emerging innovations that have been developing rapidly in recent years and have certain requirements for complete infrastructures and policy promotion, this study mainly took a sample of users in first-tier and new first-tier cities, not taking into account people in smaller cities where traditional internal combustion engine vehicles (ICEs) are predominant. The results and conclusions obtained from this study are applicable to young consumers in first-tier, new first-tier and second-tier cities where the acceptance of ICVs is relatively high. The inclusion of more diverse samples and data sources needs to be considered in future studies on the same topic. And, the data collected were not fully utilized. This dataset can also be used to study the changes in cultural values of China's young customers of different ages, gender and other human factors. In subsequent studies, consideration will be given to adding more factors in different dimensions and developing systematic assessment tools to comprehensively analyze and predict user preferences.

What is more, the method used in this study to measure individual cultural orientations is based on the Hofstede cultural dimensions theory. This theory is one of the most authoritative theories in the field of culture and has been extensively validated through surveys conducted in 72 countries. It not only shows strong practical value and interpretability but also remains applicable to the changing times. However, the model used in this study is built upon other people's research findings, and it is highly correlated with Hofstede's cultural dimensions theory, which may limit the applicability of the model. In future studies, it is necessary to integrate the unique historical characteristics and cultural concepts of each country to conduct more targeted specialized studies and optimize the indicators.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

## Appendix A

The feature importance of 18 innovative HMI features obtained through the random forest algorithm is shown in Figures A1–A17.

