Warmth trumps competence? Uncovering the influence of multimodal AI anthropomorphic interaction experience on intelligent service evaluation: Insights from the high-evoked automated social presence

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Abstract

The rapid rise of multimodal AI anthropomorphic interaction assistants has subverted the traditional human-computer interaction. Based on social cognitive theory, our study aims to validate the effectiveness of the strategy to improve users' intelligent service experience and service outcomes by evoking a high level of automated social presence through revealing the effects of both warmth perception and competence perception from multimodal AI anthropomorphic interactions on users' intelligent service evaluation. The conclusions show that: (1) Both warmth perception and competence perception can improve users' intelligent service evaluations; (2) At the beginning of car use, users are more likely to give positive evaluations for competence perception (safety), while the longer they use the car, the more likely they are to give positive evaluations for warmth perception (intimacy and friendliness); (3) Warmth perception can significantly enhance the positive impact of competence perception (safety and entertainment) on users' intelligent service evaluations. The findings of this study enrich the social cognition theory and the social presence theory, which have significant implications for the management of user experience in anthropomorphic AI interactions as well as the improvement of intelligent service quality.

Keywords: Artificial intelligence interaction, automated social presence, multimodal, anthropomorphic, social recognition, structural topic modeling

1. Introduction

In an era of increasing intelligence and robotization in the service industry, it is concerned that advances in technology are significantly changing the user experience and the evaluation of service outcomes [1]. Specifically, along with the gradual maturation of underlying technologies such as artificial intelligence (AI) and virtual reality (VR), anthropomorphic service robots are being pushed to the forefront of service in more and more industries to attract and delight users [2]. For instance, during the height of the COVID-19, consumers preferred to receive contact-free, high-quality service from hotel greeting robots rather than interact with human employees [3], and the popularity of COVID-19 has also accelerated the widespread adoption of anthropomorphic service robots [4].Accordingly, the development and application of anthropomorphic robots and the provision of an intelligent service experience that satisfies users seems to be a priority and an important strategy for improving user relations and competitiveness in a wide range of industries such as hotels, restaurants, retail, finance, education, healthcare and automotive [5, 6, 7, 8, 9, 10].

The theoretical support behind the above phenomenon lies in the fact that anthropomorphic robots have higher service efficiency and lower service costs compared to human services [4].Compared to traditional automated mechanical robots with no human characteristics or low levels of anthropomorphism (e.g., self-service machines and robotic arms), anthropomorphic robots can evoke higher levels of automated social presence (ASP) [11], which describes the degree to which consumers perceive human companionship [12, 11].The level of ASP is influenced by the degree of anthropomorphism and in turn affects the user's service experience and service evaluation [11, 13].In contrast, evoking high levels of ASP through the imbued AI technology to stimulate the social appeal of service robots to compensate for users' systematic aversion to the functional attributes of non-human entities [14], and thus improve user relationships, user experience and user evaluation [11], has become an important rationale for AI technology research and development and intelligent marketing in several industries.

In-vehicle AI voice assistants, as a direct-to-user virtual service robot, have long maintained a high level of anthropomorphism in voice cues [15]. It recognizes and responds to the user's voice commands by being embedded in AI-enabled automotive products and services, becoming not just a hub for the user to control and connect to the car, but increasingly a relationship link between the car manufacturer and the customer [16]. In the era of Industry 5.0, the focus of emerging technological innovations is gradually shifting from fuel vehicles to new energy vehicles (NEV) and placing greater emphasis on human-machine interaction and collaboration [17], which aims at sustainable and human-centered transformation [18]. Researchers therefore believe that anthropomorphic AI assistants for new energy vehicles will become one of the most popular anthropomorphic service robots in the Industry 5.0.

The current design principles of NEV in-car AI assistants are mainly function-oriented and can provide functional and entertaining services that help improve the driving experience through simple voice commands including making calls, navigating, controlling the temperature, playing music and so on [19]. But based on the theory of consumption values (TCV) and the service robot acceptance model (sRAM) [20, 21], functional appeal alone does not create sufficient user stickiness and positive user experience, and richer anthropomorphic features, such as visual modal anthropomorphic interactions, are needed to build intimacy between the user and the AI assistant on a social level by improving the emotional transfer effect and the richness of information transfer [4, 22], so that the user feels high-evoked ASP. It leads to an improved emotional experience and positive service evaluation. The development and application of a multimodal AI anthropomorphic assistant strategy caters to the intelligent transformation of NEV enterprises and helps to attract users and form brand loyalty, gaining strategic benefits in terms of brand premiums [23].

Consequently, before formulating a strategy for implementing smart agents, managers must first clearly assess how well these smart devices deliver the user experience? To what extent can they be accepted by users? And whether they have the desired effect of providing the same level of satisfaction to users as humans [24, 25]. In reality, the popular trend and use cases for in-vehicle multimodal AI anthropomorphic interaction assistants have already started to emerge with the Chinese NEV brands such as NIO, LI Auto, and XPeng, which offer voice anthropomorphic services in addition to mascot-like visual dynamic interaction effects. However, to date, there is no scientific and effective method to collect and feedback the multimodal AI anthropomorphic interaction experience of NEV users in a timely and comprehensive manner, which leads to the first research gap identified in this study.

User experience and feedback is considered an important reference to guide product design improvement and make innovation decisions [26, 27]. In order to achieve consistently satisfactory user service results for multimodal AI anthropomorphic assistants, this study attempts to employ an unsupervised machine learning approach, structural topic modelling (STM), to mine and reveal the multimodal AI anthropomorphic interaction experience of NEV users from a large amount of user-generated content (UGC) for the first time. This approach is considered superior and applicable in terms of its effectiveness in mining user opinions [28].

Compared to traditional unimodal AI voice assistants, the incorporation of social-level visualization technology allows multimodal AI anthropomorphic assistants to be more social in appearance and more interactive in behaviour [11], evoking a high level of ASP. Research on the ability of high-evoked ASP to improve user experience has yielded convincing results [29, 13], but the impact mechanism of user experience on user service evaluation due to this new social relationship entity has not been fully revealed. In particular, a second research gap has been formed regarding the dynamic impact of time on the relationship between user experience and user evaluation, which has been neglected.

The social cognition theory, with its evaluative dimensions of warmth and competence, has been shown to be effective in capturing users' perceptions of high-evoked ASP experiences [30]. We attempt to generalise the multimodal AI anthropomorphic interaction experience of NEV users in two dimensions, warmth perception and competence perception, with the help of a social cognitive evaluation framework, to empirically examine the influence of users' warmth perception and competence perception on users' evaluation of intelligent services, and to test the moderating role exerted by time in the effect of high-evoked ASP on users' service outcomes. It should be noted that we also considered the influence of the intrinsic relationship between the social perception evaluation dimension, verifying that the user's perception of warmth moderates the relationship between partial competence perception and user evaluation, which fills the third gap in the current research.

The main contribution of this study is in filling the three aforementioned research gaps in the field of service robots and NEVs. It points to a multimodal and anthropomorphic development direction for the technological research and development of service robots, and provides a big data reference for NEV enterprise managers to formulate dynamic strategies for identifying, managing and improving users' intelligent service experience and evaluation from the perspective of users' social perceptions (emotions, abilities).

2. Literature review

2.1 Automated social presence and anthropomorphic

Social presence is considered the ability to express yourself as a “real” person socially and emotionally [31], and is broadly described as a “sense of being with others” [32]. In the early, social presence mainly served as a behavioral intermediary to influence the social interaction between people (such as consumers and service providers) [33], but with the disruption of AI technology [34, 35, 36, 37] to marketing and service industry, social presence has been given a richer meaning. Since users may interact with non-human social subjects similar to humans, such as service robots, social presence is no longer limited to feeling the existence of another social entity, but a social psychological perception interacting with intelligent agents. It also includes the perception of anthropomorphic technology itself [32]. Some scholars put forward the concept of automated social presence (ASP) according to the evolution of the meaning of social presence, emphasizing that social presence is automatically triggered by technology when technology replaces human beings as the agent of social subject [11]. ASP was also ultimately interpreted as “the extent to which consumers regard the machine as another social entity” [12].

