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Exploring Factors Affecting People's Willingness to Use a Voice-Based In-Car Assistant in Electric Cars: An Empirical Study

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Abstract: Voice-based digital assistants are growing in popularity and have been acknowledged as a crucial part of in-car interaction. Currently, academic attention is being paid to various voice assistant scenarios. However, sparse literature focuses on the adoption of voice assistants within the in-vehicle context. The objective of this paper is to examine key factors influencing people's willingness to use voice assistance in electric cars. First, eight general variables were identified based on the literature review, as well as four demographic variables. These factors were then integrated to construct a hypothetical research model. After that, we carried out an empirical study to examine the structural relationships in the model based on the questionnaire survey results (N = 427). The hypothesis testing results indicated that most path relationships among variables were validated. Finally, we discussed the research findings and developed corresponding design strategies to enhance user acceptance towards in-car voice assistants, both from designers' and car enterprises' viewpoints. This article offers valuable theoretical and practical implications for the development of such technologies.

Keywords: voice assistant; in-car interaction; electric car; structural equation modelling; interactive design

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1. Introduction

The terminology "voice assistant" refers to an AI-powered digital agent that provides services or executes tasks in response to users' verbal instructions or questions [1]. This technology has been widely applied in various human–computer interaction scenarios, such as smart speakers (e.g., Amazon Alexa) or smartphones (e.g., Apple Siri) [2,3]. With the development of information and communication technology, cars have an increasingly high level of automation and are also equipped with voice assistants. Nowadays, drivers can enjoy more freedom in an electric vehicle, as they can handle more tasks and access more information when driving with the assistance of these intelligent agents [4]. In addition to functional needs (e.g., responding to commands), voice assistants also assume a critical role in fulfilling drivers' emotional needs [3].

As a core interaction approach between users and electric cars, voice assistants are becoming an area of focus [5,6]. These digital agents have benefits for both drivers and car enterprises. For drivers, a well-designed voice assistant can improve driving performance and safety and enhance the driving experience [7]. Generally, driving is an activity that requires the management of plenty of human resources when concentrating on the surrounding circumstance [8]. With the help of voice assistants, drivers can handle these tasks without too much attention, consideration, or manipulation. At present, these AI-based voice assistants can not only respond to basic instructions (e.g., playing music or making a phone call) but also provide tailored customer services based on their preferences (e.g., recommending restaurants or car parks) [9]. In this regard, voice assistants can lower drivers' recognition loads and workloads, thus ensuring driving safety [3]. Moreover, some information broadcasted by voice assistants, such as traffic status or driving routes, can help drivers to make more accurate decisions. On the other hand, some voice assistants are designed to improve drivers' emotions and user experiences during use, which is called "affective in-car interaction" [3,5]. For example, in-car assistants can arouse users' positive emotions by enhancing relational closeness. When perceiving users' unpleasant feelings, voice assistants will attempt to mitigate their stress or encourage them through a series of conversations [10].

On the other hand, voice assistants can also benefit enterprises by promoting customer purchase intentions and increasing sales of cars based on a built-in relationship between car brands and customers [9]. Currently, these intelligent agents are widely appreciated by car users. As a recent report pointed out, in-car interaction is the most common setting where the use of voice assistants on smartphones occurs, accounting for a proportion of 62% [2]. The report also suggested that over 50% of consumers in America use voice assistants in their cars, and 33% of them were monthly active users. Moreover, a study conducted by JD Power demonstrated that most car owners preferred to purchase a car equipped with the voice assistant they are familiar with. This phenomenon is widespread for Gen-Y [11]. Apart from this, the data collected by voice assistants can give car companies an in-depth grasp of driver preferences and habits, thereby keeping up with user behaviour [12].

Prior research on voice assistants has gained much attention with the innovation of electric car technology; however, several problems still exist. From a practical viewpoint, although growing social and emotional needs are expected to be fulfilled during in-car interaction, most voice assistants are yet designed to perform practical tasks [3,13]. In other words, these intelligent agents are often function-led rather than being of a user-centred design. Therefore, the user experience and willingness are overlooked when interacting with in-car assistants. From a theoretical viewpoint, there are also several literature gaps. Regarding voice assistant studies, there have been attempts to optimise voice assistants by doing experiments [5,7,14,15]. However, the focus is rarely on constructing a systematic framework to understand user acceptance or preferences towards voice assistants in electric cars. Moreover, the literature on user acceptance towards voice assistants has recently received growing attention, but few focus on the in-car context [16–20]. Regarding electric car studies, some strive to identify key influential factors to increase customer purchase intentions, but few draw on the user willingness during the in-car interaction [21–23].

China has become one of the leading global electric car sellers by 2021, and there is fierce competition in China's electric car market. Under such a background, if designed properly, voice assistants can lead to the success of a car brand to some extent. Therefore, understanding user preferences and acceptance towards voice assistants in electric cars is of high significance. The main objective of this article is to identify critical determinants of user acceptance towards in-car voice assistants and build a research model. After that, the researchers discuss the findings and develop design strategies to improve user willingness of usage. To reach the goal, three research questions were posed: First, what are the main factors influencing people's willingness to voice assistants in electric cars? Second, how can we construct a theoretical model that reveals the mechanism of user willingness to use voice assistants? Third, how can we propose design strategies to improve user acceptance during in-vehicle interaction? Our research knowledge contributions are two-fold. At the theoretical level, our research contributes to technology adoption studies by forwarding a model clarifying factors influencing user willingness to use in-car voice assistants. Based on the literature review results, the researchers explored the impact of two perceptional factors, four design factors, and four demographic factors on user acceptance through an empirical study. Overall, this study is a multidisciplinary endeavour incorporating knowledge from human–computer interaction, behavioural sciences, psychology and design sciences. At the practical level, different stakeholders can benefit from this paper's theoretical findings. For users, it can help them to acquire a more favourable driving experience when interacting with an in-car assistant. For designers, it can provide a more in-depth comprehension of user perceptions and preferences towards voice assistants, which are valuable for them in producing practical design schemes. For electric car enterprises, it can help them to develop more welcomed in-car assistants, thereby improving word of mouth and the promotion of customer purchase intentions.

2. Literature Review

2.1. In-Car Interaction

With the advancement of information technology, electric cars are often equipped with smart control systems. These systems integrate various cutting-edge technologies, such as touch panels, microphones, cameras, GPS sensors, light sensors, and algorithms [18]. Thus, in-car interaction is defined as numerous sensors used in electric cars to comprehend driver and passenger behaviour, emotions, and preferences, to provide appropriate functionalities and services for an enjoyable ride [19]. It concerns the issue of understanding and shaping the interaction dynamics between humans and vehicles [4].

The user experience of in-car interaction has recently gained much attention from electric car enterprises, as it determines customer purchase intentions and sales. Generally, driving a car requires the coordination of different parts of the human body, as well as concentration on the surrounding environment. As a result, it is necessary to understand the interaction between the driver, vehicle interface, and context. As Detjen et al. (2021) stated, technological advancements in vehicles often require an exploration of new possibilities that enrich user experiences and obtain user acceptance of the in-car interaction [18]. The design of in-car interaction should not only consider ergonomics and usability but also make users feel emotionally comfortable, thereby enhancing the driving experience [8]. When drivers maintain attentive attitudes and trust in vehicles, this type of in-car interaction could increase driving pleasure, efficiency, and safety [7].