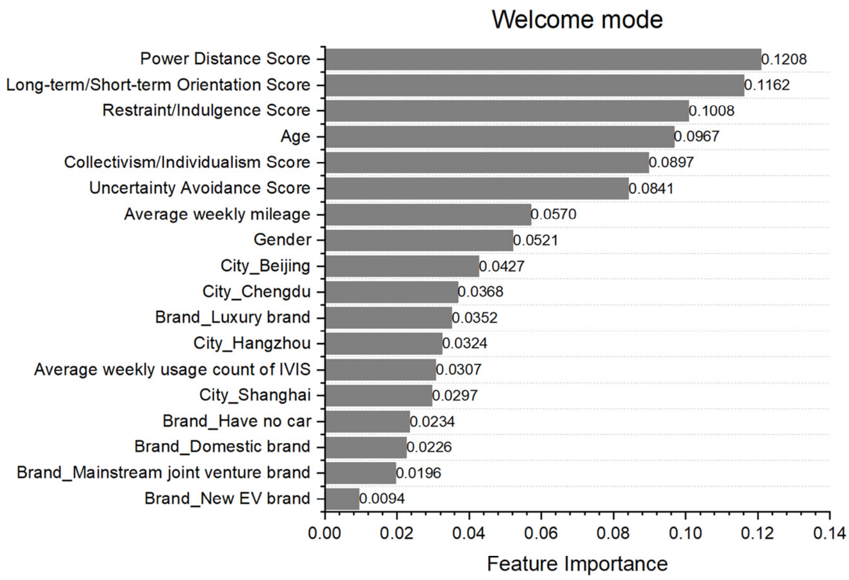


**Figure A1.** Feature importance of welcome mode.

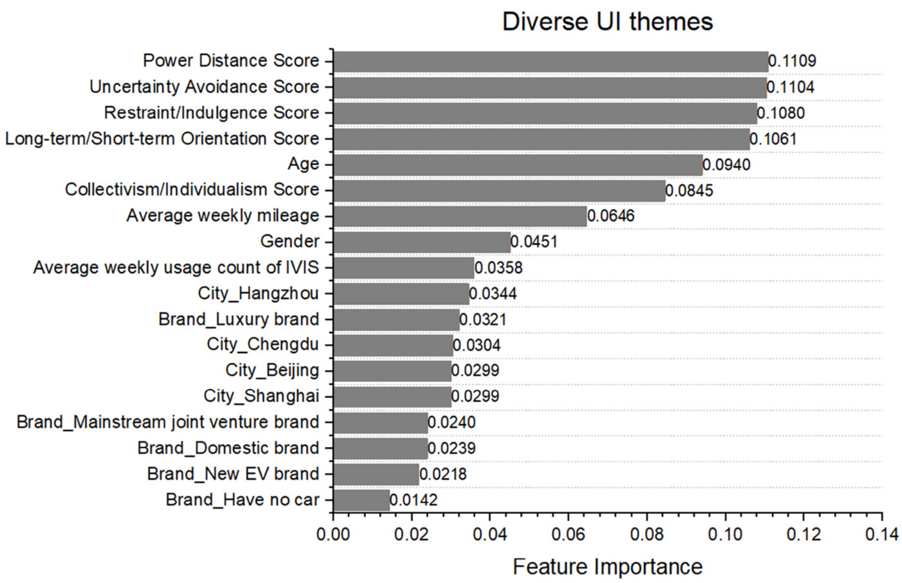


**Figure A2.** Feature importance of diverse UI themes.

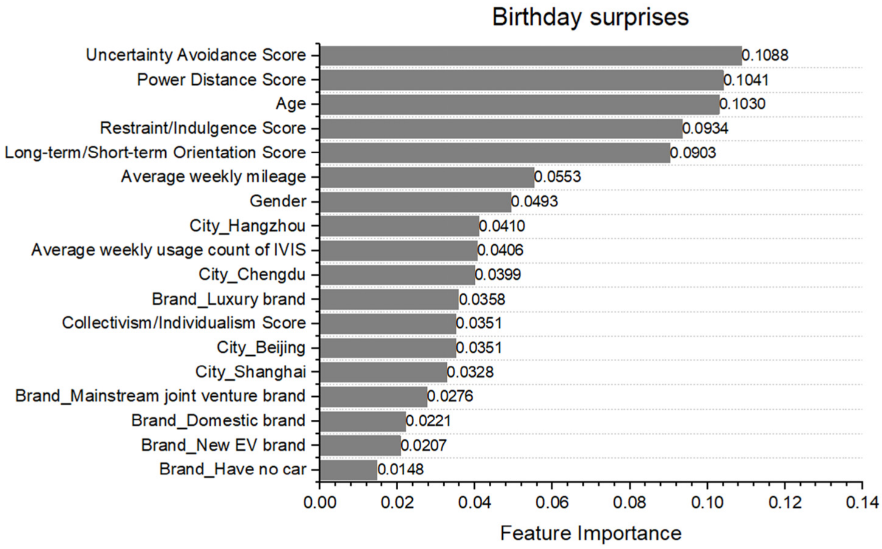


**Figure A3.** Feature importance of birthday surprises.

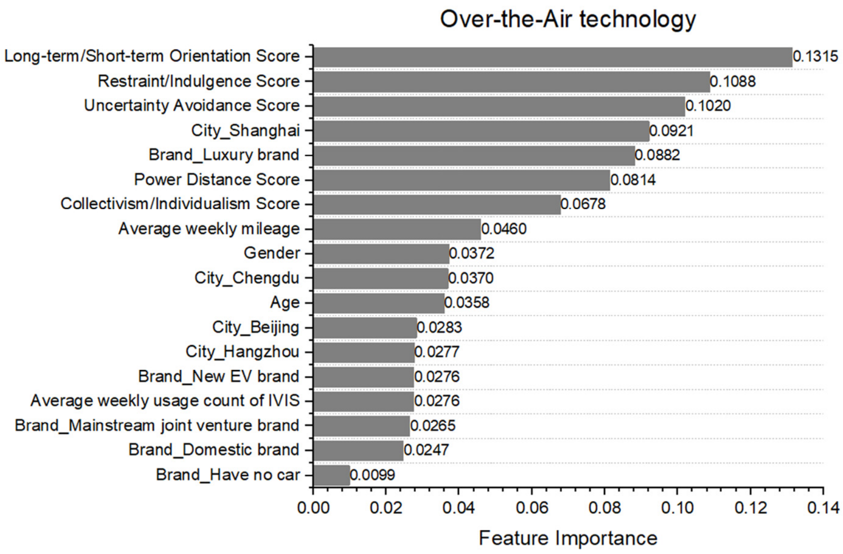