The level of automated social presence is often thought to correlate with the degree of anthropomorphism. Due to the lack of AI technology[38, 39, 40], the early traditional service robots mostly interact with users in non-anthropomorphic or mechanized images. Recently, the widely popular AI robots contain more human features. For example, natural language processing (NLP) technology drives the development of AI voice assistants, enabling robots to provide convenient services similar to human voice and dialogue [41]. The appearance of anthropomorphism has become the standard configuration of hotel and restaurant service robots [3, 10]. Compared with earlier service robots, interacting with anthropomorphic robots can make users feel that they are receiving services from another social entity, so anthropomorphic robots show a higher level of ASP [13].

Although anthropomorphism is in essence deliberately designed to create ASP [33, 11], existing studies are more from the perspective of anthropomorphism than ASP to study the positive impact of anthropomorphism's physical and emotional characteristics on user service experience and results. Studies have shown that the anthropomorphic image of chatbots will attract users to interact for a longer time [42]. The facial expression, voice function and human interaction ability of service robots will affect users' views on the service quality of robots [4]. Social cues such as eyes, appearance, movements, and gestures have been widely applied to social robots to improve their usability and communication efficiency [43]. Robots with more human-like facial features are thought to enhance their sense of reality and capability, thus promoting user participation and use [44]. Digital voice assistants have been shown to improve user trust and interaction quality by incorporating intonation into conversations to convey emotion[33]. Anthropomorphic robots should conduct emotional interaction with users by identifying, processing, and simulating human emotions [45].

Few scholars have demonstrated the impact of anthropomorphism on user service experience and results from the perspective of ASP. In fact, high levels of ASP are evoked by improvements in anthropomorphism, which in turn leads to positive consumer responses [29], such as access and willingness to pay [13]. This is because users tend to evaluate each other's expected ability when encountering homogeneous objects [46]. When facing with an anthropomorphic robot with a high level of ASP, users will have the ability and emotional expectation similar to human interaction, and tend to think that it will provide satisfactory professional services like human beings [21]. It is the shaping of high-quality service expectations that ultimately translates into positive impacts on user experience and evaluation [13].

We call for more academic attention and application demonstration to ASP research, because the future user service experience will be increasingly influenced by the degree to which technology attracts customers on the social level [11]. By injecting cutting-edge technology into services and marketing to improve personification to evoke a high level of ASP, companies can have a strong customer appeal in both capabilities and social aspects, and continue to improve user experience and reviews to remain competitive in the market.

2.2 Multimodal Mascot-like AI interaction in NEV

ASP can build social attraction by simulating real interactions with humans on services, which means that evoking high levels of ASP can be achieved by reflecting more human characteristics and social cues [14]. The NEV automobile company from

China has taken the lead in the typical application demonstration: the AI voice assistant with the visual image of mascot-like is applied in the car to improve the degree of personification by integrating the human-like appearance and sound characteristics and other social clues [43], so as to arouse the high level of ASP perception of NEV users. From the perspective of sociability of appearance and interactivity of behavior [11], we attempt to deeply explore the theoretical basis behind application demonstration, so as to support our further research.

Firstly, although the level of ASP is closely related to the degree of anthropomorphism, it is not that the higher the degree of personification, the higher the level of ASP. Only when the degree of anthropomorphism reaches a certain level will the user have a favorable impression, but when the robot is considered too real, the favorable impression will turn negative and reduce the willingness to interact, which is the so-called “uncanny valley” [47, 48]. Scholars classified the physical appearance of anthropomorphic robots and divided them into humanlike, mascot-like, and machine-like appearances [49] according to their anthropomorphic features and levels. Among them, compared with agents of machine-like robots, humanlike agents are more likely to be considered thoughtful and trustworthy by users [50]. However, there are different views that humanlike does not always bring more friendly social reactions than machine-like [43], and even causes embarrassment [51]. In contrast, although mascot-like is a moderate personification, it brings users more positive interactive experience and higher interactive acceptance [52]. Therefore, this study believes that, compared with Humanlike appearance, which is difficult to master with anthropomorphic effect, in order to evoke the best ASP level, the appearance of anthropomorphic service robot is more likely to be designed as mascot-like, especially in the private driving scene. Therefore, the mascot-like AI assistant of China’s NEV automobile enterprise has certain promotion value in intelligent product appearance design.

Secondly, the overly obvious anthropomorphic features of a single mode may backfire, but the modal integration of multiple moderately anthropomorphic features will significantly improve the acceptance of anthropomorphic features and enable users to feel a high level of ASP from more abundant social clues [43]. For example, when a car owner opens the door, a voice assistant will say “hello” while the mascot-like image on the screen turns its head toward your location and gives a smiling greeting gesture. Such anthropomorphic cues of visual and voice mode match and merge with each other, bringing users a higher level of anthropomorphic interaction experience [53]. Not only that, in the process of anthropomorphic interaction, user emotion is aroused together with ASP. Existing studies have shown that adding intonation and facial expressions into the interaction can help robots more actively convey their own emotions and respond to users' emotions[54]. Multimodal interaction will confirm and amplify the emotional experience of users [55]. Considering China's NEV automotive enterprise AI assistant's multimodal innovation in interactive behavior is an effective measure to arouse users' high-level ASP.

2.3 Social cognition, user service experience and outcome

Social cognition focuses on how human beings encode, store, retrieve and process information about members of the same species [46]. Personification of service robots enables users to generate familiar perception in the interaction process. Therefore, social cognition can be used to explain users' interactive experience of non-human entities and effectively capture users' perception of ASP [11]. Warmth and competence constitute the basic mechanisms and universal dimensions of social cognition [46], revealing people's main concerns in describing others. Previous studies about service have shown that basic mechanisms of social perception, particularly warmth and competence, can be generalized to non-human entities in commercial service Settings [30]. It means that anthropomorphic AI assistants are also useful as virtual social entities for users to rate their interactions with. Therefore, this study attempts to use warmth perception and competence perception to NEV summarize users’ multimodal AI anthropomorphic interactive experience.

Warmth is regarded as a feeling of intimacy and friendliness [46] and is a core component of human nature [46]. Warmth perception, which is understood as capturing users' assessment of goodwill intentions towards AI assistants in the intelligent service experience received by users, is related to intimate, friendly, caring, reliable, sincere and other characteristics, and is a kind of social expectation of users [46]. Existing studies have shown that when robots begin to imitate human behaviors, users can perceive human-like warmth in their interactions with them [56], which means that users may judge whether robots are warm or not based on the degree of anthropomorphism in their appearance and behavior [57]. Similarly, from the perspective of ASP, it has also been proved that highly evoked ASP can affect users' warmth perception experience [11].

Competence perception is regarded as a kind of functional expectation of users, which is related to the intelligence, efficiency, function, proficiency and skill perceived by users in intelligent service experience [46]. For example, AI voice assistants are gradually replacing search engines with powerful task processing and complex information search functions, even affecting users' purchase decisions [58]. In pursuit of personalized functional values such as convenience, entertainment and usefulness, the development of function-oriented service robots has also become an important strategy for technology providers and marketers to seize customers [41]. Different from the anthropomorphic appearance of warmth perception, function-oriented service robots evoke ASP by providing anthropomorphic value services, prompting users to generate competence perception.

In fact, since social cognition will eventually form behavioral results [46], both warmth perception and ability perception will ultimately have an impact on user service experience and results. Although current studies have verified that the warmth perception and competence perception of high-level ASP can significantly improve user service results in multiple usage scenarios [11, 13], in the NEV field, for the new virtual social entity of multimodal AI interactive assistant, it is doubtful whether the interactive experience of NEV users can be transformed into positive intelligent service evaluation under the dimension of social cognition, which is not conducive to the diffusion of innovative technologies.

