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The Applications and Challenges of Intelligent Driving Assistance System in China's New Energy Vehicle Industry

A Comprehensive Analysis on its User Experience

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The Applications and Challenges of Intelligent Driving Assistance Systems in China's New Energy Vehicle Industry: A Comprehensive Analysis on its User Experience

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ABSTRACT (MAX. 200 WORDS):
This master thesis will explore the application and challenge of Intelligent Driving Assistance System (IDAS) within China's New Energy Vehicle (NEV) industry, aiming to identify and address user experience challenges to enhance interaction with smart driving features. Quantatitive research method, by survey and its analysis, is utilized to underscore the importance of user-centric design in developing IDAS. Key findings indicate that while users appreciate the safety and convenience offered by IDAS, concerns remain in system reliability under adverse weather conditions and issues related to privacy and cybersecurity. This master thesis provides practical recommendations to improve IDAS functionalities that focus in enhancing system reliability, addressing privacy concerns, and ensureing robust cybersecurity measures. These insights may be valuable for manufacturers and policymakers that may contribute for the advancement of user-focused innovations within the NEV industry to promote broader adoption and satisfaction of intelligent driving technologies.

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1 Introduction

1.1 Context and Background

The international commitment to achieving carbon neutrality has been highlighted by numerous international agreements stemming from various climate summits. One pivotal initiative emerged from the Glasgow Climate Pact in 2021 (COP26), convened under the auspices of the United Nations Framework Convention on Climate Change (UNFCCC). A primary feature of this summit was the first formal call for coal phase-out, accompanied by framing the essential environmental needs for this transition (UNFCCC, 2021). Concurrently, New Energy Vehicles (NEVs) have emerged as significant contributors to reducing carbon emissions. As underscored by Pan et al. (2023), NEVs emit far fewer carbon emissions compared to traditional vehicles powered by fossil fuels. Thus, NEVs are aligning well with worldwide efforts to diminish the impacts of climate change.

In China, the rapid development of NEVs relies on considerable technological innovations and robust support from governmental authorities, along with favourable policies (Li et al., 2023). Additionally, this support is considered a critical turning point in the automotive industry, especially in the area of intelligent driving technologies. These advancements have established a crucial foundation for the consistent evolution of NEVs. Furthermore, the role of NEVs in enhancing both the safety and comfort of the driving experience has increasingly captured the attention of consumers and industry-related professionals, contributing to their more prevalent choice within the mainstream market (Hartwich et al., 2021).

One member of the Organization for Economic Co-operation and Development (OECD), the Norwegian government, introduced an approach that includes exemptions from NEVs' registration tax, Value Added Tax (VAT), and at least a 50% deduction on road tax to encourage the purchase of NEVs (OECD, 2021). Similarly, the Chinese government also introduced innovations for NEVs, including VAT exemptions and investments in cooperation between Shanghai authorities and Tesla's Gigafactory, which have propelled the advancement of NEV development in China. Furthermore, the NEVs in China are usually armed with the Intelligent Driving Assistance System (IDAS). This technological enhancement, IDAS, has significantly improved the capabilities of autonomous driving systems by relying on data from built-in sensors to ensure real-time responses. Such advancements are critical for maintaining safety and operational efficiency in complex driving scenarios (Gruyer & Najjaran, 2020).

Chinese NEV manufacturers are at the forefront of employing IDAS to safely navigate in complicated driving environments (Zhou et al., 2022). They utilize a combination of sensor fusion and data-driven algorithms to improve decision-making processes. The impact of IDAS, therefore, extends beyond simple vehicle operations, as it plays a transformative role in managing traffic and reducing congestion. This application of IDAS also demonstrates its significant influence in enhancing urban mobility and promoting sustainability (Yu et al., 2019).

The objective of this master thesis is to present a thorough examination of the implementation and obstacles associated with machine learning in the intelligent driving technology sector of the NEV industry in China. It will investigate how advancements in IDAS capabilities and improvements to the user experience. In addition, the foundation for forthcoming technological developments in intelligent transportation systems will be addressed during the discussion.

1.2 Problem Statement

The adoption and integration of IDAS show unique challenges that necessitate thorough investigation under the significant advancements in intelligent driving technologies within China's NEVs.

Firstly, technical challenges still are a major concerns. IDAS heavily rely on the data that collected from the built-in sensor to conduct the real-time processing and decision-making. The reliability of these technologies in varying operational environments, however, is yet to meet consumer's expectations consistently, for instance, in urban traffic and different weather conditions. The performance of features, like Assisted Parking (AP), Traffic Jam Assist (TJA), Lane Keeping Assist (LKP), as well as Traffic Sign Recognition (TSR) under diverse conditions needs comprehensive evaluation to identify recurrent issues and potential improvement (Li et al., 2020).

Secondly, the IDAS technologies raise significant data privacy and security concerns. The risk of unauthorized data access escalates, showing a threat to user privacy and trust, when the NEV is becoming increasingly connected with other potential items (Xie et al., 2022). The legal frameworks currently in place, therefore, may not sufficiently address these new challenges, which create a gap between technological advancements and regulatory protections.

Besides, user acceptance and experience also play a critical role in the adoption of intelligent driving technologies. It is evident that even though there is enthusiasm for the safety and efficiency improvements promised by these technologies, from the data gathered by survey, there is still significant apprehension regarding their reliability and ease of use (Taherdoost, 2018). Furthermore, the users' trust on these technologies is still particularly fragile in critical situations, for instance, the bad weather conditions, where the technology's decision-making is tested under stress.

Lastly, the socio-economic implications of widespread adoption of intelligent driving technologies are profound. Issues, like the affordability of NEVs with advanced intelligent systems, the impact on insurance, and long-term benefits of reducing traffic incidents, need to be addressed. These factors may contribute to the market dynamics, which may influence consumer decisions and policy directions (Ajayi et al., 2021).

In conclusion, this master thesis explores technical challenges, data privacy and security concerns that arose from IDAS technologies, user acceptance and experience, as well as socio-economic implications of the adoption of IDAS under the advancements in the field of IDAS.