**Figure A4.** Feature importance of over-the-air technology.

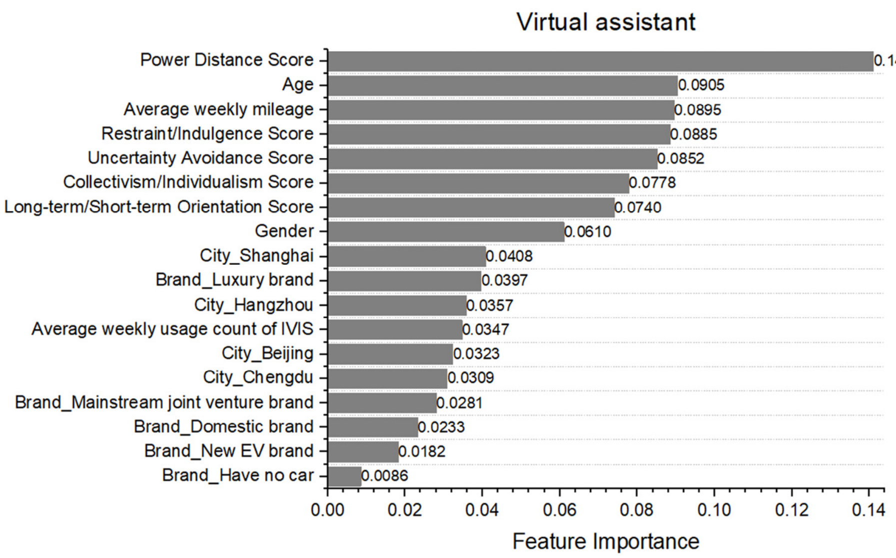


**Figure A5.** Feature importance of virtual assistant.

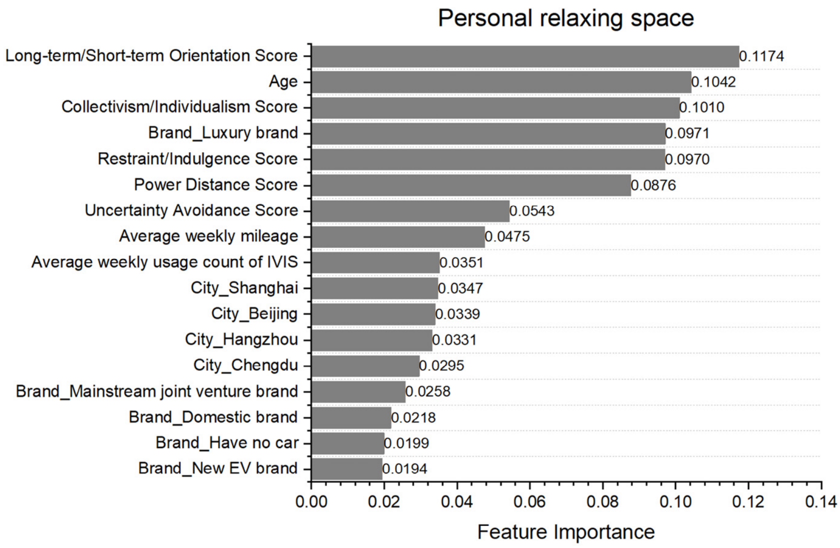


**Figure A6.** Feature importance of personal relaxing space.