Existing studies on warmth perception and competence perception are mostly static, ignoring the effects of time of use or the user's AI interaction frequency. Users' service experience and evaluation may change over time, and researches on mining users' real-time opinions based on text analysis technology based on machine learning have become popular [59, 60]. Considering that it takes time to develop a close relationship between NEV users and the on-board multimodal AI anthropomorphic assistant, we took into additional consideration the impact of driving time on the relationship between user interaction experience and evaluation. In addition, the internal influence between the dimensions of social cognitive evaluation should also be considered separately, because there is evidence that the warmth perception of users can significantly mitigate the service failure of anthropomorphic robots [61, 62].

2.4 User-generated content and structural topic modeling

After experiencing a product or service, users write and post a variety of review information related to their feelings and feedback, and such information is authentic and timely, reflecting users' real opinions and reactions. The popularity of social media and third-party online platforms has led to an explosion in the amount of user-generated content (online reviews), which has led to an increasing emphasis on obtaining users' perceptions and experiences of product use from their reviews [63]. Unlike traditional methods that rely on questionnaires, interviews, and focus groups to understand users' real needs and determine product development and marketing strategies, UGC, as a high-quality alternative source of information, provides managers with new and rich data opportunities to measure consumers' perceptions, attitudes, and intentions [64]. Several recent studies have used a variety of text mining and analytics techniques to measure, among other things, users' service experience and satisfaction based on user-generated content [65]. In addition, with the continuous upgrading of AI technology [66, 67, 68, 69] and the reduction of information access costs, it has become increasingly easy to obtain a large amount of UGC from online platforms. Based on the above analysis, this study attempts to use UGC from different NEV brands as a data source for identifying and quantifying multimodal AI anthropomorphic interaction experiences to support subsequent research.

This study attempts to cluster topics of NEV user-generated content with the support of a disruptive text analytics approach, Structural Topic Modelling (STM), in order to reveal the user's multimodal AI anthropomorphic interaction experience. Topic model (STM) is a statistical model for clustering the latent semantic structure of textual data in an unsupervised machine learning manner, which is widely used in research related to user-generated content [14]. This family of methods assumes that topics are distributions of words and documents are mixtures of topics, where each word has a probability of belonging to a particular topic. By examining the co-occurrence relationships between words in a text document, a set of words with the highest co-occurrence probability, i.e., topics, is output. The key innovation of the structural topic model used in this study, as opposed to other methods in the same category such as LDA, is that it takes into account the effect of covariate data on the topic prevalence in a document, allows the user to merge arbitrary metadata into the topic model, and explains local topic prevalence by estimating the relationship between the topic and the sample document metadata [59]. In a recent study Han used STM to mine the significant value of real-time user-focused content in unstructured data [28], demonstrating the feasibility and effectiveness of using structural topic modelling to obtain real-time user insights from large amounts of use-generated content [70, 71].

In our case, metadata refers to online data obtained from DCar website, including owner ID, vehicle model purchased, vehicle purchased time, review text, review votes, intelligent rating and other information. Figure 1 shows the graphical illustration of STM and visualizes the text analysis process. And the key processes of STM can be summarized as follows [28].

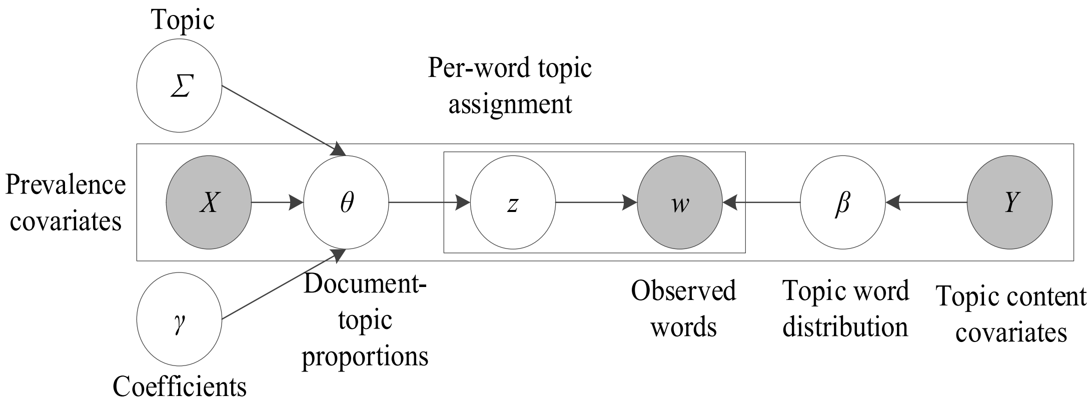

Fig.1. A graphical illustration of STM approach [72]

As shown in equation (1), STM is a hierarchical model, in which the prevalence of each topic of document *d* (denoted as θ_d) is derived from the logical-normal distribution, and its average value is a function of the document covariate X_d. In this paper, the document *d* represents a review provided by uesrs.

$$\theta_d \sim LogisticNormal\ (X_{d\gamma}, \sum) \quad (1)$$

Then, given the topic-popularity vector, a specific topic $z_{d,n}$ is associated with the position that needs to be filled through the following process, where *n* is the index of each word in document *d* in equation (2):

$$z_{d,n} \sim Multinomial\ (\theta_d) \quad (2)$$

Next, in equation (3), assigned the words $w_{d,n}$ of each document to the topics:

$$w_{d,n} \sim Multinomial\ (\beta_{d,z}) \quad (3)$$

where $\beta_{d,z}$ is the probability of choosing vocabulary word *w* to fill a certain position in document *d* given the topic assignment variable *z*.

3. Methodology

For convenience, the overall framework of research design is constructed in Figure 2, and the specific process of data acquisition and analysis is revealed. Specifically, we first selected three Chinese NEV brands as samples, and obtained 7998 long texts from real vehicle owners. Then, we filtered the valid texts related to "multimodal AI anthropomorphic interaction" from the 7998 long texts by setting keywords, totaling 3481 phrases, which constitutes our database. Then, after text cleaning, we performed STM to obtain the results of topic clustering and assigned labels based on the high-frequency words of the topics to reveal the user's AI anthropomorphic interaction experience. Finally, the impact of the user's AI anthropomorphic interaction experience on the intelligent service evaluation was examined by constructing an empirical model, taking into account the moderating effects of time and the warmth perception topics.