1.3 Research Questions and Objectives

1.3.1 Research Questions

This study is guided by the overarching research question: What are the specific challenges when using IDAS and its applications in NEV in China?

1.3.2 Study Objectives

To address this research question comprehensively, the study will follow several specific objectives.

First, the study aims to identify the user experience challenges associated with IDAS in NEVs. This objective involves a detailed investigation into the specific issues users encounter, focusing on system usability, interface design, and the overall user-friendliness of these advanced technologies. By understanding the pain points and barriers that affect user interactions with intelligent driving features, the study seeks to provide a foundational understanding of the user experience challenges.

The second purpose of the study is to collect user comments and insights by the survey, which will collect and review the feedback and opinions from NEV users on IDAS functionality's features. The surveys will be created and sent out to a wide range of users, and the data collected will be thoroughly examined to get quantitative information on user satisfaction. This analysis will also help highlight certain areas that require improvement, based on the real experiences and preferences of the users. The objective of this procedure is to acquire a thorough understanding of user experiences.

Lastly, the study will suggest practical suggestions for improving the user experience of IDAS capabilities in NEVs. Using the information gathered from the previous objectives, practical suggestions will be given based on the difficulties that have been identified. The goal of these recommendations will be to enhance the intuitiveness, user-friendliness, and responsiveness of IDAS to better cater to user needs. The primary objective is to offer a comprehensive plan for manufacturers and developers to enhance the design and functioning of IDAS features, and improve user engagement and happiness.

1.3.3 Study Significance

The study intends to gain a comprehensive understanding of the user experience difficulties related to IDAS features in China's NEV sector by accomplishing these objectives. The results will provide practical strategies for improving user involvement and contentment, supporting the overarching objective of advancing user-focused intelligent driving technologies. This research aims to narrow the divide between technology improvements and user expectations to foster greater adoption and more efficient utilization of intelligent driving technologies in NEVs.

1.4 Hypothesis

Based on the theoretical background and the identified challenges, the following hypotheses are proposed to understand the impact of various factors on the performance and UX of IDAS in NEVs in China.

H1: Weather Conditions may Affect Technology Performance

The first hypothesis posits that adverse weather conditions can impair the performance of intelligent driving systems. As highlighted by Thakur & Rajalakshmi (2023), weather conditions such as rain, fog, and snow can degrade sensor performance and data processing capabilities, thus reducing the efficacy of these systems. This issue is crucial in the context of Hassenzahl's model, particularly regarding the pragmatic qualities, which emphasize the functional reliability and safety of technology. Supporting this hypothesis, research by Grant (2022) and Muhammad et al. (2020) demonstrates that while IDAS can utilize optimized sensor data processing, adverse weather conditions still present significant challenges. The decline in system performance during such conditions can lead to decreased user satisfaction and trust in the system's reliability, thereby negatively impacting the system's overall effectiveness and user perception.

H2: Technological Challenges may Affect User Frustration

The second hypothesis suggests that technological challenges, such as technical malfunctions and the complexity of operating IDAS, significantly contribute to user frustration. This hypothesis aligns with Hassenzahl's model, wherein technical malfunctions correspond to pragmatic qualities affecting the functional reliability and efficiency of the systems. Complexity in operation, on the other hand, pertains to hedonic qualities, impacting users' emotional and experiential satisfaction. Studies by Chan (2017) and Knapper et al. (2016) underscore that while adaptive systems based on IDAS can enhance user satisfaction, they should be intuitive and error-free to avoid user frustration. Frequent technical issues, such as system malfunctions, slow response times, and inaccuracies in voice recognition systems, may lead to increased driver frustration, thereby diminishing the positive impacts of these advanced features.

Further corroboration comes from research by Haugeland et al. (2022) and Adam et al. (2020), which highlights the importance of system reliability and user-friendly interfaces. These studies illustrate that technical malfunctions reduce practical utility and reliability, while operational complexity decreases the emotional and experiential satisfaction of users. Such challenges can make the system less enjoyable and more stressful to use, detracting from the overall UX.

In conclusion, the major challenges identified in this study's hypothesis are the impact of adverse weather conditions on the performance of IDAS features and the technical malfunctions, along with the operational complexity of these systems. These factors are expected to be key contributors to user dissatisfaction. These hypotheses are based in discussed challenges and theoretical framework by corresponding academic master thesis.

2 Theoretical Background

2.1 Application of Intelligent Driving Assistance System in New Energy Vehicles

2.1.1 Research Status and Progress

IDAS have evolved dramatically in recent years under the policy reforms of the Chinese government, especially in China's NEV market. These IDAS include many highly usable functions, especially the ability of cameras to identify traffic congestion on the road, determine road selection, and recognize road signs when the vehicle is running. For instance, advanced 360-degree surround detection functions can use cameras and sensors installed on the vehicle to identify obstacles in advance to remind drivers to avoid possible dangers on the road (Chen et al., 2015).

Adaptive Cruise Control (ACC) and Lane Keeping Assist (LKA) are the two most representative functions of IDAS currently. One of the most commonly used functions in daily lives, the ACC system automatically adjusts the vehicle's speed to ensure that it always maintains a safe distance from the vehicle ahead. By using this system, it is easy to reduce the driver's driving stress during long journeys or traffic jams as it is not easy and tiring for people to keep a high level of concentration on the steering wheel for more than two hours (Barry, 2022). This function also reduces the possibility of sudden braking when the driver is not paying attention by controlling the vehicle to travel at a constant speed, which will directly improve the passenger's riding comfort and improve the overall traffic flow in urban traffic. Similarly, the LKA system uses a camera to monitor lane markings and help the vehicle stay in the center of the lane. For example, when the drivers are driving on the highway, they may be distracted and cause the vehicle to deviate from the lane and LKA will automatically control the steering wheel to adjust the vehicle as a whole to the correct road, which significantly improving driving safety (Bachute & Subhedar, 2021). In addition, these systems can keep the vehicle in the lane, which is especially useful during long-distance high-speed driving. The application of ACC and LKA technology in NEVs reflects the user's emphasis on improving driving safety. By utilizing sensor technology and real-time data processing, ACC and LKA systems are also an important step forward in achieving the big goal of fully autonomous driving.