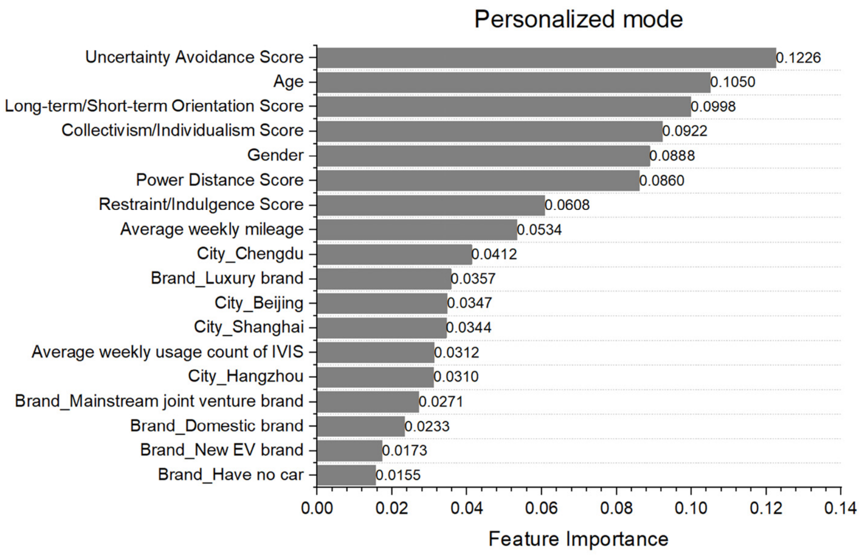


**Figure A7.** Feature importance of personalized mode.

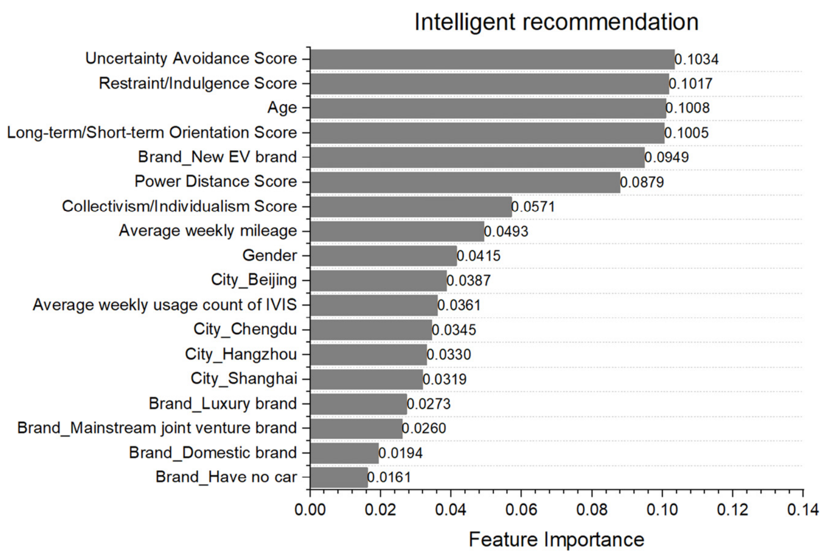


**Figure A8.** Feature importance of intelligent recommendation.

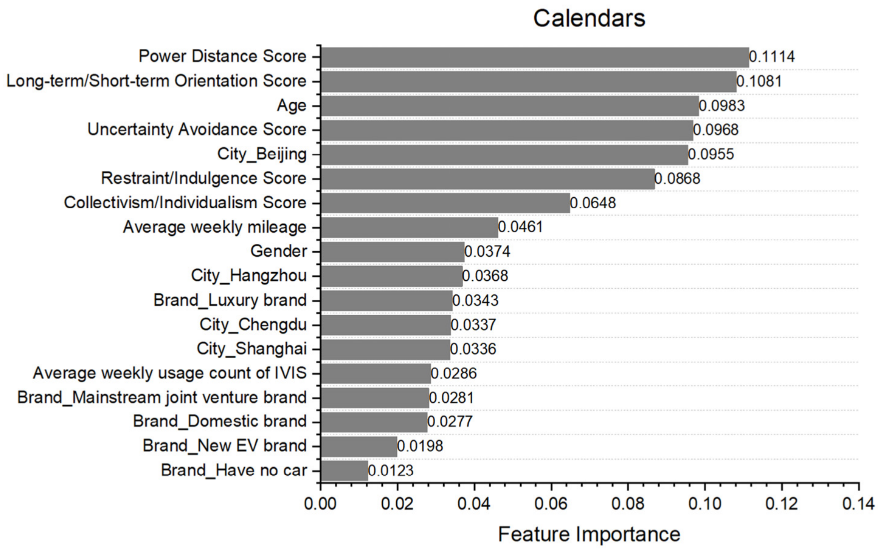