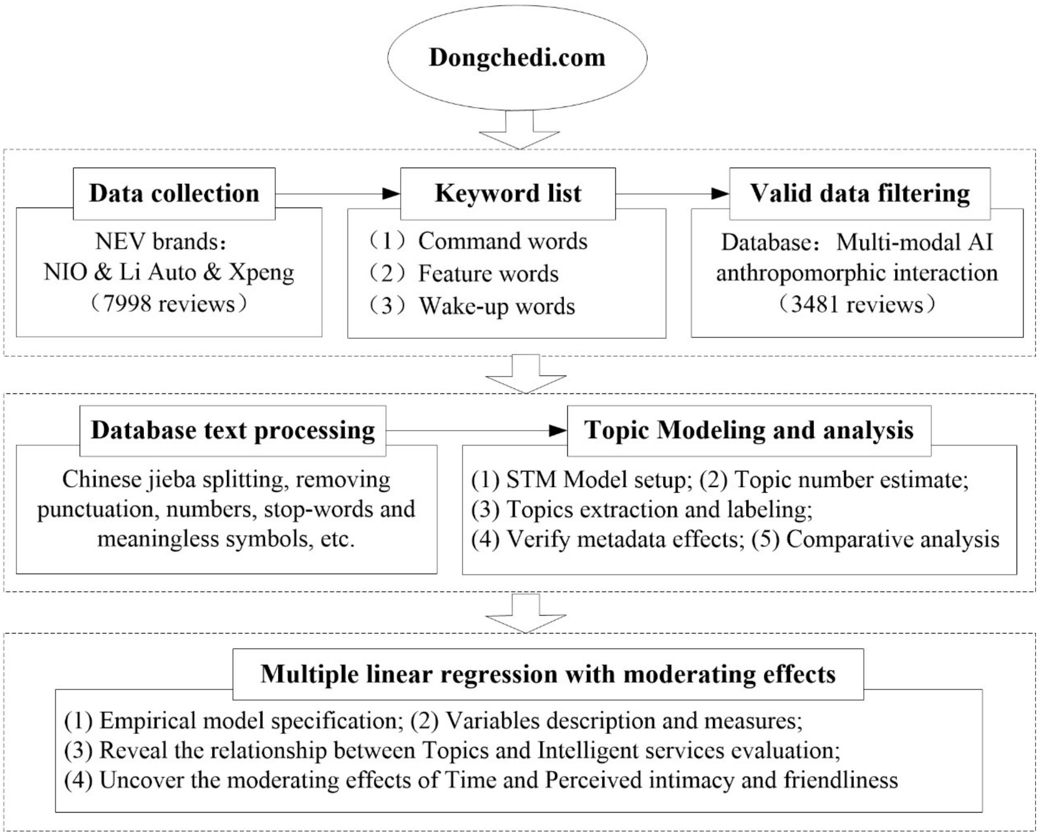

Fig. 2. Overall framework for research design.

3.1 Data acquisition and preparation

This study attempts to obtain NEV users' service experience and feedback on multimodal AI anthropomorphic interaction assistant from a large number of UGC through text mining and topic modelling. Due to NEV brands equipped with voice and visual anthropomorphic interaction assistants account for a relatively small proportion, Li Auto, NIO and Xpeng are selected as the three NEV sample enterprises with the highest automated social presence arousal level based on automobile sales volume. Figure 3 shows NIO's on-board multimodal AI assistant Nomi with its rich Mascot like visual interaction. We utilize a Python-based web crawler to obtain the online review data from the DCar website (UCL: https://www.dongchedi.com/) of three NEV enterprises from June 2018 to September 2022, a total of 7,998. As one of China's largest online vehicle evaluation platforms, the DCar website allows real car owners to share their experience and evaluation results. However, the research about UGC and NEV has not been widely concerned by scholars.

Because online reviews are collected without a filter, there are few direct references to "multimodal AI anthropomorphic interaction" in the obtained review text. However, it is clearly relevant in context. For example, comments including "Chatbots," "Human-computer interaction," "Nomi," "Cute expressions" clearly relate to "multimodal AI anthropomorphic interaction," but do not mention the term directly. In order to reduce the interference of noisy data and avoid the omission of valid data, it is necessary to set specific keywords for the screening of valid comments. Specifically, we construct a list of filter keywords from three dimensions: (a) instruction words including Chat "Awaken", "Interaction", "Accompany", "Voice control", "Emoji Switch" and so on, (b) feature words such as "Intelligent", "Anthropomorphic", "Visual", "Dialogue", "Expression", "Assistant", "Robot", and (c) wake words. Generally, most NEV brands will use the AI assistant's name as their own voice interaction wake words. For instance: "Hi, Nomi", "Hi, Little P", "Hello, Li Xiang". After sifting through the keyword list, the final result is a dataset containing 3,481 valid comments.

To make data set documentation compatible with unsupervised machine learning techniques, the last step of data collection and preparation is to use natural language processing (NLP) to clean the text dataset, including Chinese segmentation, removing punctuation, numbers, stopwords, and nonsensical symbols, and saving several specific words. This is similar with Chinese text topic extraction research [73].

Fig.3. Nomi and its various mascot-like visual expressions

3.2 Topic model set-up

We applied STM to our dataset, that is, in the data set collected in this study, the text of each review is treated as a document, and the collection of each document is treated as a complete corpus. The *stm* package in R is used to develop a model for our analysis [74], in which the content of car comments and specific words in the corpus are used as document and lexical input respectively. In R software, the execution process of STM package is shown in Figure 4. The ingest and preprocessing of the data was carried out before the topic clustering was executed, and then the optimal number of topics was determined by choosing the K-value, and a series of visual presentations were carried out. The prevalence function is shown in equation (4):

$$\textit{prevalence} \sim \textit{review votes} + s(\textit{vehicle purchased time}) \tag{4}$$

where *s* is the smoothing function of vehicle purchased time, and *review votes* is one of the covariables of topic popularity, indicating how many useful votes a comment gets. It is worth noting that covariables are replaced by other metadata items (such as forward and append comments) when checking the robustness of the results. Since the results are nearly identical, we will only report the results under the review votes setting for simplicity.

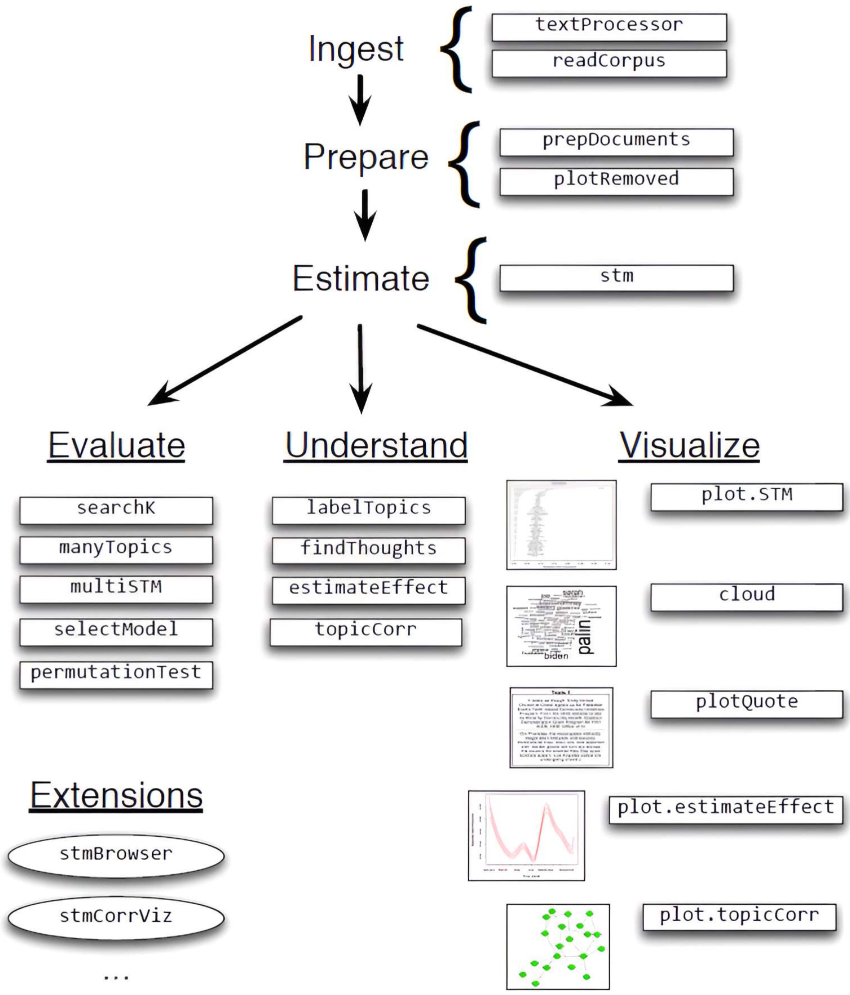

Fig.4. Execution diagram of the STM package based on R software[74]

3.3 Topic number estimation

In order to achieve a better topic clustering, it is necessary to determine the optimal number of topics *K*. As one of the most important user-specified parameters in STM, the determination of *K* value is conducive to the substantive interpretation of model results [75]. However, the optimal *K* value does not mean the maximum fitting [76], and the influence of intrinsic nature of the corpus should be taken into account [77]. Since the corpus constructed by us has been screened by specific keywords, it is highly related to "multimodal AI anthropomorphic interaction" in content and has certain homogeneity, so *K* should not be too large. Using the function *SearchK* [78] in the *stm* and *furr* package in R, we determined the optimal number of topics by evaluating the fitting index of the training model on the sparse matrix within the range of *K* values from 3 to 15. Among them, held-out likelihood is used to measure the recognition of a topic by comparing the similarity of word distribution [79]. Semantic coherence verifies the internal coherence of a particular topic by measuring the frequency of co-occurrence between the words most likely to occur in the original corpus. High held-out likelihood and well-performed semantic coherence means that Top words in the same topic are likely to appear together in the document and are likely not to appear in other topics. By comparing the fitting index changes corresponding to different K values shown in Figure 5. Considering the local maximum of held-out likelihood and semantic coherence in Figure 5-1 and Figure 5-3, and the local minimum of residuals and lower bound in Figure 5-2 and Figure 5-4, when K=5, we believe that the theme clustering effect reaches the local optimum. Therefore, a 5-topic model solution is selected for this study.