2.2. Voice Assistant

Voice assistants are generally smart digital agents designed to understand natural language and give responses through speech synthesis under different application scenarios [6]. Compared with other technologies, these voice-based digital agents have five unique features [20]. First, their images or speech styles simulate human traits, as customers prefer voice assistants of a human kind. Second, their interfaces are characterised by natural and conversational styles. Third, they are controlled by verbal instructions so that a user's hands can be kept free. Fourth, they can deliver tailored services and adapt to customer behaviour. Fifth, they are equipped with sensitive always-on microphones for always listening. In the present study, voice assistants are also called voice-based in-car assistants, belonging to a type of interactive tool during in-car interaction. These smart agents serve as a mediator between drivers and electric cars, enabling users to access information and handle tasks more conveniently and efficiently [9]. Moreover, the advancement of AI technology enables voice assistants to learn and adapt to user habits, speech patterns and preferences. These make voice assistants a competitive point in the global electric car market.

The present landscape of in-car commercial in-car voice assistants can be categorised into three types [21]. The first type of voice assistant is developed based on the collaboration of car manufacturers and a third party. For instance, Ford and Lincoln's vehicles are widely equipped with Amazon Alexa, while Volvo, General Motors, Polestar, and Renault are going with Android Automotive OS. The second type is developed solely by a tech giant, such as Google's Assistant via Android Auto and Apple's Siri via CarPlay. The third type of voice assistant is developed by car manufacturers themselves, for example, Mercedes-Benz's MBUX and BMW's IPA6. The innovation of voice assistants has also been observed in China's electric car markets. There are currently more than 150 electric car brands in China [22]. Among them, NIO, Xiaopeng, Lixiang and BYD Auto are top domestic sellers. These car manufacturers have committed massive funds to voice assistant development, and most have their own name-brand voice assistants. For instance, Xiaopeng developed its name-brand voice assistant called "Xiao P", enabling users to control their cars flexibly and smoothly. Compared with other in-car interaction systems, Xiao P has advanced functions, such as continuous dialogue, immediate interruption, invalid sentence filtering, dual-sound area recognition, and image customisation. BYD Auto is another electric car giant in China market and has developed an in-car assistant called "Xiaodi". Besides the basic control function, "Xiaodi" can independently position sound sources, activate smart control systems, and recognise children's voice.

2.3. User Willingness or Acceptance of In-Car Voice Assistants

Previous literature striving to enhance user acceptance towards voice assistants primarily falls into three fields: computer sciences (human–computer interaction), design sciences, and behavioural sciences. In the human–computer interaction field, researchers attempt to optimise the interaction process between drivers and in-car voice assistants. Some argue that arousing people's emotional resonance is an effective strategy. For example, Braun et al. (2019) found that an affective voice assistant with empathetic effects is the most promising during in-vehicle interaction, compared with other interactive approaches [23]. Their other study indicated that personalised voice assistants could positively affect user acceptance, trust, and workload [5]. Moreover, some attempts have been made to improve the function of voice assistants to enhance user experiences. For example, Gordon and Breazeal (2015) developed PANDA, a parental affective in-car assistant, mediating interaction between parent drivers and their children [24]. The agent also served to engage, entertain, and educate the children in the back seats. In addition, some try to minimise driver cognitive loads or working loads. For instance, Schmidt et al. (2020) categorised driver cognitive loads into four levels: low, medium, medium–high and high, and then applied the findings to develop proactive voice assistant suggestions during in-vehicle interaction [12].

In design sciences, scholars have attempted to utilise novel research methods for practical design. For instance, Row et al. (2020) introduced a pet–morphic design approach and identified a set of pet-dog behavioural characteristics for in-vehicle voice assistant design [7]. They then explored how to implement these design characteristics in different driving contexts. Ringfort-Felner et al. (2022) employed a design fiction approach to investigate the association between drivers and a virtual in-car assistant, "Kiro," and in what way it could fulfil user social experiences [3]. Meck and Precht (2021) conducted an exploratory study and developed linguistic-based guidelines for the prompt design of in-car voice assistants on syntactical, grammatical, and lexical levels [25]. Ji et al. (2019) explored the influence of information type and speaker gender on user preferences during in-car interaction [26]. The results showed that both were influential factors affecting user choices.

In behavioural sciences, exploring the mechanism of people's willingness to use voice assistants is still a new research arena. For instance, Wolf (2021) investigated the impact of voice assistants on people's trust, purchase intentions and emotions via a multivariate analysis [27]. The result revealed that a human voice assistant could promote purchasing behaviour and reduce negative emotions. Liu et al. (2021) found that user preferences towards voice assistants were associated with a series of design feature factors, including personality traits, voice pitch, voice speed, language style, and so on [28]. Vimalkumar et al. (2021) proposed an extended UTAUT2 model to examine the influence of privacy-related factors on the adoption of voice assistants in India [20]. Their findings suggested that perceived risk and perceived trust could indirectly affect people's behavioural intentions and adoptions, in addition to the traditional UTAUT2 constructs. Pitardi and Marriott (2021) integrated human–computer interaction theories and para-social relationship theory to identify in what way perceived trust and attitudes play a part [29]. They found that perceived usefulness, perceived ease of use, enjoyment, social presence, social cognition, and privacy concerns were effective predictors. McLean and Osei-Frimpong (2019) developed a framework that extends U&GT theories to examine user adoptions and motivations for using in-home voice assistants [30]. Their studies illustrated that individuals were mainly driven by three types of benefits from voice assistants: utilitarian benefits, symbolic benefits, and social benefits. Fernandes and Oliveira (2021) explored the drivers of consumers voice assistant adaptation in service encounters from three perspectives: functional, social, and rational [16]. Overall, it can be derived that the literature on voice assistant adoption has been investigated in different scenarios, such as smart homes, mobile phones, and service encounters [16,20,30]. However, few have focused on the in-vehicle context.

3. Hypotheses Development and Research Model

Based on the literature review results, we identified eight variables to construct a theoretical model that reveals user willingness to use in-car voice assistants, see Figure 1. These variables can be categorised into three aspects: perceptional factors (familiarity and privacy concern), design factors (anthropomorphism, interaction, interface design, and personalisation), and demographic factors (gender, age, educational level, and experience).