**Figure A9.** Feature importance of calendars.

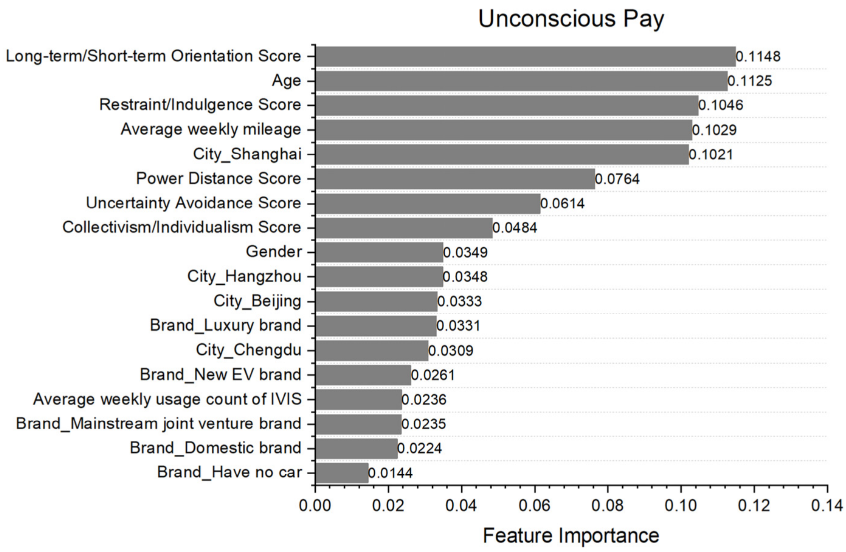


**Figure A10.** Feature importance of unconscious pay.

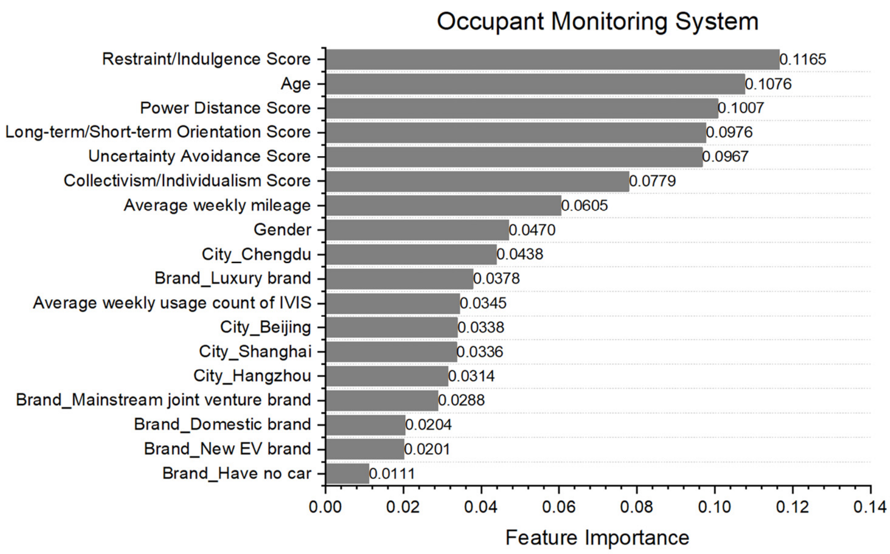


**Figure A11.** Feature importance of occupant monitoring system.

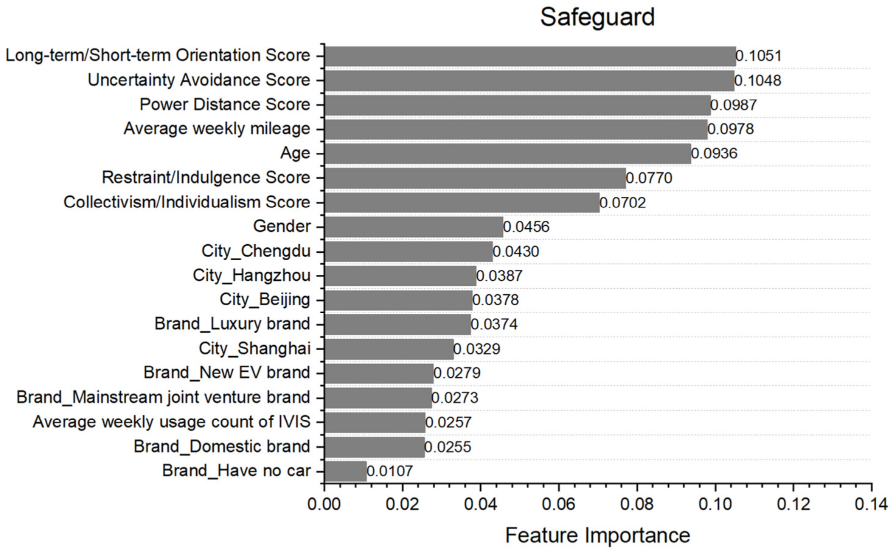