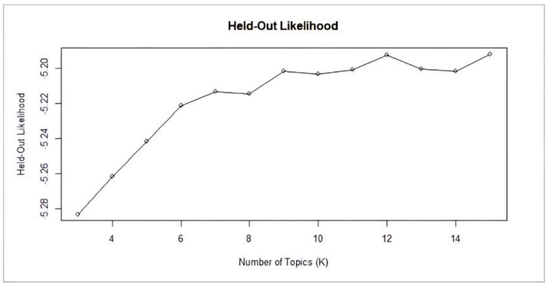

Fig. 5-1. The held-out likelihood index

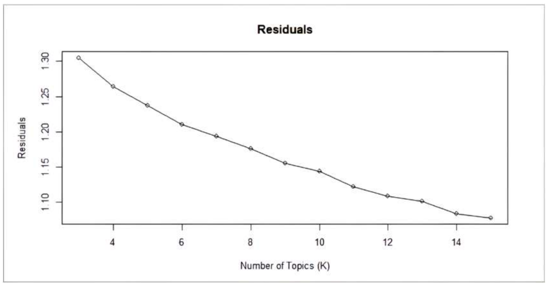

Fig. 5-2. The residuals index

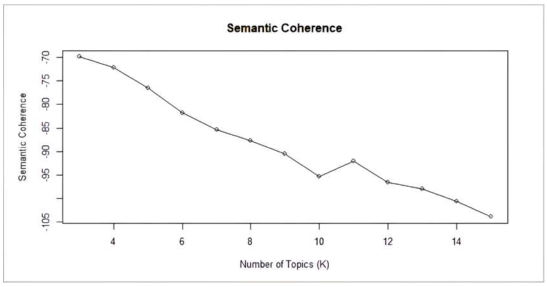

Fig. 5-3. The semantic coherence index

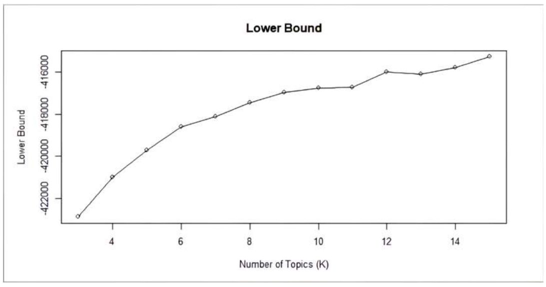

Fig. 5-4. The lower bound index

4. Results and findings

In this section, the results of STM execution are first presented, and the differences among topics are evaluated by combining top words and representative review examples, in an attempt to perceive the multi-use experience of NEV users on the multimodal AI anthropomorphic interaction assistant from different topic of the same cluster. Then, based on the Social Cognition Theory, through the construction of regression model, an empirical analysis is developed to explore the relationship between the extracted topics and intelligent services evaluation. The effect mechanism of users' social cognition generated by high-evoked automated social presence on their behavior results is final revealed.

4.1 Topic labeling and summary

Based on the optimal number of topics (*K*) identified above, our STM model extracts five of the most popular topics from a large number of reviews, all of which are highly relevant to the in-car multimodal AI anthropomorphic interactive experience, and most representative of the content of 3,481 reviews from June 2018 to September 2022. It means that the review data set we constructed is representative, and that the applied topic modeling method has some advantages in identifying unique topics with similar characteristics from the review content. Table 1 summarizes the extracted topic results. The third column is the proportion of topics output by STM model, and the fourth column is the list of the first 9 words output for each topic. These words have the highest probability of appearing in this topic, but the lowest probability of appearing in other topics, which can be used as the basis for distinguishing among topics. As mentioned earlier, each topic represents a potential distribution of words to which each word in the document may be assigned. We recruit two social science researchers to determine the assignment of topic labels by analyzing the top words for each topic and reviewing a large sample of representative comments. Topics are divided into different categories based on the assigned tags, which are explained in more detail in a later section.

Table 1. Topic labeling and summary

Topic rank	Topic label	Topic ratio	Top words
Topic Category: Warmth perception			
Topic1	Perceived intimacy and friendliness	25.07%	Nomi, 喜欢(love), 互动(interaction), 陪伴(accompany), 可爱(cute), 孩子(kids), 感觉(feeling), 氛围(atmosphere), 机器人(robot)
Topic Category: Competence perception			
Topic4	Perceived safety	24.73%	语音(voice), 智能(intelligent), 辅助(assistance), 功能(function), 驾驶(driving), 安全(safety), 自动(automatic), 识别(recognition), 交互(interaction)

Topic3	Perceived value	20.66%	服务(service), 性价比(value for money), 感觉(feeling), 品牌(brand), 体验(experience), 用车(usage), Nomi, 满意(satisfaction), 提车(get car)
Topic2	Perceived convenience	15.50%	便利(convenience), 座椅(seats), 空调(air conditioner), 控制(control), 语音(voice), 模式(mode), 调节(adjustment), Nomi, 主动(active)
Topic5	Perceived entertainment	14.04%	娱乐(entertainment), 车机(car computer), 音乐(music), 系统(system), 升级(upgrade), 定制(custom), 理想(Li Auto), ota, 启动(launch)

4.2 Comparative analysis of STM results

As one of the main forms of cognitive evaluation, social cognition has been widely accepted and applied to capture the social perception of non-human entities [80, 11]. The two evaluation dimensions of warmth and ability contained in social cognition [46] can cover the social desirability and utilitarian desirability of users [81], which can comprehensively describe and reflect the perception and experience of users on non-human entities. Therefore, we classify the topics related to multimodal AI anthropomorphic interactive experience from two dimensions of warmth perception and competence perception, and theorize the response of NEV users to encountering high arousal ASP in services from the perspective of social cognition.

4.2.1 The category Warmth Perception

As shown in Table1, Topic1 (Perceived intimacy and friendliness) has the highest share of friendliness at 25.07%, indicating that this topic is the most popular among users. As can be seen from the top words of output, Topic 1 mainly reflects the emotional experience of multimodal interaction with Nomi and other mascot like AI assistants. This emotional experience is not just a single like or praise, but a complex warmth perception composed of a variety of emotional elements in different situations. We try to break down this warmth perception in more detail.