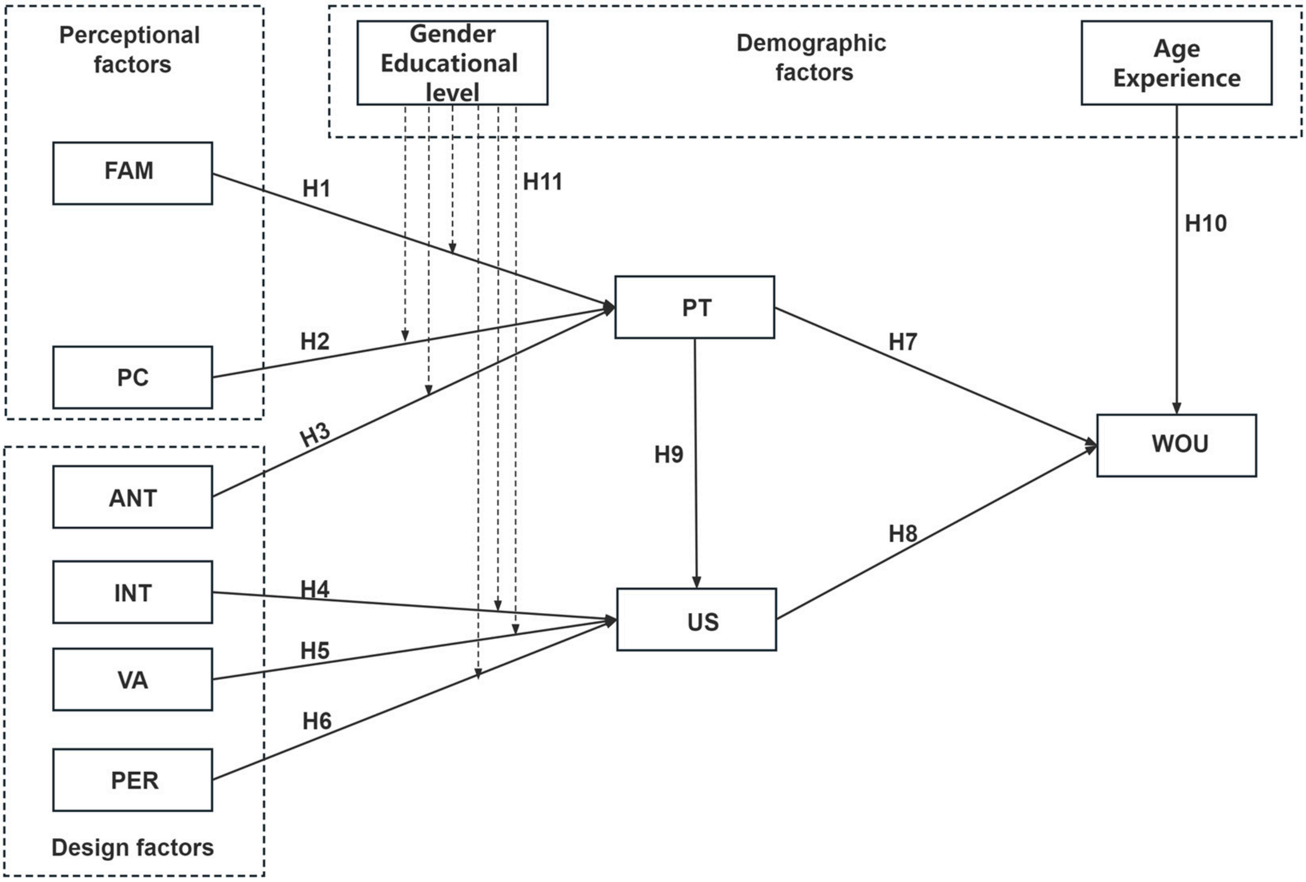

Figure 1. Theoretical model.

3.1. Familiarity

Familiarity is one perceptional factor in the model, and it has been defined by several scholars in previous research. Gefen et al. (2003) argued that familiarity represented customer understanding of an entity based on their prior interactions, experience, and learning of "the what, who, how, and when of what is happening" [31]. Alba and Hutchison (1987) defined familiarity as one's accumulated product-related or service-related experience of a consumer good, which might be direct or indirect [32]. This factor can be reflected in various aspects, for example, advertisement and propaganda, consumption and usage, interactions with salespeople, and word of mouth [33]. In the current study, we defined familiarity as user perceptions and assessments of voice assistants based on previous and direct experiential exchanges. In the context of voice assistant adoption, familiarity can play a two-sided role in customer-perceived trust, depending on whether their prior experience is positive or negative. This assumption has been validated in previous technology adoption studies [34]. In some cases, consumer familiarity with voice assistants can even affect their purchase intentions [11]. Based on the above elaborations, we came up with the following hypothesis:

H1. *Familiarity positively influences perceived trust with in-car voice assistants.*

3.2. Privacy Concern

In the current research, privacy concern denotes to what extent people perceive that using an in-car assistant may infringe on their privacy [35]. Users' personal information, such as address lists, chatting information, or preferences, may be collected and misused by service providers when interacting with voice assistants. Unfortunately, privacy risks are inevitable during in-vehicle interaction, as most voice assistants are designed to collect consumer data for better behaviour adaptation. This issue may destroy people's perceived trust in technologies and damage customer relationships. In practical situations, people have raised a series of debates to discuss how personal information is collected and misused by large companies such as Google or Facebook [36]. In academic fields, privacy loss has proved to be a primary barrier to user acceptance of technologies [37]. Martin (2018) found that consumers perceived privacy risk could lead to a reduction in trust when scanning a website [38]. The finding was also validated in Chang et al.'s (2017) research [39]. Liu and Tao's (2021) study showed that loss of privacy would trigger unwillingness to use smart healthcare services [40]. In the scenario of voice assistants, Buteau and Lee (2021) found that privacy concerns were adverse drivers for people's attitudes to usage [41]. In this paper, we argue that increasing privacy concerns might trigger trust loss. Thus, the hypothesis was:

H2. *Privacy concerns negatively influence perceived trust with in-car voice assistants.*

3.3. Anthropomorphism

Anthropomorphism was forwarded as one design factor. It describes people's tendency to attribute human physical features, emotions, intentions, and motivations to nonhuman agents [42]. This factor has been studied in many technology scenarios, including service robots, smart homes, and mobile phone applications [43]. In the context of digital voice assistants, research on anthropomorphic characteristics has three emerging mainstreams: human-like images, human-like voices and voice assistant humanity. In the present study, we primarily concentrated on the last aspect: voice assistant humanity, which describes people's voice assistant imitations of human psychological characteristics, for example, consciousness, mind, and emotions. In academic fields, researchers have contributed their knowledge to reveal the relationship between anthropomorphism and people's perceptions or emotions. The well-known Uncanny Valley Theory, proposed by robotics professor Masahiro Mori, uncovered the relationship between an object's degree of resemblance to humans and human likeness to the object [44]. Grounded on this theory, studies have discussed both the positive and negative impact of AI agents' anthropomorphism on user responses and intentions [45,46]. Sometimes, the effect of anthropomorphism on user attitudes may be mediated by other factors [40]. In the context of in-car voice assistant usage, it is assumed that customers tend to concentrate on the human-like mental features of voice assistants when providing services. Thus, we constructed the following hypothesis:

H3. *Anthropomorphism positively influences perceived trust with using in-car voice assistants.*

3.4. Interaction

Interaction is the second proposed design feature of voice assistants, which has different definitions in previous empirical studies. For instance, Johnson et al. (2006) stated that interaction could be reflected in three aspects: responsiveness, nonverbal information, and speed of response [47]. Dicianno et al. (2015) argued that interaction is a type of ability that describes how technologies communicate with users in a bidirectional way [48]. Birkmeyer et al. (2021) deemed that interaction was significantly associated with the possibility of an APP for providing feedback [49]. Further, Wu (2006) believed that one's perceived interactivity might differ from the other [50]. Synthesising previous research findings, the current study theorises interaction as one's subjective experience when interacting with voice assistants. This factor can be reflected in three facets: feedback speed, communication quality, and perceived control. Prior research has indicated that interaction could lead to user satisfaction towards the MHealth APP and increase the usability of smartphones [49,51]. During the driving process, people often prefer voice assistants that can provide immediate feedback and easily control and deliver valuable information to enhance driving experience. Hence, this factor could be added to the model and the following hypothesis was:

H4. *Interaction positively influences user satisfaction towards in-car voice assistants.*

3.5. Visual Appeal

The factor "visual appeal" concerns a series of visual design elements, such as colours, images, layouts and structure, styles, animation, and so on. Visual design is omnipresent during in-vehicle interaction, determining user first impressions of voice assistants. This factor involves the user interface design and virtual role image design of a voice assistant in the current study. Generally, the interface and appearance of voice assistants should be appealing, understandable, and logically structured to fulfil users' emotional needs. The main reason is that an aesthetically pleasing product or object appears more effective to humans by its sensual appeal [52]. Previous studies have revealed the impact of the interface or appearance design of intelligent technologies on user psychological status. For instance, Lv et al.'s (2021) research suggested that the cuteness design of AI assistants could affect customer tolerance of service failure [53]. Song and Luximon (2021) found that facial width-to-height ratios and face shapes of a robot could influence customers' trustworthiness and purchase intentions [54]. In the scenario of voice assistants, Mishra et al. (2022) argued that the visual appeal of interfaces could contribute to user utilitarian value [45]. In this regard, visual appeal was assumed as a success factor for continuous usage intentions, and we built the following hypothesis:

H5. *Visual appeal positively influences user satisfaction with using in-car voice assistants.*

3.6. Personalisation

Many voice assistants today incorporate characteristics of personalisation. In the present study, this term refers to the degree to which users can enjoy targeted services from voice assistants based on their characteristics [35]. These days, AI-powered voice assistants have become more intelligent agents with personalities [55]. Based on the communication and user data, they will continuously update and finally adapt to user behaviour and habits. Currently, an in-car assistant with tailored services has become one focus of competition for car manufacturers. As Braun et al. (2018) stated, personalisation can help users to maintain an attachment to cars, even if ownership and driving are becoming a thing of the past [23]. Many empirical studies have highlighted the impact of personalisation on people's adoption intentions of recommended agents. For example, Birkmeyer et al. (2021) found that personalisation was a strong predictor of user satisfaction during MHealth app usage [49]. Liu and Tao's (2022) study suggested this factor could increase perceived trust [40]. In addition, it is worth noting that when it comes to in-vehicle usage, the personalisation of voice assistants should vary according to the specific context, for example, whether the task is associated with driving [5]. Based on the above discussions, we came up with the following hypothesis:

H6. *Personalisation positively influences user satisfaction with using in-car voice assistants.*

3.7. Perceived Trust

We deduced and conceptualised perceived trust as one of the pillars that directly influences user willingness to use voice assistants. Trust-related research has recently become a focusing area in many disciplines, including computer sciences, behavioural sciences and marketing sciences. In technology adoption studies, perceived trust is often reflected in people's expectations and confidence towards the reliability level of certain technologies [56]. In the present study, people's perceived trust in voice assistants can help them handle the uncertainty or potential risks during adoption. Unlike other technology adoption scenarios, people's trust in the in-car context is particularly essential, which is attributed to three causes. First, driving is an activity that concerns a user's security and safety. Second, users may encounter the risk of privacy breaches, as a vast amount of user data are collected by voice assistants during in-car interaction. Third, current voice assistants are often required to engage in fully-fledged social conversations with users, during which trust is necessary [3]. The role of perceived trust has been emphasised in prior technology adoption studies. For instance, Pal et al. (2022) found that a high level of trust was a prerequisite for the usage willingness of voice-based electric devices [57]. Similarly, Vimalkumar et al. (2021) found that perceived trust effectively predicted the public acceptance of AI-based conversational agents [20]. Pitardi and Marriott's (2021) findings also suggested that trust in voice assistants was associated with people's attitudes towards usage intentions [29]. Based on the above illustration, the following hypothesis is formulated:

H7. *Perceived trust positively influences willingness to use in-car voice assistants.*

3.8. User Satisfaction

User satisfaction was anticipated to be one construct in this investigation. This factor is derived from the well-known information success model proposed by Delone and McLean [58]. In the model, user satisfaction represents the extent to which users are contented with the information system. As time goes by, the definition of user satisfaction concerns more perspectives (than just "information" only), which describes individuals' assessments of their overall experience with the system [59]. In Xinli's (2015) study, the concept was described as the extent to which an individual perceives a system to be useful [60]. The present research captured Hossain's (2016) depiction and defined it as the user's subjective feelings when interacting with in-car voice assistants [59]. Generally, when user requirements are satisfied, they will be more willing to adopt a technology. This statement has also been empirically validated in prior studies. For instance, Birkmeyer et al. (2021) mentioned that user satisfaction could affect word of mouth and people's intentions to use MHealth apps [49]. In another study, it became a driver of student usage intention of e-learning systems [61]. In addition, a satisfactory voice assistant may also increase its trustworthiness. Thus, the hypotheses were forwarded as follows:

H8. *User satisfaction positively influences people's willingness to use in-car voice assistants.*

H9. *User satisfaction positively influences people's perceived trust in in-car voice assistants.*

3.9. Demographic Factors

Previous literature has also attempted to examine the impact of various demographic factors on user acceptance towards technology. These factors contain gender, age, educational level, income level, usage experience, and so on. The influence of demographic factors mainly falls into two facets: direct impacts [62–65] and moderating effects [16,40,66,67]. In the current study, four demographic characteristics were added and examined in the model, which are gender, age, educational level, and usage experience. Notably, the user experience of electric cars can roughly be regarded as the user experience of in-car voice assistants, since nearly all-electric cars are equipped with a voice assistant at present. Generally, people's interest and preferences for a novel technology may change when they grow older [68]. Moreover, a recent report indicated that people are more willing to accept a technology that they are familiar with [11]. Regarding the factors "gender and educational level", they can be moderators for technology adoption [40,69]. Synthesizing the above studies, we assumed that age and experience might be a direct predictor of people's willingness to use voice assistants, while gender and educational level might play a moderating role in the proposed model.

Thus, the hypotheses were forwarded as follows:

H10a. *Age positively influences people's willingness to use in-car voice assistants.*

H10b. *Experience positively influences people's willingness to use in-car voice assistants.*

H11a. *Gender positively moderates the aforementioned relationships from H1 to H6.*

H11b. *Educational level positively moderates the aforementioned relationships from H1 to H6.*

4. Methodology

This work strives to identify the determinants that affect people's willingness to use voice assistants in electric cars. We constructed a structural model to reveal the mechanism of people's usage willingness based on the literature review results to reach this goal. After that, we employed an SEM approach to validate the effectiveness of the model based on hypothesis testing.

4.1. Measurement Development

Three levels of latent variables comprise the research model. The external level contains two perceptional factors (familiarity and privacy concerns) and four design feature factors (anthropomorphism, interaction, visual appeal, and personalisation); the medium level contains two perceptional factors (perceived trust and user satisfaction); the inner level represents user acceptance of voice assistants (willingness to use). These latent variables were measured by 3–4 observed variables. The researcher used a five-point Likert scale to measure the observed variables, where the numbers "1", "2", "3", "4", and "5" denote "strongly disagree", "disagree", "neutral", "agree", and "strongly agree", respectively. All measurement items were adapted and developed from previous studies, as shown in Table 1.

Table 1. Variables and measurement items.