As technology continues to evolve, the complexity of IDAS is increasing. The earliest technological innovations focused on improving ACC and LKA. Additional features are being considered to improve driving assistance and safety these days. This development and change can be seen in innovative projects such as Baidu Apollo and Alibaba TAI, which are working to push the limits of intelligent driver assistance technology, as described by Peng et al. (2020). This effort not only highlights the rapid development trend of technology, but also clearly points out that intelligent driver assistance technology has an important role in future transportation strategies. With the use of this cooperative model, the development of new technologies has been accelerated, which also helps to enhance the competitiveness of the entire industry.

2.1.2 Key Technologies in Intelligent Driving Assistance System

Combined sensors in IDAS play a vital role. This system combines data from cameras, radars, lidars, and other sensors to simulate and analyze the environment around the vehicle in real time. By implementing multi-angle strategic measures, the decision-making performance under vehicle driving conditions can be effectively improved, which was proposed by Yeong et al. (2021). The integration of different types of sensors can provide a more stable and reliable environmental perception, which is crucial for maintaining safety and efficiency during operation. Integrated sensor technology takes advantages of various sensors, such as high-resolution cameras, radar's precise ranging capabilities, and LiDAR's mapping capabilities in complex environments, and can effectively overcome the limitations of single sensor technology. For example, although the dim light environment will cause certain interference to the camera, radar and LiDAR can provide highly accurate distance measurement and precise target recognition data to neutralize this unfavorable state. Therefore, this joint attempt enhances the vehicle's ability to identify and respond to sudden obstacles, road changes, and other vehicle risks (Smith, 2019), which may significantly improve the safety factor and stability of the intelligent driving assistance system. In addition, machine learning technology has been improved to enable more powerful sensor integration, allowing real-time data processing and self-adaptive learning, thereby gaining a deeper understanding of the vehicle's relationship with its environment and its response strategy (Pandharipande et al., 2023).

One of the main functions of the ACC (Adaptive Cruise Control) system is to automatically adjust the vehicle's speed to ensure that the vehicle can maintain a safe passing distance from the car in front. The adoption of this strategy enhances comfort and confidentiality when driving long distances or in crowded vehicles. For example, XPeng's ACC control system adopts a dynamic speed correction mechanism to provide drivers with a smooth driving experience (Doll, 2023). Advanced radar and camera technology enables ACC to accurately track the distance of the vehicle in front and adjust the speed in real time to maintain a predetermined trailing distance, thereby reducing the risk of rear-end collisions.

Lane Keeping Assist (LKA) systems employ cameras for identifying lane markings and assisting vehicles in maintaining their lane. The likelihood of accidents occurring outside the lane is diminished, enhancing safety on the road. The LKA system of NIO employs advanced cameras and sensors for lane positioning control, which may guarantee the consistent alignment of vehicles in the lane at all times (Chen, 2024). These systems, through relentless tracking of lane markings and precise direction adjustments, aid in averting accidents during prolonged high-speed driving or while drivers are distracted (Waykole, Shiwakoti, & Stasinopoulos, 2021).

APS, or Automated Parking systems, employ sensors and cameras for spatial identification and auto-manage of vehicles while parking (Piao et al., 2021). Such an innovation alleviates tension during parking, particularly in confined or packed areas. XPeng Motor and NIO both embraced APS technology to offer single-click automated parking options, greatly enhancing the user experience by lessening park-related stress (Chen, 2024). Not only are these systems capable of identifying appropriate parking areas, but they also effortlessly pull vehicles into them with little input from drivers, thus reduces damage caused by vehicle collisions or scratches during parking and enhancing parking efficiency in city settings.

Traffic Jam Assist (TJA) monitors the acceleration, deceleration, and maneuvering of the car under sluggish and crowded traffic scenarios. Such measurements reduce vehicular strain in congested areas to enhance overall driving proficiency. NIO's TJA system facilitates fluid navigation in heavy traffic, enhancing driver ease and lessening mental strain (Dorlecontrols, 2024). The TJA system facilitates stop-and-go operations in busy traffic automatically, easing the tedium and annoyance of traffic jams, enhancing driving pleasure, and decreasing accidents due to driver exhaustion and distractions.

Blind Spot Detection (BSD) employs radar detectors to surveil the vehicle's hidden areas and notify the driver of possible dangers. Safety is enhanced through identifying vehicles in the blind spot and issuing prompt alerts upon lane change. The BSD system by XPeng persistently tracks blind spots and offers drivers both visual and auditory warnings, aiding in the prevention of accidents from blind spot collisions (Kim, Yang, & Kim, 2023). This technology has the capability to alert drivers about vehicles coming from the rear and side, a vital aspect for secure lane transitions and consolidations, especially during congestion.

Cameras are employed by Driver Monitoring Systems (DMS) to observe drivers' focus and fatigue levels, and set up immediate alerts to avert crashes resulting from driver distraction or exhaustion. The DMS system at NIO senses driver weariness and lack of attention, alerting when needed to maintain the driver's alert and safety during driving (McVey, 2024). Through observing facial cues, ocular motions, and the posture of the head, DMS effectively evaluates the vehicle's vigilance, issuing alerts or implementing necessary adjustments if the driver doesn't react, thus greatly enhancing vehicular safety.

In China, the introduction of 5G networks significantly improves the capacity of machine learning for self-driving technologies. This faster, more reliable network connectivity is important for the effective execution of communications between the vehicles and between the vehicles and road infrastructure in a city environment (McClellan, Cervelló-Pastor, & Sallent, 2020; Tanveer et al., 2021), which is the most critical element for successful autonomous vehicle fleets (Chen et al., 2020). This is important for efficient interactions between vehicles and the roadway environment, including other vehicles.