First of all, in addition to the name and emotional words, "accompany" is one of the most frequently mentioned specific instruction words by users, and is also an important emotional function of the multimodal AI anthropomorphic assistant. We sum up the three main applications of the "accompany" feature from the representative comment examples of STM output:

(1) Commuting Driving: *"Favourite: Nomi robot, don't underestimate this little robot, it will chat and interact with you, with a sense of ritual. You can have its company every day when you go to and from work, you can spit to it when you are in a bad mood and share with it when you are in a good mood, so that your transport is no longer a machine but a warm companion."*

(2) Dark Driving: *"Nomi is also my favourite point, it makes me, the overtime dog, never feel lonely on my way home alone late at night, the longest love is companionship, isn't it?"*

(3) Long Driving: *"Also the soul of the whole car, nomi, is very loving. He comes with a lot of expressions and switches between positions while the music is playing. It's not so boring on long drives with him."*

We found that compared with the traditional Disembodied agents AI voice assistant, the Embodied mascot-like figures improved the anthropomorphic perception of the AI assistant. Therefore, anthropic companionship during Commuting Driving scenes has narrowed the psychological distance from drivers [82], and then modulated their negative emotions [83] and transmitted warm positive emotions [83], which may be people judge whether robots are warm or not based on their degree of anthropomorphism [57]. The integration of visual and voice modals will strengthen and confirm the emotional clues contained in the interactive experience [84], thus amplifying the emotional power of warmth. Whether it is Dark Driving or Long Driving, the multimodal AI anthropomorphic interactive assistant relieves the driver's sense of loneliness [85], making the driver emotionally dependent on its company in various situations and regard it as an indispensable close partner [4]. Therefore, constant companionship establishes an intimate relationship between the driver and the AI assistant such as Nomi [86], which is a specific emotional element constituting warmth perception.

Secondly, the AI interaction in the car is not the driver's privilege. Passengers can also gain the warmth perception through the multimodal interaction with the mascot like AI assistant, especially the children in the family. As listed in the top words, "cute" and "kids" are also mentioned frequently. Although the improvement of anthropomorphism can strengthen users' perception of warmth [47], due to the existence of the uncanny Valley effect, over-anthropomorphic social robots will cause users to fear [47, 48]. And Nomi's AI assistant, with its cute mascot appearance, keeps the anthropomorphism down to a level of friendliness that children enjoy. Based on the output representative examples, in the context of family participation, the friendly perception brought about by the cute mascot is the prerequisite emotional element of warmth perception.

"Pros: Little Nomi is a favourite toy for children. With its cute expressions and interesting dialogue, it can bring more joy to children and the Nomi has become a growing partner for little children."

As described by current scholars on warmth perception, warmth is a feeling of intimacy and friendliness [46]. In the warm perception dimension of social cognitive effect, the user's multimodal AI anthropomorphic interactive experience can be specifically decomposed into perceived intimacy and perceived friendliness.

4.2.2 The category Competence Perception

This is the category with the largest proportion of topics in NEV user reviews, including 4 topics, which focus on reflecting the multimodal AI anthropomorphic interactive experience of NEV users from the perspective of competence perception.

Topic 4 (Perceived safety) accounts for 24.73%, second only to Topic1, which reflects NEV users' high concern for safety experience when interacting with AI. Studies have shown that in the coming era of autonomous driving, in-car AI assistants should not only be used as a tool to passively respond to driver instructions, but also play a role of active collaboration [87]. For example, active recognition of drivers' mental and health states and generation of dialogue for danger warning [83, 87], and reduction of driving distraction through driving assistance and function sharing to ensure safety [88]. Compared with traditional voice assistants, mascot-like AI assistant can generate dialogue and visual interaction to realize multimode safety hazard warning and safety auxiliary feedback, helping drivers to obtain more rich and effective safety information, so as to obtain better safe driving experience. A sample of representative comments further reveals NEV users' recognition of the security role of multimodal AI anthropomorphic assistant.

[Topic 4 Perceived safety] *"On rainy days, instead of tapping the screen while driving to turn on the in-car functions, I directly call out to nomi to turn it on, helping me to concentrate on driving without distractions affecting safety and providing us with a great safe driving mode while driving."*

Topic 3 (Perceived value) accounts for 20.66%. According to the frequently mentioned "value for money" in top words, this topic mainly focuses on NEV users' weighing of the use cost and service experience of multimodal AI anthropomorphic assistant. Based on the representative examples, we found that the AI interaction cost mainly comes from the cost of selecting the mascot-like AI assistant like Nomi when buying the car. With the accumulation of driving time and the increase of interaction frequency, users become emotionally dependent on the high-quality and differentiated intelligent service experience provided by the multimodal AI anthropomorphic assistant. Attitudes towards AI assistants have changed from "low- cost performance" and "non-essential product" to "great value for money" and "must-have product." It can be seen that satisfactory high-quality service experience will make users accept certain product premium [89], and even further translate into brand premium [90].

[Topic 3 Perceived value] *"In addition, NOMI is indeed a bonus, at first it seems useless, but over time, it is really a great thing to have someone in the car, sometimes new expressions appear, which will bring you a completely different surprise. Although it needs to be optional, this money is very necessary."*

Topic 2 (Perceived convenience) and Topic 5 (Perceived entertainment) account for 15.50% and 14.04%, respectively, which mainly reflects NEV users' concern on the convenience and entertainment experience brought by the multimodal AI anthropomorphic assistant. Existing studies have shown that perceived convenience, perceived usefulness and perceived entertainment are considered as the three main effectiveness motivations for using AI assistants [91, 41]. Among them, convenience and usefulness are considered to overlap in experience, because both of these perceptions are based on the powerful functions of AI assistants. Therefore, only perceived convenience and perceived entertainment are discussed in this study. According to a sample of representative comments, NEV users can control the Nomi by voice to complete a series of convenience and entertainment functions such as seats, air conditioning, navigation and playing music.

Different from the traditional voice assistant, the multimodal AI anthropomorphic assistant will give the user visual emotional feedback throughout the whole process of task execution. With the switching of various visual expressions of Nomi, it adds some social expectations to a single functional attribute and makes the originally boring instruction execution process more interesting. It is this interest that improves users' tolerance of AI assistant service failure [61, 62] and the possibility of perceived service satisfaction [51]. In addition, the AI assistant has Embodied mascot-like figure, which also gives richer customized entertainment service experience. For example, businesses are offering personalized accessories like hats and glasses that fit the Nomi.

[Topic 2 Perceived convenience] *"Most of the functions can be controlled by voice through nomi. It is like a warm companion accompanying me, talking to me, opening and* *closing the windows, helping me navigate, switching on and off the air conditioning and music, and feeling a great sense of convenience and intelligence on the road."*

[Topic 5 Perceived entertainment] *"My friends said they would all like to have a Nomi installed separately if they could have it on another brand of car. I also customized two little hats for cute little Nomi, and she looks even cuter in them."*

4.3 Empirical analysis and findings

4.3.1 Empirical model specification, variables, and measures

It should be noted that although the 5 topics under the warmth perception and competence perception dimension feedback the real experience of multimodal AI anthropomorphic interaction, they cannot reveal whether and how these experiences affect the intelligent service evaluation given by NEV users. Therefore, it is necessary to construct a regression model for the next step of empirical test. In order to make the process of empirical test clearer, our regression analysis will be divided into three parts. And the variable design and measurements are shown in Table 2.

Table 2. Summary of variables design and measures.

Variable				**Short**	**Operationalization**
DV	Intelligent Service Evaluation			ISE	NEV uers' intelligent service rating from 1 to 5
IV	Warmth Perception	Topic1	Perceived Intimacy and Friendliness	PIF	Percentage of Topic1 in NEV user reviews
		Topic2	Perceived Convenience	PC	Percentage of Topic2 in NEV user reviews
	Competence Perception	Topic3	Perceived Value	PV	Percentage of Topic3 in NEV user reviews
		Topic4	Perceived Safety	PS	Percentage of Topic4 in NEV user reviews
		Topic5	Perceived Entertainment	PE	Percentage of Topic5 in NEV user reviews
MV	Car Use Time			Time	Days between NEV purchase date and user review date
	Topic1 Perceived Intimacy and Friendliness			PIF	Percentage of Topic1 in NEV user reviews

DV: Dependent variable; IV: Independent variable; MV: Moderating variable CV: Control variable

(1) Regression Analysis Part I

We first tested the direct effects of 5 themes on the intelligent service evaluation given by NEV users, to reveal how the warm perception and competence perception under high-evoked automated social presence evoked the effects of intelligent service evaluation. The model was set up in equation (5):

$$\boldsymbol{ISE_i} = \sum_{k=1}^{K} A^k \cdot Topic_i^k + \delta + \varepsilon_i \tag{5}$$

where the independent variable $Topic_i^k$ represents the proportion of topic k in the comment i, $k \in \{1,2,3,4,5\}$. The value of $Topic_i^k$ can be output through the *stm* package in the R programming tool. And A^k is the corresponding coefficient of $Topic_i^k$, δ is the intercept, and ε_i is the standard errors of the model. The dependent variable *Intelligent service evaluation$_i$* is measured by the intelligent rating corresponding to each automobile review. The DCar website allows NEV users to rate the intelligent car service to evaluate their satisfaction with the intelligent service. On a 5-point scale, 1 is very dissatisfied and 5 is very satisfied.