Construct	Measurement Item	Reference
Familiarity (FAM)	FAM1: I am familiar with voice assistant-related information and knowledge. FAM2: I am familiar with voice assistant brands and products. FAM3: I am familiar with services provided by voice assistants and their functions. FAM4: I am familiar with how to operate voice assistants.	[33]
Privacy concern (PC)	PC1: I am concerned that voice assistants may collect too much of my personal information and data. PC2: I am concerned that voice assistants may use my personal information and data for other aims without my authorisation. PC3: I am concerned that voice assistants may share my personal information and data with other entities without my authorisation.	[40]
Anthropomorphism (ANT)	ANT1: Voice assistants have consciousness. ANT2: Voice assistants have a mind of their own. ANT3: Voice assistants have their own free will. ANT4: Voice assistants will experience emotions.	[46]
Interaction (INT)	INT: I know how to control voice assistants efficiently. INT2: Voice assistants quickly respond to my input and instructions. INT3: Voice assistants provide appropriate auditory and visual feedback (e.g., sounds, images). INT4: All in all, I think voice assistants are very interactive.	[49,51]

Table 1. *Cont.*

Construct	Measurement Item	Reference
Visual appeal (VA)	VA1: The interface design of voice assistants is appealing. VA2: The interface design of voice assistants is logically structured and designed. VA3: The virtual role image design of voice assistants is well-designed. VA4: All in all, I like the visual design of voice assistants.	[45]
Personalisation (PER)	PER1: Voice assistants provide personalised services that are based on my information. PER2: Voice assistants personalise my driving experience with vehicles based on my personal preferences. PER3: Voice assistants are tailored to my needs. PER4: Voice assistants are configured according to my wishes and individual needs.	[40]
Perceived trust (PT)	PT1: I feel voice assistants to be trustworthy. PT2: I feel voice assistants are reliable. PT3: I feel voice assistants are controllable. PT4: I feel voice assistants are competent.	[56]
User satisfaction (US)	US1: The use of voice assistants gives me pleasure. US2: I am satisfied with the functions of voice assistants. US3: I am satisfied with the range of services offered by voice assistants. US4: All in all, I am satisfied with voice assistants.	[49]
Willingness to use (WTU)	WTU1: I am willing to receive services delivered by voice assistants. WTU2: I am willing to use voice assistants in the future. WTU3: I plan to use voice assistants continuously in the future. WTU4: I am willing to recommend voice assistants to my friends.	[40,49]

4.2. Questionnaire Design and Pilot Study

The researchers conducted a questionnaire survey for data collection and an SEM approach for data analysis. The questionnaire comprised three sections. The first section started with a brief introduction of the research objective and the terminology "electric cars" and "in-car voice assistant". It aimed to help informants gain a fundamental understanding of the research background. The second section was to obtain informant demographic profiles, including gender, age, educational level, and driving experience. Following these measures was one question asking people's attitudes towards the influence of voice assistants on in-car interaction. The third section was designed to measure all observed variables using a five-point Likert scale. Before the large-scale survey, we conducted a pilot study to judge whether these questions were appropriate for data collection. Based on respondent feedback from the pilot study, the questionnaire was revised to make the contents easier to understand.

4.3. Data Collection, Sampling, and Data Analysis

During the questionnaire survey, informants were required to have experience in driving electric cars and using in-car voice assistants. In addition, we preferred to survey people with related knowledge backgrounds, including human–computer interaction, interaction design, technology acceptance and user design experience. The questionnaires were created and distributed through an online platform called "Wenjuanxing". In general, the statistical and explanatory power of SEM is affected by sample sizes [70,71]. In that regard, we referred to several rules of thumb from the previous literature to identify an appropriate sample size. First, we considered the ratio of the number of cases (n) to the number of measured variables (p), which is often recommended as 10:1 [72]. As our model has 35 observed variables, the basal sample size should be at least 350. In addition, researchers needed to focus on these factors that led to an adjustment of sample sizes in SEM, which included model complexity, normality of data, and measured variables per latent variable number [70,73]. Synthesizing these above cases, we argued that 400 to 500 was a suitable sample size for this study. Therefore, we distributed 450 online questionnaires, and finally, we received a total of 427 valid answers for further analysis. SPSS 25.0 and MPLUS version 7.4 software were utilised during the data analysis phase. The former was used for descriptive analysis and reliability testing, and the latter was used for confirmatory factor analysis (CFA) and path analysis.

5. Results

5.1. Sample Characteristics

Table 2 shows the demographic information of the participants. Of the 427 participants, 213 were males, and 214 were females. Their ages could be divided into five groups: below 20 (65 people), 20–30 (101 people), 30–40 (84 people), 40–50 (88 people), and over 50 (89 people). Regarding educational level, 44 informants were educated to junior high school or under, 67 respondents were educated to the high school level, 143 respondents had a diploma degree, 124 respondents had a bachelor's degree, and 49 respondents had a master's degree or above. Regarding driving experience, the intervals were under one year, 1–3 years, 3–5 years, and over five years, which had 109, 101, 106, and 111 people, respectively. Additionally, it is worth noting that over half of the participants argued that there might be a significant association between voice assistant design and in-car interaction.

Table 2. Demographic information and partial contents of the questionnaire survey.

Attribute	Value	Frequency	Percent
Gender	Male	213	49.9%
	Female	214	50.1%
Age	Below 20	65	15.2%
	21–30	101	23.7%
	31–40	84	19.7%
	41–50	88	20.6%
	Above 50	89	20.8%
Educational level	Under Junior high school	44	10.3%
	High school	67	15.7%
	Diploma	143	33.5%
	Bachelor's degree	124	29.0%
	Master's degree and above	49	11.5%
Electric car driving experience (years)	<1	109	25.5%
	1–3	101	23.7%
	3–5	106	24.8%
	>5	111	26.0%
The impact of voice assistants on in-car interaction	Very low	74	17.3%
	Low	69	16.2%
	Moderate	84	19.7%
	High	114	26.7%
	Very high	86	20.1%

5.2. Reliability, Validity, and Fit Index of the Measurement Model

Table 3 demonstrated several indices which served in the reliability and validity testing of the constructs, including Cronbach's Alpha value, standardised factor loading, averaged variance extracted (AVE), and composite reliability. It can be found that all Cronbach's Alpha values of latent variables were above 0.7, indicating a good internal consistency [74]. Furthermore, these latent variables also showed acceptable levels of composite reliability (CR) (over 0.7) [75]. On the other hand, considering the value of two validity indices—average variance extracted (AVE) and standardised factor loadings—exceeded 0.5 and 0.7, respectively, we could conclude that the model had adequate convergent validity [76]. In addition, the model's discriminant validity was examined by comparing the latent variables' square root of the AVE and correlation coefficient, see Table 4. The results showed that the measurement model had an acceptable discriminant validity [77].

Table 3. Reliability and unidimensionality.