Beyond these frameworks, IDAS are integrating more sophisticated Machine Learning (ML) algorithms to boost their functionalities. Predictive maintenance systems use advanced ML methods, which enable them to carefully evaluate the data collected by sensors to identify potential problem points in advance. ML is contributing effectively to real-time traffic prediction (Mihaita et al., 2023) and intelligent driving in China and penetrating deeply with the strong promotion of leading Artificial Intelligence (AI) companies and startups. These companies use ML algorithms to obtain historical data and analyze real-time traffic data to optimize routes to reduce congestion with smart vehicles. For example, Pony.ai, a major Chinese player in this field, uses machine learning and deep learning in its prediction module, which can predict the movements of numerous road agents and enhance the decision-making process in complex road scenarios; it started in 2017 Testing autonomous vehicles on public roads in California (Steinberg, 2021). Furthermore, China's favorable regulatory environment and positive market forecasts are also driving the development of smart cars through significant investments in testing grounds and infrastructure to support Chinese authorities in deploying smart cars (Chen, Kuo, & Lee, 2020).

In summary, IDAS is a driving factor in China's huge progress in intelligent driving, which emphasizes on sensor fusion, decision-making and real-time traffic prediction. In addition to optimizing routes and reducing traffic congestion, the application of IDAS in traffic management also aligns with the Chinese authorities’ strategic vision for its smart car market – one of which is the support of for regulatory environment that provides more opportunities for NEVs compliance space. These NEV manufactures and companies could redefine how Chinese people travel method when such technologies are developed.

2.2 Challenge of Intelligent Driving Assistance System in New Energy Vehicle

2.2.1 Technological Challenges

Sensor Fusion and Reliability

The reliability of sense fusion remains a primary concern by authority and customers in the development of IDAS in the field of NEVs. Sensor fusion is the integration of data from multiple sources, such as cameras on board, radars, and LiDAR, to create a comprehensive model of the vehicle environment. The integration of various data sources, however, presents the significant challenges, particularly in the terms of alignment and calibration (Yeong et al., 2021). These systems need to contend with data that discrepancies that arises from sensor inaccuracies, particularly in the adverse weather conditions or in complex urban environments. Furthermore, the reliability of these systems can be a harmful factor as the latency in data transmission and processing, resulting that the advancements in sensor technology and algorithms is necessary to enhance the data consistency and system robustness.

Challenges of Real-time Data Processing

Real-time data processing is critical for the essential IDAS functionalities and requires instantaneous analysis of sensor data to facilitate the timely decision-making. The integration of ML algorithm is necessary for autonomous navigation and can allow the predictive capabilities. These systems, however, face the challenge of processing large amount of data from multiple sensor sources without delay. Therefore, the computational power is vital for the computer on board as the vehicles with high-performance computing solution will increase the system complexity and cost of systems (Chougule et al., 2024). It remains a gap in achieving the low-latency processing, resulting for a safe and reliable autonomous driving in all traffic conditions, even though the hardware and software are both in the progress for optimization (Liu at al., 2024).

Limitation of ML and AI in the Field of IDAS

Although ML and AI are pivotal in the development of IDAS, it still has the limitations that they can impact safety and reliability of IDAS. Mohseni et al. (2019) claim that one of the major issues is data bias where the algorithms trained on non-representative data sets may fail to perform adequately across real-world driving scenarios. Furthermore, ML models may be overfit to their training data from the and resulting in making them less adaptive or adaptable to new or unforeseen conditions on the roads (Caruana, Lawrence, & Giles, 2000). Another critical concern, suggested by Dosh-Velez & Kim (2017), is that the interpretability of AI decisions, which is crucial for user trust and the authority's legal accountability of autonomous systems.

Cybersecurity Concerns in IDAS

As IDAS increasingly rely on connectivity and data exchange to its function, cybersecurity emerges as a critical issue raised by the NEV customers users as this system is susceptible to a range of cyber threats, from remote hacking to data breaches, which can lead the system jeopardize for vehicle safety and compromise passenger privacy (Mecheva & Kakanakov, 2020; Dewangan et al., 2024). Furthermore, the integration of wireless communication between the vehicle and its central server further exposes IDAS to vulnerabilities that can be exploited to manipulate vehicle behaviour or seal sensitive data, and other researchers (Mecheva & Kakanakov, 2020; Tran et al., 2023) think the deployment of robust cybersecurity measures is therefore critical to safeguard these systems to against potential cyber threats and to uphold the integrity and reliability of IDAS. Ensuring robust cybersecurity measures, therefore, is essential to protect against such threats and maintain the integrity and reliability of IDAS.

2.2.2 Regulatory Challenges

There are still the significant regulatory challenges that may hinder IDAS's broader deployment and acceptance, even though their rapid development and implementation. These challenges primarily include the lack of standardization and concerns regarding legal liability.

Lack of Standardization

One of the primary regulatory problems in the development of IDAS is the absence of uniform standards across different jurisdictions. Koller & Matawa (2021) claimed that the framework, that the development of common regulatory framework, will help to overcome a series of roadway and traffic complexities that introduced by Automotive Vehicle (AV) operating within the current infrastructure. This lack of standardization, therefore, can lead to inconsistency in the performance of IDAS across different regions, resulting the complication in both development and deployment of NEVs and their user experience. The diversity in road conditions, traffic acts, and vehicle standards need a harmonized approach to ensure the IDAS operate effectively regardless of location as such cutting-edge nature of such technologies means that the regulatory frameworks often lag technological advancements, and struggling to keep pace with the rapid innovations, therefore, each region's specific standards should be meticulously by manufactures, which makes technological rollouts slower and interoperability across borders (Masek et al., 2016).

Legal Liability

Another critical challenge is determining legal liability in the event of an accident that involving vehicles that equipped with IDAS. Complexities may be raised in defining the roles or responsibilities of the driver or the technologies for the systems with integration of systems like ACC, LKA, or TJA. In the case that the technology fails or partially contributes to an incident that brings a question that who, the manufacturer, the software developer, or the driver, holds the responsibility for such incident. Therefore, current legal frameworks are hard to alloocate the responsibilities accurately when incident occurs as these technologies blur the lines between driver control or automated systems (Douma & Palodichuk, 2012; Dhar, 2016). Additionally, legal precedents have yet to fully adapt to these scenarios and often leave any unresolved legal problems that can let consumers and manufacturers make the decisions later (Eastman, 2016).

2.2.3 Ethical Challenges

The development and application of IDAS have brought not only technological advancements, but also ethical considerations that raise significant concerns about decision-making and critical situations and privacy.