(2) Regression Analysis Part II

On the basis of Part I, the adjustment variable $Time_i$ is added to represent the driving time corresponding to comment i, which is measured by the time interval between the date of car purchase and the date of data acquisition. This study believes that it is necessary to consider the potential influence of car use time on the direct effect from a "dynamic" perspective. It is because different frequencies of AI interaction bring different user experiences, and the social cognition and service evaluation of AI assistants will also change. For example, from the initial resistance and neglect of AI interaction to the gradual emotional dependence on AI assistant. Modify the model in equation (6):

$$\boldsymbol{ISE_i} = \sum_{k=1}^{K} A^k \cdot Topic_i^k + B \cdot Time_i + \sum_{k=1}^{K} C^k \cdot (Topic_i^k \times Time_i) + \delta + \varepsilon_i \tag{6}$$

Among them, which B is suitable for the corresponding coefficient of $Time_i$, C^k for interactive items ($Topic_i^k \times Time_i$) of the corresponding coefficient, $k \in \{1, 2, 3, 4, 5\}$.

(3) Regression Analysis Part III

Based on Part I, the independent variable Perceived intimacy and friendliness (Topic 1) is changed to a moderating variable. In this study, it is also necessary to consider the potential influence of warmth perception on direct effects. Previous studies focused on the separate or comparative analysis of the influence of two dimensions of social cognition (warmth and competence) on the results of user behavior [47, 13], but the interaction between warmth perception and competence perception, especially the influence of warmth perception on the relationship between competence perception and user service evaluation, has been ignored. Modify the model in equation (7):

$$\boldsymbol{ISE_i} = \sum_{k=1}^{K} A^k \cdot Topic_i^k + B \cdot Topic_i^1 + \sum_{k=1}^{K} C^k \cdot (Topic_i^k \times Topic_i^1) + \delta + \varepsilon_i \qquad (7)$$

where B is the corresponding coefficient of $Topic_i^1$, which represents the proportion of Topic 1 in comment i. C^k for interactive items ($Topic_i^k \times Topic_i^1$), the corresponding coefficient $k \in \{2,3,4,5\}$.

4.3.2 The relationship between Topics and Intelligent service evaluation

We carried out the empirical analysis on the three models constructed by Stata software, and the summary results are shown in Table 3. In the direct effect analysis of Part I, the five topics of two dimensions have been proved to have a significant positive impact on the intelligent service evaluation, which means that the multimodal AI anthropomorphic interactive experience with high evoking ASP can prompt NEV users to give a more positive intelligent service evaluation. It is consistent with Davenport's research conclusion that "high level of ASP will lead to good consumer response" [29].

Table 3. Multiple linear regression results.

Regression Analysis Part I					
Category	Warmth perception	Competence perception			
Variable	Topic1	Topic2	Topic3	Topic4	Topic5
	Perceived intimacy and friendliness	Perceived convenience	Perceived value	Perceived safety	Perceived entertainment
Direct effects	4.3211*** (168.56)	4.4058*** (127.79)	4.4298*** (144.77)	4.4550*** (188.10)	4.2618*** (120.27)
Regression Analysis Part II					
Variable	Model1	Model2	Model3	Model4	Model5
Moderating Effects					
Topic1 PIF	1.3643*** (7.59)	3.6900*** (66.79)	3.4775*** (56.53)	3.0695*** (48.40)	3.2618*** (62.21)
Topic2 PC	3.9779*** (62.03)	2.4437*** (11.35)	3.4290*** (50.99)	2.9865*** (41.36)	3.2064*** (53.39)
Topic3 PV	3.9025*** (58.82)	3.5638*** (54.33)	3.4595*** (18.34)	2.8824*** (38.96)	3.1046*** (50.20)
Topic4 PS	3.8605*** (55.05)	3.4751*** (51.53)	3.2342*** (44.58)	4.5340*** (29.29)	2.9953*** (47.01)
Topic5 PE	3.8294*** (56.72)	3.4696*** (53.12)	3.2428*** (47.07)	2.7833*** (37.16)	4.7677*** (21.54)
$Time_i$	0.0790***	0.1465***	0.1888***	0.2694***	0.2310***

	(7.09)	(13.83)	(16.53)	(22.18)	(23.45)
PIF×$Time_i$	0.5218*** (12.19)				
PC×$Time_i$		0.2293*** (4.82)			
PV×$Time_i$			-0.0234 (-0.55)		
PS×$Time_i$				-0.3074*** (-8.69)	
PE×$Time_i$					-0.3225*** (-6.95)

Regression Analysis Part III

Variable	Model1	Model2	Model3	Model4
Moderating Effects				
Topic2 PC	(107.98)	4.3750***	4.3988***	4.4025***
	4.4330***	(121.17)	(126.53)	(125.83)
Topic3 PV	(71.65)	4.4785***	4.4402***	4.4299***
	4.4078***	(80.00)	(142.51)	(142.05)
Topic4 PS	(139.29)	4.4220***	4.2707***	4.4548***
	4.4276***	(171.43)	(119.44)	(176.34)
Topic5 PE	(174.98)	4.2338***	4.2790***	4.0612***
	4.2413***	(115.01)	(119.03)	(72.77)
Topic1 PIF_i	4.3295*** (107.98)	4.3589*** (91.04)	4.1271*** (107.34)	4.2005*** (118.80)
PC×PIF_i	-0.3064 (-0.88)			
PV×PIF_i		-0.4179 (-1.40)		
PS×PIF_i			1.6565*** (6.23)	
PE×PIF_i				1.5811*** (4.31)

Notes: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Specifically, among the 5 topics, Topic4 Perceived convenience has the greatest effect (4.4550) on intelligent service evaluation, followed by Topic2 Perceived convenience (4.4058). Both are higher than Topic1 for Perceived intimacy and friendliness (4.3211). This indicates that although Topic1 received the highest NEV user attention (25.07%), it did not translate into a decisive factor affecting user service results. NEV users seem to be more likely to rate intelligent services more highly because of the safe and convenient experience they get. Thus, it can be seen that merely enhancing the warmth perception of intimacy and friendliness by increasing the degree of anthropomorphism does not necessarily lead to better service, and functional attributes need to be taken into account. Ability is a basic feature of robots, so no matter how anthropomorphic a robot is, its ability level should be guaranteed [47], especially in the driving process involving life safety demands. However, it is only obtained in static situations, and the dynamic effects of driving time and AI interaction frequency still need to be considered.

4.3.3 The moderating effect of Time

In the analysis of the moderating effect in Part II, the addition of the moderating variable *Time* significantly positively moderates the positive influence of Topic 1 and Topic 2 on the evaluation of intelligent service, but the strengthening effect on Topic 1 (0.5218) is significantly greater than that on Topic 2 (0.2293). *Time* significantly moderates the positive impact of Topic 4 and Topic 5 on the evaluation of intelligent service, but the weakening effect on Topic 5 (-0.3225) is significantly stronger than that on Topic 4 (-0.3074). In addition, the impact of Topic 3 Perceived value on evaluation is verified to be independent of *Time*.