Construct	Cronbach's Alpha	Variable	Standardised Factor Loading	AVE	Composite Reliability
Familiarity (FAM)	0.886	FAM1 FAM2 FAM3 FAM4	0.868 0.779 0.786 0.820	0.663	0.887
Privacy concern (PC)	0.885	PC1 PC2 PC3	0.859 0.877 0.811	0.722	0.886
Anthropomorphism (ANT)	0.899	ANT1 ANT2 ANT3 ANT4	0.797 0.852 0.832 0.839	0.689	0.899
Interaction (INT)	0.884	INT1 INT2 INT3 INT4	0.789 0.812 0.817 0.822	0.656	0.884
Visual appeal (VA)	0.876	VA1 VA2 VA3 VA4	0.782 0.827 0.793 0.795	0.639	0.876
Personalisation (PER)	0.890	PER1 PER2 PER3 PER4	0.820 0.811 0.817 0.826	0.670	0.890
Perceived trust (PT)	0.881	PT1 PT2 PT3 PT4	0.801 0.818 0.821 0.787	0.651	0.882
User satisfaction (US)	0.877	US1 US2 US3 US4	0.777 0.807 0.818 0.799	0.641	0.877
Willingness to use (WTU)	0.874	WTU1 WTU2 WTU3 WTU4	0.800 0.791 0.826 0.768	0.634	0.874

Note: square roots of AVE are on a diagonal; AVE = averaged variance extracted.

Table 4. Correlation matrix of the measurements.

Construct	AVE	FAM	PC	ANT	INT	VA	PER	PT	US	WTU
FAM	0.663	(0.814)								
PC	0.722	0.182 **	(0.850)							
ANT	0.689	0.554 ***	0.248 **	(0.830)						
INT	0.656	0.248 ***	0.092	0.512 ***	(0.810)					
VA	0.639	0.717 ***	0.174 **	0.572 ***	0.729 ***	(0.799)				
PER	0.67	0.733 ***	0.170 **	0.497 ***	0.684 ***	0.658 ***	(0.819)			
PT	0.651	0.653 **	0.071	0.548 ***	0.682 ***	0.740 ***	0.709 ***	(0.807)		
US	0.641	0.759 ***	0.099	0.476 ***	0.681 ***	0.699 ***	0.685 ***	0.670 ***	(0.801)	
WTU	0.634	0.618 ***	0.203 ***	0.510 ***	0.642 ***	0.731 ***	0.583 ***	0.724 ***	0.595 ***	(0.796)

Note: ** $p < 0.01$; *** $p < 0.001$; the square root of AVE is on a diagonal; AVE = averaged variance extracted.

The indices of the model's goodness of fit are demonstrated in Table 5, including chi-square, df, chi-square/df, the root mean square residual (SRMR), the root mean square error of approximation (RMSEA), normed-fit Tucker–Lewis Index (TLI), and comparative fit index (CFI). The results suggested both the measurement model (chi-square/df = 1.094, SRMR = 0.026, RMSEA = 0.018, TLI = 0.992, and CFI = 0.993) and structural model (chi-square/df = 1.313, SRMR = 0.043, RMSEA = 0.027, TLI = 0.981, and CFI = 0.983) had good model fits.

Table 5. Goodness of fit of the models.

Research Model	Chi-Square	df	Chi-Square/df	TLI	CFI	RMSEA	SRMR
Benchmark value	/	/	1–5	>0.9	>0.9	<0.08	<0.08
Measurement model	597.463	524	1.094	0.992	0.993	0.018	0.026
Structural model	931.344	679	1.372	0.973	0.975	0.030	0.058

5.3. The Results of Path Analysis

Besides the quality of the measurement model, we also examined structural relationships in the research model. As shown in Table 6 and Figure 2, nine proposed hypotheses were accepted except H9 and H10a. Among them, six of eight path relationships showed high statistical significance, one path relationship (H4) showed moderate statistical significance, and two path relationships (H2) and (H10a) showed low statistical significance. First, people's perceived trust was significantly influenced by two perceptional factors: familiarity ($p < 0.001$, t = 18.027) and privacy concerns ($p < 0.05$, t = −2.388 and one design factor: anthropomorphism ($p < 0.001$, t = 4.065). Therefore, H1, H2, and H3 were accepted. Moreover, user satisfaction was associated with three design feature factors, including interaction ($p < 0.01$, t = 2.960), visual appeal ($p < 0.001$, t = 3.957), and personalisation ($p < 0.001$, t = 4.396). Thus, H4, H5, and H6 were supported. Perceived trust ($p < 0.001$, t = 10.810) and user satisfaction ($p < 0.01$, t =4.200) were two predictors of willingness to use, supporting H7 and H8, respectively. However, we did not observe a significant structural relationship between user satisfaction and perceived trust ($p > 0.05$, t = −1.863), so H9 was rejected. Regarding the control variables, we found that experience could affect the willingness to use ($p < 0.05$ t = 2.506); however, there was no association between age and willingness to use ($p > 0.05$, t = −0.378). Therefore, H10a was rejected and H10b was accepted.

Table 6. The results of path analysis.

Hypothesis	Path Direction	Standardised Coefficient	Standard Error	T Statistics	*p*-Value	Result
H1	FAM → PT	0.715	0.040	18.027	0.000	Accepted
H2	PC → PT	−0.093	0.039	−2.388	0.017	Accepted
H3	ANT → PT	0.195	0.048	4.065	0.000	Accepted
H4	INT → US	0.209	0.070	2.960	0.003	Accepted
H5	VA → US	0.288	0.073	3.957	0.000	Accepted
H6	PER → US	0.275	0.063	4.396	0.000	Accepted
H7	PT → WTU	0.577	0.053	10.810	0.000	Accepted
H8	US → WTU	0.245	0.058	4.200	0.000	Accepted
H9	PT → US	0.126	0.068	1.863	0.062	Rejected
H10a	AGE → WTU	0.014	0.038	0.378	0.705	Rejected
H10b	EXPERIENCE → WTU	0.096	0.038	2.506	0.012	Accepted