Decision-making in Critical Situations

One of the most debated ethical issues in the deployment of IDAS is the decision-making in critical, life-threatening situations, and its circumstance often be referred to 'trolley problem' in the field of AV content (Thomson, 1984). This dilemma highlights the controversial decision-making process that AVs have to navigate during the unavoidable scenario: whether to prioritize the safety of passengers inside the vehicle or the pedestrians outside. Gogoll & Müller (2017) suggest that the settings of a universal ethical standard, rather than allowing individual's preferences, could serve the society and community better, but the questions remain on how such universal ethics can accommodate the diverse cultural and ethical expectations prevalent across different regions, which may influence the legal outcomes of AVs' actions. Further complicating the issues is the practical implementation of these ethical decisions. Current discussions proposed by academia that a framework was introduced, for instance, Ethical Valence Theory, such theory aims to equitably address the expectations and safety for all road users and present a nuanced approach to AV decision-making processes (Choi & Ji, 2016; Kizilcec, 2016).

Privacy Concerns

Another potential ethical challenge is related to privacy. IDAS heavily reply on data collected through sensors and inside cameras to function effectively. These technologies may capture vehicular data and massive extensive personal information, for instance, drivers' habits, biometric data and frequently visited locations, and its collection, storage and processing pose substantial privacy risks, which underscores the critical importance of addressing privacy risks (Wani, 2024). Furthermore, some NEV may armed with driver behaviour monitoring systems, which will or may classify and analyse driver's actions, can inadvertently breach individual privacy by continuously tracking personal behaviour, like facial expressions, hand movements, and even posture (Cas et al., 2022).

2.3 Examples of Strategies in Intelligent Driving Assistance System

This section introduces the strategies adopted by two of China's leading new energy vehicle manufacturers: Xpeng Motors and NIO. This section introduces strategies for utilizing machine learning in intelligent driving assistance systems. This way, one can clearly understand the exact machine learning application used and how it can contribute significantly to improving IDAS systems.

2.3.1 XPeng Motors: Integrating Machine Learning for Enhanced Intelligent Driving Assistance System

Chinese automotive innovator Xpeng Motors uses machine learning for intelligent driving assistance systems. Xpeng Motors developed XPILOT – a standalone driving solution that analyzes vehicle sensor data and video and integrates it with advanced machine learning algorithms. Information collaboration allows for complex and changing driving situation models, allowing the vehicle to make informed and timely judgments during operation. Xpeng 2023 research reveals just how precise and flexible the vehicle can be. It points to a positive approach, as Xpeng uses real-world data from one of its largest fleets to power machine learning models, laying the foundation for XPILOT. Sustained throughput of data is key to continuous model learning and development, which can improve model performance in increasingly complex driving scenarios. The XPILOT algorithm focuses on pattern recognition, combined with predictive analytics capabilities and skilled decision-making under conditions of high uncertainty. Xpeng Motors leverages this strategic deep learning technology to improve the system's effectiveness in identifying objects, mapping trajectories, and assessing potential hazards, all of which lead to the result of a faster, smarter self-driving system. Another popular product from Xpeng Motors is navigation navigation for highway driving in the P7 model. Xpeng Motors claims to be a leader in automotive technology powered by machine learning and autonomous driving systems, and it shows. Xpeng Motors applies machine learning technology to autonomous driving, ultimately turning cars into sentient beings with self-improvement and real-time decision-making capabilities.

2.3.2 NIO: Advancing User Experience thorough Machine Learning

NIO has emerged quickly in the new energy vehicle market, and its intelligent driving assistance capabilities have been fine-tuned to provide a better user experience. Much of the integration of artificial intelligence into vehicles is achieved through the concept of the flagship autonomous driving system called NIO Pilot and the NOMI in-vehicle assistant. NIO's application of machine learning does more than just give way to simple autonomous navigation; it infuses artificial intelligence in a way that touches the fabric of customer interactions (NIO, 2023). The same goes for NOMI, the in-car AI assistant; it personalizes the driving experience and learns from the user's behavior to cater to their own preferences in a way that reflects the former. The latter resonates with NIO Exploration’s claims about enhanced self-driving technology in EVs like NIO’s ES8 and the systematic adaptation proposed by Li et al. (2024) in their Think2Drive model for realistic autonomous driving scenarios.

The reason that machine learning is important for achieving vehicle safety cannot be elaborated further is that this is also specifically found by Chen et al. (2015), redefining new multimodal datasets and learning affordances for direct perception in autonomous driving. It enhances situational awareness in the same analytical process NIO performs while on the road, while fine-tuning safety protocols based on driving patterns and external factors. Proven through applications, the efficiency of NIO's ES6 and ES8 models in enhancing autonomous driving functions, predictive maintenance, and optimizing energy systems has become a model for machine learning application demonstrations. These capabilities are reminiscent of those discussed in (Chen, 2024), focusing on self-driving cars and their computational details. These advances resonate with lane change safety estimation using long short-term memory (LSTM) by Liu et al. (2023) as well as in terms of public opinion regarding self-driving cars, suggesting that informed public knowledge is crucial to the acceptance of such a huge technological development.
These are the overall integration of machine learning that help drive the top technologies provided by NIO; to some extent, this may be a mirror of one of the most trending developments in the future of intelligent driving assistance systems - allowing us to see the future, intelligent driving It will not only be about the journey, but also the destination. NIO test cases are not only living testaments to current capabilities, but also beacons of potential advancements where

the harmony of machine learning and vehicle technology could redefine the paradigm of car travel.

In summary, the companies XPeng Motors and NIO are at the very forefront of the application of machine learning to intelligent driving assistance systems. However, while XPeng has a larger drive on machine learning for the purpose of refining autonomous driving capabilities, NIO extends the technology to further enhance user interactiveness and safety. These are not only the case studies of what machine learning can bring in the current times but also the future development within the NEV sector and the automotive industry in China. This evolution is still in process, and the future really does look promising for machine learning in improvements to autonomous driving and in further increases in user experience with intelligent vehicles.