**Figure A12.** Feature importance of safeguard.

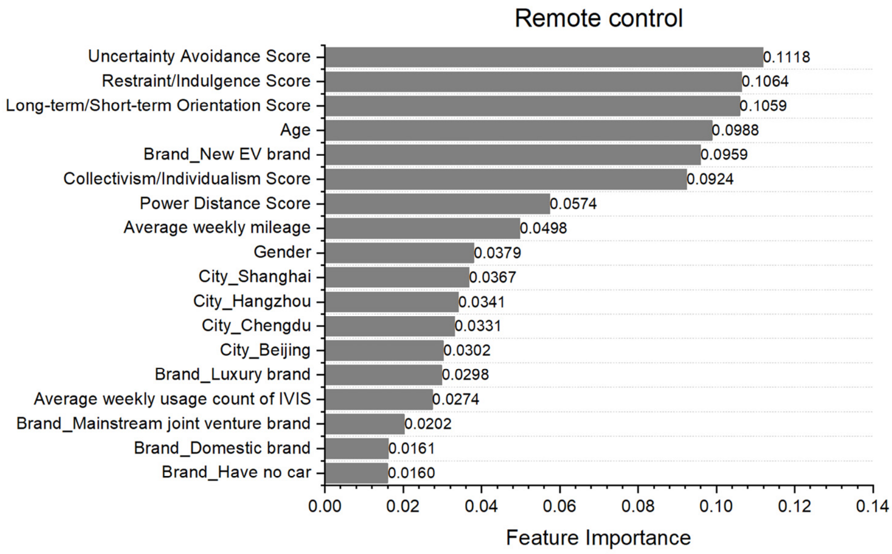


**Figure A13.** Feature importance of remote control.

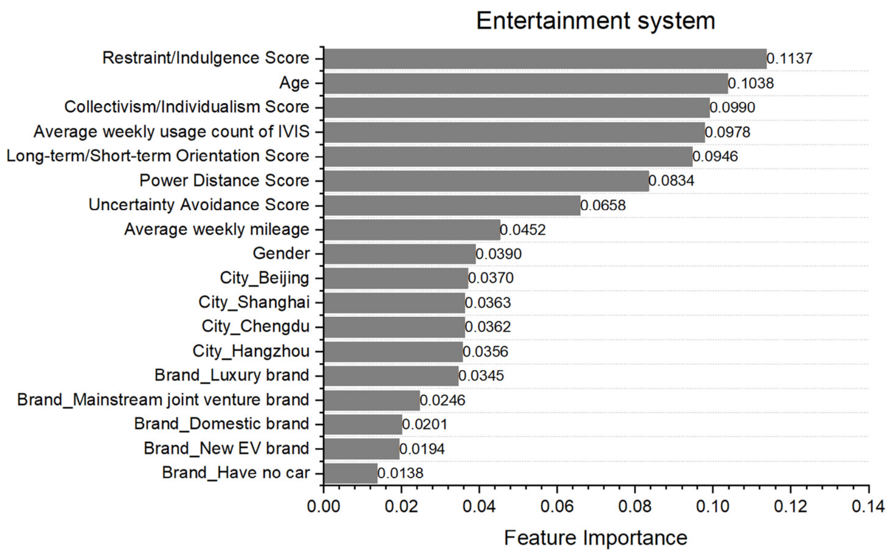


**Figure A14.** Feature importance of entertainment system.

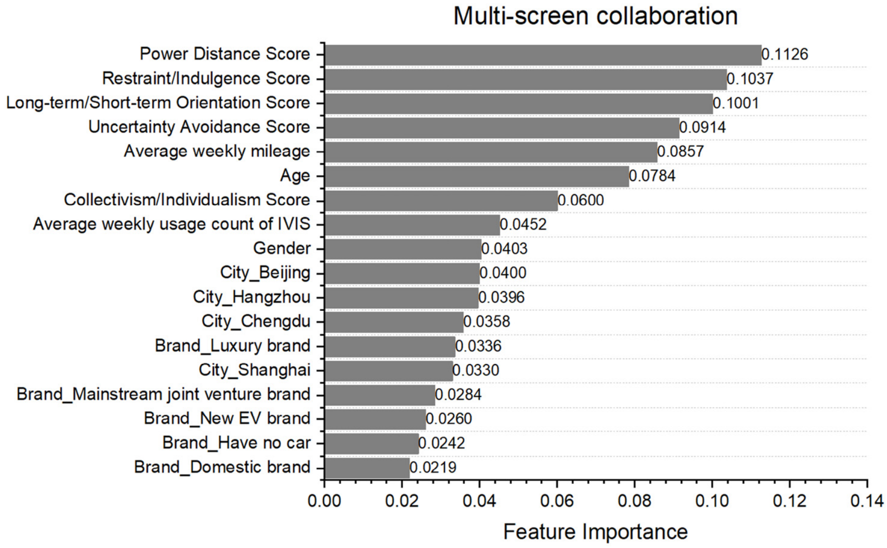