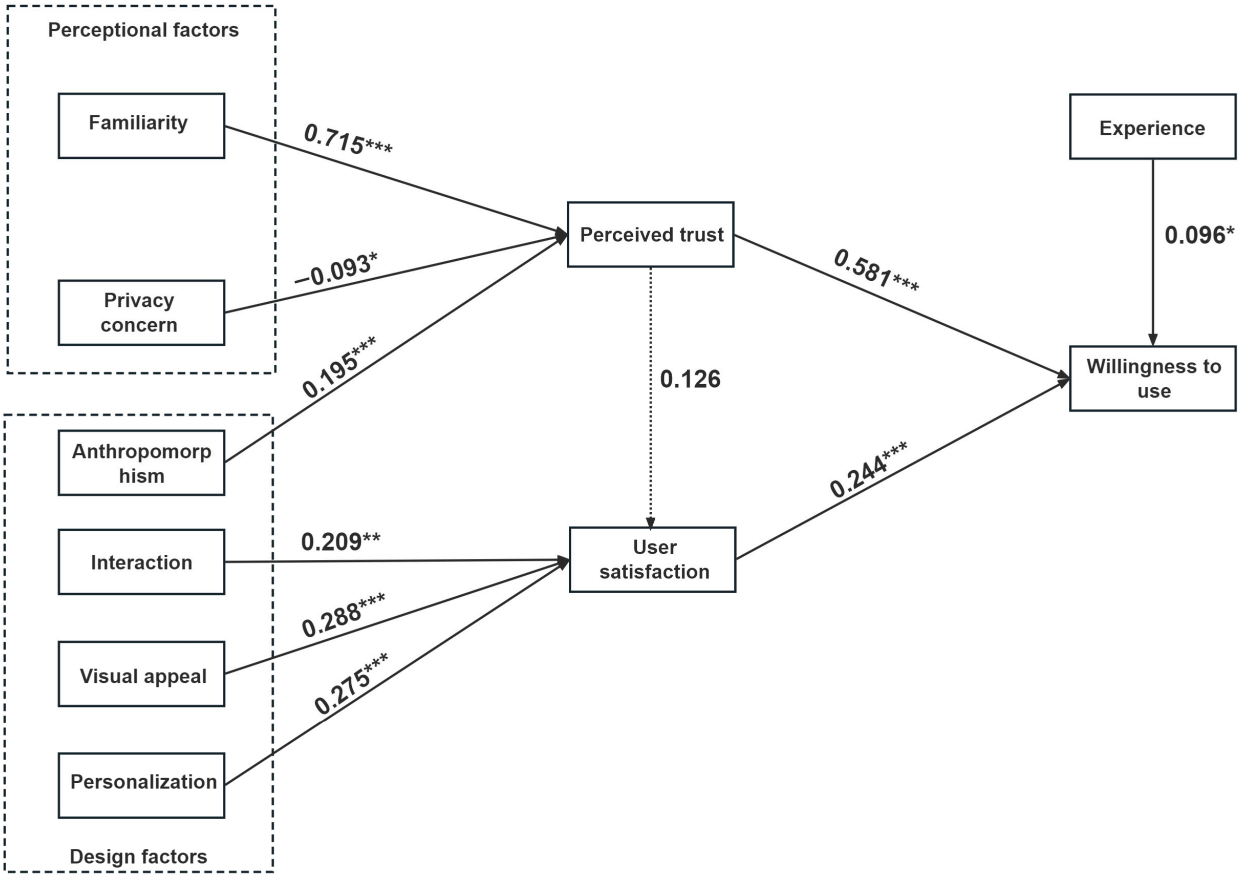

Figure 2. The path analysis results. Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

5.4. Moderating Effects Analysis

The researchers carried out a multigroup analysis to test the moderating effects of gender and educational level. Notably, the gender group contains males and females. The five educational levels were incorporated into two groups, where "Under Junior high school", "High school", and "Diploma" were counted as a low-level group while "Bachelor's degree" and "Master's degree and above" were counted as a high-level group. The results of the multigroup analysis suggested one of the path relationships was moderated by the demographic factors, see Tables 7 and 8. For gender, there were no significant differences between males and females for such path relationships in the model. For educational level, we found that high educational level groups were more likely to be influenced in the path relationship (PC → PT) compared to the low educational level groups ($p < 0.01$). In other words, educational level plays a moderating role in the relationship between privacy concerns and perceived trust. Therefore, H11a was rejected while H11b was partially supported.

Table 7. The results of multigroup analysis (gender).

Path Direction	Group 1 (Male)	Group 2 (Female)	Sig. Diffi.
FAM → PT	0.763 ***	0.669 ***	0.053
PC → PT	−0.059	−0.120	0.061
ANT → PT	0.224 ***	0.171 *	0.063
INT → US	0.240 *	0.117	0.126
VA → US	0.150	0.420 ***	−0.288
PER → US	0.253 **	0.322 ***	−0.055

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 8. The results of multigroup analysis (educational level).

Path Direction	Group 1 (Low Level)	Group 2 (High Level)	Sig. Diffi.
FAM → PT	0.945 ***	0.670 ***	0.227
PC → PT	0.041	−0.210 **	0.253 **
ANT → PT	0.038	0.296 **	−0.298
INT → US	0.556	0.170	0.378
VA → US	0.385	0.302	0.038
PER → US	1.062	0.286	0.800

Note: ** $p < 0.01$; *** $p < 0.001$.

6. Discussion and Implementation

This study proposed a systematic model that revealed the mechanism of user willingness to use voice assistants in electric cars. The six exogenous factors can be categorised into perceptional factors (familiarity and privacy concerns) and design factors (anthropomorphism, interaction, visual appeal, and personalisation). All exogenous factors demonstrated statistically significant relationships with two endogenous factors (perceived trust and user satisfaction) and finally contributed to people's willingness to use. Regarding the demographic variables, experience had a direct positive impact on people's willingness to use, while educational level played a moderating role between privacy concerns and perceived trust. In this regard, the results can offer both theoretical and design implications.

Perceived trust is one of the two fundamental pillars for people's willingness to use voice assistants. It had a positive and significant impact on people's willingness to use voice assistants. The result is in line with several prior studies [16,20,78]. In effect, trust is a key determinant in human–computer interactions [29,30]. In many situations, this factor serves as a mediator between exogenous factors and user acceptance [29,39,40]. In this paper, it was significantly associated with two perceptional factors and one design factor. In practical situations, we should attempt to increase people's perceived trust towards technology adoption.

Satisfaction is the second core factor that links exogenous factors and the willingness to use. Although this factor has not been verified in voice assistant-related studies, we found similar effects in other technology acceptance studies [49,59]. Customers will be more willing to adopt a voice assistant when they are satisfied with it. This factor can also be described as "user experience"—a terminology from the human–computer interaction field. In practical design, designers and decision makers should attempt to improve user satisfaction or the user experience to make the product more acceptable.

Familiarity is one of the two crucial predictors of people's perceived trust. This means that people with adequate knowledge or user experience will show more trust in voice assistants, which indirectly echoes Liu et al.'s (2021) and Arianne Walker's (2019) findings [11,33]. The factor "familiarity" showed a positive effect on people's perceived trust. It is because familiarity minimises the uncertainty of expectation through an increased understanding of what has happened in the past [34]. These days, electric car drivers in China have experienced the convenience and comfort brought by well-designed in-car assistants. For some Chinese electric car enterprises (e.g., Xiaopeng and BYD Auto), voice assistant design has become a core competence. Thus, users tend to hold positive attitudes and impressions of voice assistants. For car enterprises, it is recommended that they disseminate information and knowledge of voice assistants to novice drivers to increase their familiarity. On the other hand, car enterprises could consider deepening people's impression of car brands by developing a brand anthropomorphisation strategy. During this phase, designers can steer user perceptions to achieve associated branding outcomes through various design strategies, for example, designing a human-like brand voice and human-like consumer-brand dialogue [1].

In the current research, we saw a negative relationship between privacy concerns and perceived trust. This finding is in accordance with previous technology acceptance studies [39,40]. However, the structural relationship was slightly significant. This means that if customers realise their privacy is given out during voice assistant usage, their trust may not change too much. We argued that it could be attributed to two reasons. First, people generally pay more attention to safety and reliability issues in a driving context. Although the loss of privacy is a noteworthy issue, it is not closely associated with driver safety or security. Therefore, this variable's priority of attention may not be high regarding trust-related issues. Second, unlike other voice assistant scenarios, in-car voice assistants concern few financial issues. Nowadays, many people in China hold discreet attitudes towards situations involving financial transactions because financial fraud has become a widespread phenomenon. However, in a case that concerns a few financial issues, for example, in-car interaction, people may not care too much about privacy risks. In this regard, even when people realise privacy loss through voice assistant use, their trust may not drop too much.