2.4 Role and Impact of User Experience in Intelligent Driving Assistance System

In the field of IDAS, understanding and enhancing User Experience (UX) is already a top priority for acceptance, satisfaction, and safety (Hassenzahl, 2004) as it emphasizes on hedonic and utilitarian qualities as important considerations in the development of functional and emotionally satisfying products, the user model developed by Marc Hassenzahl provides a well-crafted framework for the evaluation and design of these technologies.

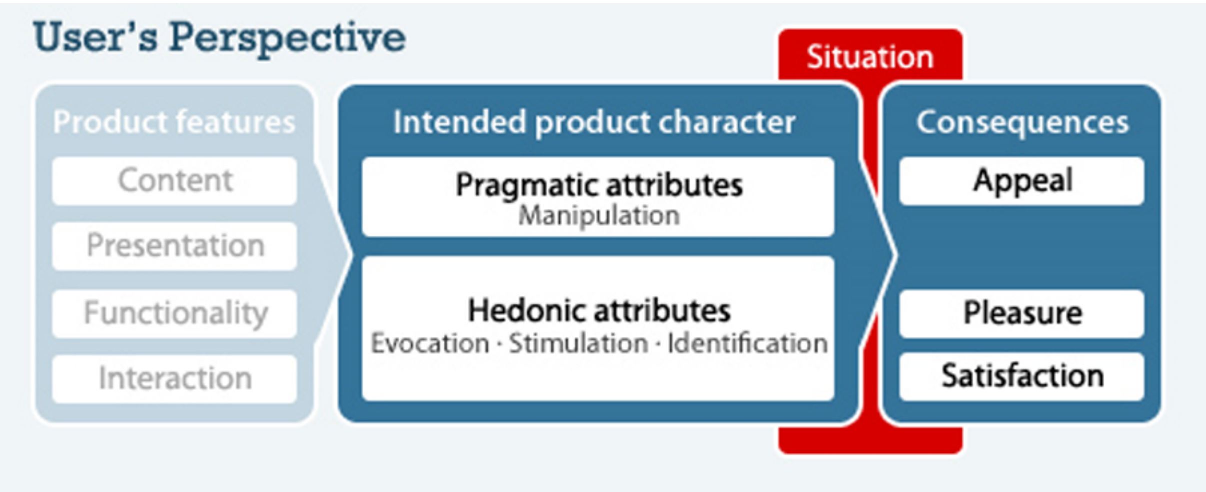

Figure 1 Hassenzahl's Model

Source: Hassenzahl 2006

Hassenzhal's model suggests that a user's entire UX experience with a product is determined by its utilitarian and hedonic characteristics. These characteristics jointly influence users' emotional responses and evaluations of product attractiveness and quality. This framework is useful in trying to understand how different features of a product meet a user's needs in a given interaction.

IDAS improves vehicle safety and helps to improve user experience. And Hassenzahl's model suggests that both practical and hedonic aspects of UX are improved because of customized driving functions and reduced need for human involvement (Bachute & Subhedar, 2021).

Hassenzahl's model focuses on practical aspects that related to how a product works and is used. This is the level of effectiveness achieved by such systems in meeting functional requirements in the field of IDAS. Professionals designed this data analysis to demonstrate how IDAS can shape and change vehicle safety levels and improve user experience. These improvements will reflect the pragmatic aspects of Hassenzhal's paradigm and goals are achieved through safer and more convenient methods, thereby improve driving efficiency and effectiveness.

In addition, Stanford University also found that in cars equipped with IDAS (with functions such as automatic parking or lane keeping assistance), users' driving satisfaction can directly increase by 30%. This study clearly demonstrates how machine learning can be used for driving comfort and safety.

However, technical challenges can cause significant user frustration, impacting user experience globally. This is because as the systems of intelligent driving systems become more and more complex, users often face some technical problems, including system failures, slow response times, and lack of accuracy in voice recognition systems (Chan, 2017). This can be very frustrating because the good impact of advanced features is ruined. This was demonstrated in a case by Knapper et al. (2016), when drivers report experiencing more frequent technical problems in vehicle technology mode, their level of frustration increases, which subsequently affects their satisfaction with the driving task.

The evidence can therefore focus on the predictive capabilities provided by machine learning techniques in improving safety. This is also an example of how intelligent driving assistance systems can reduce manual operations and provide a personalized experience through the driving system. In general, modern automotive technology is driven by machine learning (Schwarz et al., 2022). Such capabilities are currently moving towards bringing ease and convenience to consumers through smart features. For example, when controlling traffic conditions, intelligent voice systems and the implementation of advanced driver assistance systems (ADAS) are utilized. Generally speaking, machine learning utilizes the analysis of user preferences and their behavior to personalize driving user interface design (Meng et al., 2020).

In addition to functionality, Hassenzal's model also focuses on hedonic qualities, which are described as characteristics related to emotional needs such as good appearance, personal pleasure, and enjoyment. These hedonic characteristics can be seen in the way the vehicle interface is designed, the sensory feedback when interacting with the system, and the aesthetics of the digital screens and controls in intelligent driving systems. This is based on the work of Pucillo and Cascini in 2014. Recent advances in AI-driven in-vehicle systems are in and applied to new energy vehicles. These facilities automatically fine-tune the smart lighting system and seat memory functions to make the ride experience very comfortable for the driver and passengers (Balaji et al., 2024). In addition, advanced intelligent voice recognition technology makes the in-car entertainment system more sensitive to user instructions, thereby greatly promoting the interaction between the in-car entertainment system and passengers. Ali et al. (2021) also found that ML directly contributed to improving the quality of the intelligent driving experience and further enabled the personalized customization of the user interface.

In fact, the development of smart features such as interactive voice systems and advanced driver assistance is a good example of elements that can be both useful and fun. Such technology increases comfort and safety; therefore, stress levels while driving are reduced. For example, ACC and AP systems. These systems learn from driver behavior in order to react differently to different types of driving (Saputro, 2023). As technology advances, smart driving technology not only brings practicality through driving efficiency, but also enhances pleasure through customized contacts, increasing emotional investment and confidence in smart driving technology.