**Figure A15.** Feature importance of multi-screen collaboration.

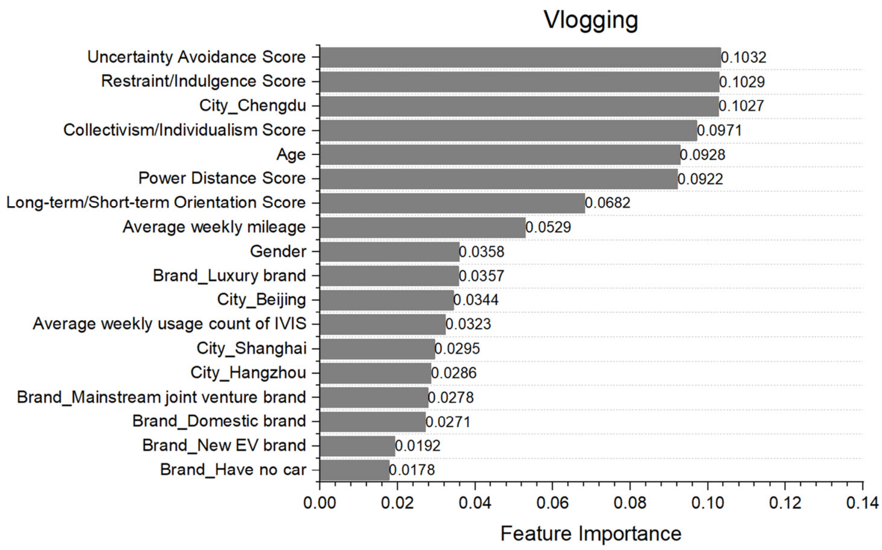


**Figure A16.** Feature importance of vlogging.

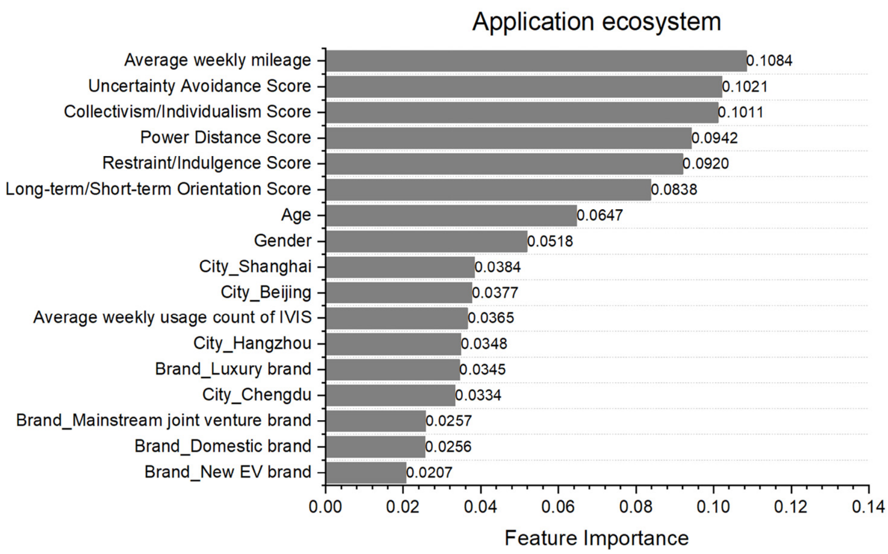


**Figure A17.** Feature importance of application ecosystem.

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