In other words, with the increase of driving time and AI interaction frequency, NEV users are most likely to get better intelligent service because of Perceived intimacy and friendliness, followed by Perceived convenience. This leads to an interesting phenomenon: in static situations, NEV users tend to make intelligent service evaluations based on Perceived safety, but in dynamic situations, Perceived intimacy and friendliness become criteria for friendliness. It shows that it takes time to establish a close relationship between users and AI assistants. Once this emotional dependence plays a role, the warm perception based on high evocative ASP will be an important means to improve intelligent service experience and evaluation [23], and the role of competence perception will be weakened.

Perceived entertainment and Perceived safety do not seem to stand the test of time in the hearts of NEV users. After repeatedly sorting out the review text, it is found that perhaps because the AI interaction system is not upgraded in time and the entertainment function is too simple, frequent interaction causes NEV users to gradually lose the initial sense of freshness and pleasure [51], and even become tired of interactive experience. For example, one user said, "I'm tired of seeing the facial expressions of NOMI." In addition, perhaps because the longer you use the car, the more likely it is that the AI assistant service will fail. In other application scenarios (such as hotels or restaurants), the failure of robot service may be forgiven by users because of its cute appearance [52] or humorous language [62], but the failure of AI intelligent service in the driving process will bring huge security threat and fear experience to users, thus reducing users' willingness to interact and positive comments. For example, one user said that "the Internet disconnection on the highway made Nomi slow and even completely ignore me, just like a photo".

4.3.4 The moderating role of Perceived intimacy and friendliness

In the moderating effect analysis of Part III, the change of the independent variable Topic 1 significantly positively moderates the positive impact of Topic 4 and Topic 5 on the evaluation of intelligent service, and the strengthening effect on Topic 4 (1.6565) is significantly greater than that on Topic 5 (1.5811). Perhaps it is because the close and friendly partnership established between users and the multimodal AI anthropomorphic assistant strengthens users' trust [25, 43], acceptance [25], reliability [43] and willingness to use the AI assistant [92]. Therefore, compared with the AI assistant without anthropomorphic features or single mode, the security and entertainment functions of the competence perception dimension can be better developed and played. However, Topic 1 cannot be proved to improve the functional experience of perceived convenience and perceived value. The findings reveal the internal relationship between the two dimensions of social cognition (warmth and competence) on user service outcomes.

5. Conclusion and discussion

5.1 Conclusion

Based on user-generated content (online reviews), this study aims to capture and summarize the interactive experience between NEV users and on-board multimodal AI anthropomorphic assistants according to two evaluation dimensions of social cognition (warmth and competence), and further reveal the complicated effects of warm perception and ability perception brought by AI assistant high-evoked ASP on user intelligent service evaluation. Considering the dual effects of the intrinsic relationship between time and social cognition, our research provides valuable insights into the use of anthropomorphic features and multimodal interactions to evoke high levels of ASP and thereby improve the service experience of on-board AI robots and the effectiveness of the results. The findings are of great significance to the product improvement of service robot and the intelligent transformation of new energy vehicles in the era of industry 5.0.

5.2 Theoretical Implications

The theoretical significance of this research is mainly reflected in the following aspects. Firstly, the feasibility, effectiveness and superiority of applying unsupervised machine learning method to unstructured data are verified. In this study, the DCar website, a high-quality data source that has not been paid much attention by scholars, is selected and disruptive technology such as text mining and structural topic modelling are applied to help us obtain valuable user insights from a large amount of user-generated content. In addition, quantification of user AI interaction experience is realized by STM output topic proportion, which break the limitation of quantity of traditional questionnaire data, and created conditions for further testing how high-evoked ASP user service experience affects user service results. This is a useful attempt to apply big data text analysis technology to user experience management.

Secondly, our study enriches existing research results related to automated social presence and provides new insights. The level of automated social presence is often thought to be related to the degree of anthropomorphism of non-human entities [13]. But it doesn't mean that a high level of automated social presence is evoked by a highly anthropomorphic feature, such as a human-like appearance. Rather, this study believes that only moderate personification (such as mascot-like appearance) can stimulate a high level of automated social presence and translate into satisfying service experience and results for users. In addition, from the perspective of emotional transmission effect during AI interaction [22], we also confirmed that multimodal AI anthropomorphic assistant can evoke a high level of automated social presence and thus improve users' service evaluation.

Thirdly, our research extends the application scenarios of social cognition theory to NEV and multimodal anthropomorphic service robots, and has important significance for revealing users' specific perception of high-level ASP and improving the results of intelligent service. Existing research shows that user-generated content is an important data source for enterprises to gain insight into and manage user experience and sum [27]. We extract five highly condensed topics from NEV review texts through topic modelling. The multimodal AI anthropomorphic interactive experience of NEV users is revealed from the dimensions of warmth perception and ability perception in social cognition respectively. Among them, perceived intimacy and friendliness (25.07%) is the most popular friendliness among users. Users' perception of AI assistant's ability mainly consists of perceived safety (24.73%), perceived value (20.66%), perceived convenience (15.50%), and perceived entertainment (14.04%).

Fourthly, an empirical analysis is conducted to reveal the influence of NEV users' social cognition of high evocative ASP on the evaluation of intelligent service. The results show that, from the static perspective without considering time, the user experience represented by the 5 topics can significantly improve user evaluation, but users tend to give higher evaluation because of perceived safety. In a dynamic perspective taking into account friendliness, the positive influence of perceived intimacy and friendliness on user evaluation increases with increasing frequency of interaction. However, time will weaken the positive influence of ability perception (especially perceived safety) on user evaluation. Put it in another way, new customers are more focused on a secure experience, while old customers are more focused on a close and friendly man-machine relationship. Considering the influence of the intrinsic relationship of social cognition, users are more likely to be satisfied with Perceived safety and Perceived entertainment because of warmth perception.

5.3 Managerial Implications

The study also provides several managerial implications. Firstly, the user experience management for NEV enterprises. We have made technological attempts to identify user generated content and supervise user AI interactive experience, which has important enlightening significance for identifying user intelligent service needs, improving user participation in product design process, and enhancing the results of intelligent service.

Secondly, the improvement direction of AI interactive products for new energy automobile enterprises. This study verifies the feasibility of invoking a high level of ASP through anthropomorphism and multimodal to improve intelligent service satisfaction. Therefore, it is suggested that enterprises add virtual reality and NLP technology to change the current task-oriented product research and development direction, strengthen the social attraction of AI assistant through technical means, and consider the in-depth development and continuous update of security, convenience, cost-effective and entertainment capabilities while establishing a close and friendly relationship with users.

Thirdly, intelligent marketing strategy for new energy vehicles. Based on the influence of different car duration on user AI interaction experience and evaluation obtained in this study, differentiated marketing solutions are developed to distinguish new and old users. For new customers, we should not overemphasize the social attraction brought by AI interaction, but also emphasize the strong ability guarantee of AI assistant. But for old users, we should focus on the emotional marketing.

Finally, we provide operational improvement guidelines for third-party e-platforms. It should guide NEV automobile enterprises to access, make full use of the advantages of third-party platforms, pay real-time attention to the owners' intelligent service experience feedback and evaluation changes, listen to the voices of owners, and respond quickly to the owners' intelligent concerns.

5.4 Limitations

Despite several interesting and valuable insights obtained by our research, there are a few limitations that will be improved in future research. Firstly, this study only selected the Chinese data of a single online automobile platform, and did not collect the information of English and other languages, resulting in too single sample enterprises and sample data. In future studies, we consider collecting review data in multiple languages from multiple third-party online platforms to verify the conclusions of the study. Secondly, due to the small number of new energy vehicle brands supporting multimodal AI anthropomorphic interaction, the amount of effective data is limited, and the time series of data is too short to effectively analyze the topic prevalence.

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