Key technical limitations need to be addressed for a better user experience. When technology fails to meet users' expectations, it can become irritating and reduce users' enjoyment and emotional attachment to the technology itself (Haugeland et al., 2022). Through the use of technology, some of these issues are alleviated and the experience becomes better via effective troubleshooting, user-friendly design, and sustained performance. Resolving technical issues quickly and effectively may increase user satisfaction and emotional attachment to IDAS (Adam et al., 2020). As these systems advance, they are able to accurately predict individual needs and preferences, resulting in a more personalized and enjoyable experience for every journey. Due to the deep integration and optimization of various IDAS technologies, the future driving experience will be safer, more efficient, more comfortable and more enjoyable, which shows that smart transportation technology has a promising future (Alatabani et al., 2022).

The biggest challenge by IDAS is to achieve the perfect balance between practicality and enjoyment in a way that is barely noticeable to users. Resonating with humans on some emotional level makes it more attachment and fun for the technology. The application of Hassenzhal's concepts in designing IDAS will encourage a holistic consideration of both the practical and hedonic aspects of the user experience. By simultaneously understanding and utilizing these factors, manufacturers can ensure that the smart driving technologies they develop are effective, efficient, fun, and engaging. This attitude will increase consumer acceptance of the technology as well as trust in the technology itself (Pucillo & Cascini, 2014).

3 Methodology

3.1 Quantitative Research Approach

In this study, quantitative research approach was used as this method has advantages in several key application areas. This includes examining the relationship between gender and IDAS selection, the frequency of use of different age groups, the impact of technology on user frustration, the relationship between users' reasons and concerns for choosing IDAS, the correlation between technical problems and frequency of use, and the relationship between system performance and technical challenges experienced in adverse weather conditions.

First, quantitative research methods may efficiently process large data samples (Watson, 2015), which conducts as a tool to explore whether gender has an impact on users' choice of IDAS. Understanding the differences in technology acceptance among gender groups is crucial to understanding their differences. The collection and in-depth analysis of a large number of data samples is not only to reveal the impact of gender in decision-making IDAS, but also to help more deeply understand the interactive relationship between gender and other demographic indicators (such as age and preferred vehicle name). These suggestions are crucial for formulating market strategies targeting gender differences and promoting relevant technologies on gender equality.

Next, this quantitative analysis tool has an irreplaceable advantage in studying the differences in the frequency of use of IDAS by users of different age groups. After a detailed statistical analysis of various data, different system usage data may be evaluated as it can be quantitative tool to give a deeper understanding of the importance of age or other attribute in technology application and acceptance and help IDAS providers to formulate more target user training and promotion strategies to ensure that all groups of users can understand how to use the various functions of IDAS features to improve their satisfaction and actual efficiency of system.

In addition, the obvious statistical reasoning ability in quantitative analysis methods can be used to explore how technical difficulties affect user disappointment. With the help of quantitative analysis methods, systematically identifying common technical problems can be found and deeply measurement on the negative user experience caused by these problems.

Analyses of quantitative data make it much easier to explain the close relationships between the choice intentions of users and their concerns. For instance, the choice of autonomous driving functions could be inhibited by users due to fear of safety risks, or the decisions may be engendered by concerns of technical failure. Such psychological factors are important in understanding the design of safer and more user-friendly systems and formulating effective market strategies, otherwise would remain blind to the psychological expectations of users.

This study discusses the technical problems of IDAS and their impact for users. In-depth quantitative analysis, including the existing and potential technical problems, will be used to ensure whether users' willingness and acceptance of IDAS. And the result of this quantitative result will be useful for the IDAS's developers and manufacturers as it inextricably related to the continuous use by users and popularity of technology. The IDAS trust by users and customer satisfaction can be enhanced by identifying and solving technical difficulties, which will help in further promoting the application and popularity of the techniques of intelligent driving assistance among a wider scope of users.

Finally, by using quantitative research methods, relationship between the performance evaluation of intelligent driving assistance systems in adverse weather conditions and the technical challenges faced by users can be evaluate. The environmental variables that affect the performance and UX of IDAS will be analyzed as quantitative methods can help developer to clarify and transcend technical constraints under special and adverse environmental conditions, and further enhancement on overall performance and stability of system.

In general, the reason for adopting this quantitative research method is that it can systematically solve the questions in the above research, verify the hypothesis, and provide solid scientific research support for the upgrading and advancement of IDAS. Quantitative analysis not only reveals the macro trend and structure, but also ensures the objective accuracy and consistency of the research data, thus providing valuable evidence support for the progress of China's NEV industry.

3.2 Survey Design

3.2.1 Objective of Survey

The objective of this survey is to comprehensively analyse the UX of IDAS in China's NEV industry market. Some core aspects of UX, including usability, customer satisfaction, safety perceptions, and other potential technological challenges encountered, will be focused on.

1. **Weather Conditions and System Performance (H1):** one of the main purposes of this survey is that explore how various weather conditions may impact the functionality and reliability of IDAS. It assesses user trust and safety perceptions, especially in adverse weather conditions that may demand increased reliance on these systems.

2. **Technological Challenges and User Frustration (H2):** this survey also finds the potential solutions to address the technological challenges users encounter, such as system errors, adaptability to environmental changes, and concerns that related to data security and privacy. User frustration and its correlation with these technological hurdles will be measured by this survey.

In assessing usability, intuitive nature and user-friendliness of IDAS features will be explored and ease of interaction and the learning curve that associated with mastering these systems will be focused. Furthermore, satisfaction is measured through users' contentment on functionality and reliability of IDAS, and the systems' performance across various conditions, and its efficacy in regular use will be evaluated. Additionally, safety perceptions are investigated to understand user trust in the IDAS-related technology, particularly under adverse weather conditions or critical driving situations that demand reliance on assistance systems. The survey also addresses the technological challenges that users may face, including the frequency of system errors, system's adaptability to environmental changes, and concerns related to data security and privacy.

This survey will employ a quantitative research methodology and utilize a structured questionnaire composed of multiple-choice, single-choice, and Likert scale questions. This approach will collect a series of data that across a broad demographic of NEV users to ensure a comprehensive understanding of the UX with IDAS. Participants are assured of strict confidentiality and collected data will comply General Data Protection Regulation (GDPR) standards to emphasise the gathered information will be used solely for academic purposes.