Anthropomorphism is also a significant predictor of perceived trust, which mirrors Liu and Tao's (2022) research on smart healthcare services [40]. This means that voice assistants embedded with human psychological features receive more appreciation and trust from customers. One explanation is that it allows customers to have a more natural conversation with digital agents [79]. Additionally, voice assistants with anthropomorphic features can regulate customer emotions and feelings. As mentioned above, anthropomorphism in the present study involves human-like psychological traits, such as minds, consciousness, and emotions. Hence, voice assistants are expected to be more intelligent and able to empathise with customers. For instance, voice assistants can be designed to monitor a driver's real-time mental status, and then offer appropriate responses or recommendations to regulate their feelings. In addition, a voice assistant can provide initiative services or tips to demonstrate its humanity, for example, providing greetings or wishes on customer birthdays or other important dates.

Then, we saw that interaction played a noteworthy role in determining user satisfaction. That is, the more interactive people feel with a voice assistant, the more satisfied they will be. This finding is in line with Birkmeyer et al.'s (2021) and Hossain's (2016) research [49,59]. In this study, voice assistants with good interaction quality should be easy to control and provide appropriate feedback. This is especially important during the driving context because it can minimise user distraction and allow users to pay more attention to driving tasks. Therefore, an interactive voice assistant can contribute to improving the driving experience and user satisfaction. Essentially, voice assistants are designed to serve as a tool to mediate the interaction between user and vehicle, so the interaction quality is a key part [9]. For designers and car enterprises, they are recommended to enrich the function of a voice assistant to improve its interaction quality. For instance, given that the Internet may be disconnected when cars move to specific areas, Toyota incorporated Google to develop a voice assistant that provides most services under an offline status. This design can effectively avoid disruption and make the process smoother. Additionally, voice assistants can be designed to distinguish voices from multiple zones and then respond to one given zone. This function can ensure that drivers' verbal instructions are not disturbed by passenger voices, to increase the interaction efficiency.

Furthermore, the visual appeal also has a positive and significant influence on user satisfaction, which mirrors Mishra et al.'s (2022) research on smart voice assistants [45]. The visual appeal of a voice assistant contains two aspects: interface design and virtual role image design. The former should be designed with logical structures and clear layouts to minimise driver recognition load during use. The latter should demonstrate a friendly, kind, and helpful virtual assistant image to arouse customers' positive emotions. As Dr Norman described in his book "Emotional Design", aesthetically pleasing products appear more effective to customers, as customers can experience affinity with a product that appeals to them [80]. In practical design, the appearance of voice assistants can also serve as a platform that promotes corporate image and culture. To reach this goal, designers can integrate corporate logos and identity into the virtual character design of voice assistants.

In addition, the interface style can be designed to change from time to time, to mirror drivers' moods, weather conditions, and traffic conditions.

Personalisation is another critical predictor of user satisfaction towards in-car voice assistants. The result is in accordance with previous technology acceptance studies [49,81]. It indicates that when customers' personalised requirements are fulfilled, they will be more willing to accept a voice assistant. These days, voice assistants are not only a tool that simply handles tasks but are also designed to adapt to various customer behaviours and characteristics. Designers assume responsibility for integrating customers' personalised requirements into the functional design of in-car voice assistants. One recommendation is personalised voice design. For example, voice assistants can be set to recognise dialects in different areas to fit customers whose mandarin is not standardised. Moreover, the assistant's language features can be set to mimic a customer's family member or friend's language features to make sense of intimacy and familiarity. On the other hand, voice assistants can deliver personalised services based on user data. For instance, voice assistants can monitor drivers' real-time physical and physiological status based on smart sensors and then give appropriate suggestions and recommendations.

Usage experience is a direct predictor of people's adoption in willingness towards using voice assistants. This effect is similar to the findings for other technology acceptance scenarios [65,82]. This means that regular customers are more willing to use voice assistants than new customers. In that regard, enterprises can enhance the familiarity of voice assistants through activities in experience stores. In addition, we also found that educational level could moderate the relationship between privacy concerns and perceived trust. This indicates that people with high educational levels pay more attention to privacy issues of technology adoption. The finding is in accordance with Yaprakli and Unalan's (2017) research on smartphone usage [83].

7. Conclusions

In-car voice assistants are growing in popularity and becoming an area of focus these days. A well-designed voice assistant can not only enhance the driving experience but can also help electric car enterprises gain a critical edge in competition. However, knowledge of the factors influencing people's willingness to use in-car voice assistants remains scarce. This article acknowledges that this field requires further exploration and strives to construct a model by comprehending people's willingness to use voice assistants. Eight key determinants were identified from the review of the previous literature to form the research model, which are familiarity, privacy concern, anthropomorphism, interaction, visual appeal and personalisation, perceived trust, and user satisfaction. We then carried out an empirical study (N = 427) to test the proposed hypotheses by using an SEM approach. According to the hypothesis testing results, most structural relationships among variables were accepted. The final research model has two layers. At the inner layer, perceived trust and user satisfaction are two pillars directly contributing to people's willingness to use. At the outer layer, perceived trust is significantly impacted by two perceptional factors (familiarity and privacy concerns) and one design factor (anthropomorphism). Meanwhile, user satisfaction was significantly impacted by three design factors (interaction, visual appeal, and personalisation). In addition, experience had a direct impact on usage willingness and educational level was a moderator for privacy concerns and perceived trust. Finally, we discussed corresponding design strategies to enhance user acceptance from designers' and car enterprises' views. Thus, this paper is a typical endeavour to offer technology acceptance solutions with the following knowledge contributions.

From a theoretical viewpoint, this paper contributes to the literature on smart assistant technologies, which is still in its infancy. To be specific, although academic attention has been paid to various scenarios of voice assistants, there is still a sparse exploration of voice assistants in the in-vehicle context. Unlike previous empirical studies extended from established adoption frameworks (e.g., TAM and IS), we rearranged these variables and expanded dimensions to construct a new model. In this model, we not only consider people's perceptional factors as prior technology adoption literature does but also focus on voice assistant design attributes. In addition, our study integrates cross-disciplinary knowledge, including behavioural sciences, design sciences, and HCI. According to Dr Norman's emotional design theory, the factors "interaction" and "visual appeal" can correspond to visceral-level design attributes and behavioural-level design attributes, respectively.

From a practical viewpoint, this paper enables researchers to have a systematic understanding of user acceptance mechanisms towards in-car voice assistants. Several design strategies aiming to increase people's usage willingness were presented in the discussion section. Thus, different stakeholders can benefit from this study. Electric car users will be more likely to enjoy the interaction with voice assistants while driving. Designers can apply the findings to design practices and understand how to redesign or improve the current voice assistant to enhance the user experience during in-car interaction. Car enterprises will have a clearer understanding when investing funds and resources in voice assistant development. Improving voice assistants can please their users and promote their purchase intentions. In this regard, our findings can help car enterprises gain an advantageous position in a fiercely competitive market.

However, it is undeniable that our research bears some shortcomings and limitations. First, the research method utilised in the present study is relatively limited. This study only used a quantitative approach (SEM) to reveal the structural relationships among variables, which did not allow an in-depth qualitative exploration of users' views during usage. As a previous study demonstrated, a combination of qualitative and quantitative methods could provide more comprehensive insights [20]. Hence, we recommend using a sequential mixed-method approach in future studies. Second, we did not consider "perceived safety" as a variable in the research model, although safety is of paramount concern in driving studies [84]. In this study, the variable "privacy concern" involves user data safety, while "interaction" is partly associated with distraction. However, there is not an in-depth investigation of "perceived safety" and its influential factors. Therefore, future studies are recommended to examine safety-related factors.

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