The insights gathered from this survey will illustrate the current landscapes of IDAS UX in NEVs and underscore further technological advancement. This will not only enrich academic discourse, but also provide critical feedback that which is necessary for refining the design and functionality of intelligent driving technologies for manufacturers and developers, aiming to increase the IDAS's safety and user satisfaction.

3.2.2 Development of Survey

Survey's Design

The rapid advancement and integration of IDAS in NEVs underscore a transformative stage in automotive technology, particularly in the context of driving safety and UX. The survey was carefully designed to capture a broad spectrum of user interactions and concerns that related to the IDAS and details and inspirations rely on the literature review that both the progression and hurdles of these systems.

As mentioned by Chen et al. (2015) and Barry (2022), they illustrated the effectiveness of ACC and LKA, resulting that technologies may reduce the driver's workload and enhance road environmental safety. These primary elements were designed for survey that may ask public's perception of such features of these technologies, and their reliability and actual safety benefits that experienced by users. For instance, questions on system performance in adverse weather conditions are directly influenced by notable capabilities of ACC and LKA in maintain vehicle control and safety under challenging environmental factors.

Furthermore, the survey contains a section on user concerns that aligns with the findings by Yeong et al. (2021), who emphasize the cortical role of integrated sensor technologies, for instance, sensor fusion, in improving the decision-making capabilities of IDAS. The literature guided survey's inquiry into challenges users may face, such as system errors or poor performance in specific conditions, which reflects the complexity and reliability issues that mentioned in academic circles.

Moreover, Pent et al. (2020) highlighted expansion of ML's applications in the field of IDAS, they think the advancements from companies like Baidu or Alibaba may inspires questions that related to future technology adoption and trust in AI-enhanced functionalities. The survey aims to seek the understanding of user's readiness to embrace more complicated driving systems, which aligns the industry's move towards fully autonomous driving solutions.

Additionally, cybersecurity concerns that mentioned by Mecheva & Kakanakov (2020) and Tran et al. (2023) are also the critical issues and will be explored by this survey, which reflects the growing importance of data security in IDAS and promote public concerns on data privacy and the potential for unauthorized data breach.

In summary, the survey is designed to capture a comprehensive understanding of the UX with IDAS in NEVs, deeply discussed in the challenges and applications of such technologies. The survey is aimed to contribute the insights into both efficacy and the areas that needing focus in the evolution of IDAS by aligning survey's questions with documented technological advancements and user-reported issues.

Question Design: Multiple Choice Questions, Single Choice Questions, and Likert Scale Questions

The questions of this survey were carefully designed from literature review and findings in the field of IDAS and the survey comprise a balanced mix of multiple choice, single choice, as well as Likert scale questions, each question was utilized to capture the anonymized data that from users' perceptions, behaviours, and satisfaction of IDAS features.

Multiple Choice Questions were employed to assess users' familiarity and frequency of use of various IDAS features and functionalities, for instance, ACC, LKA, or APS. These questions allow the participant to select multiple options that resulting providing the breadth and depth in understanding the range of systems that drivers may interacted with, as highlighted by Chen et al. (2024).

Single Choice Questions were utilized to figure out the specific users' preferences or behaviour, for instance, the preferred IDAS features. This approach is based on the insights from Barry (2022), who discussed the different prioritization of IDAS functions by drivers based on their individual's stress and safety concerns, and help in determining the most valuable IDAS features, which may aid in correcting user preferences with the technical data on system performance and safety enhancements.

Likert Scale Questions will be used to measure the level of agreement or satisfaction of IDAS performance, reliability, and overall impact of IDAS on driving experience. This method is particularly useful for capturing degree of user sentiment and testing hypotheses that related to user frustration and system efficacy, as discussed in part of theoretical background in this master thesis. The use of Likert scale facilitates analysis of user attitudes and can be directly compared with the findings by Yeong et al. (2021) that quantified users' trust and perceived reliability in different IDAS functionalities.

The integration of these question types into this survey ensures a comprehensive collection of quantitative data and crucial for the robust statistical analysis needed to validate the study's hypotheses. Furthermore, each question and its structure were developed with the objective that this survey may maximize response rates and data reliability to ensure the results could be effectively used to inform the advancements in IDAS development and deployment. Furthermore, the designed approach may ensure the survey align with the real-world applications and challenges of IDAS features that mentioned in the theoretical background.

3.2.3 Sampling Method

Utilizing a convenience sampling approach, the research focuses on present proprietors of NIO and XPeng automobiles that are outfitted with cutting-edge intelligent driving technologies. The survey will encompass a minimum of 511 participants in total, the obtained sample size, therefore, is deemed sufficient to attain statistical significance, thereby guaranteeing that the gathered data furnishes a dependable foundation for scrutinizing user experiences and discerning prevalent trends. The investigation seeks to bolster the credibility and dependability of the results by encompassing a broad spectrum of user perceptions and experiences through the inclusion of a diverse cohort of participants who actively employ these cutting-edge technologies (Easily, 2023).

3.2.4 Data Collection Process

Multiple stages comprise the data collection procedure to guarantee the data's integrity and dependability. Participant recruitment is executed via diverse channels, encompassing online forums, social media communities devoted to NEV aficionados, and direct engagement with the user communities of NIO and XPeng. Implementing this extensive recruitment approach guarantees the acquisition of a varied and emblematic sample. Online administration of the survey facilitates efficient and widespread participation. All respondents are provided with a hyperlink to the survey, comprehensive guidelines, and guarantees of privacy and anonymity. These factors serve to motivate respondents to provide candid and precise accounts of their experiences. Responses are monitored throughout the duration of data capture to guarantee an equitable representation of users from both NIO and XPeng. Subsequent notifications are dispatched to optimize response rates and rectify any potential challenges that participants may face.

3.2.5 Type of Questionnaire of Survey

The questionnaire developed for this study employs 4 distinct types, each of them serves as a unique purpose in collecting comprehensive data in UX with intelligent driving technologies.

Single choice (Questions 1, 2, 4, 5, and 6) is utilized primarily to collect demographic information, for instance, gender and age group, which helps in segmenting the data for targeted analysis. Besides, as this information is data-sensitive, the designed age is in age group and gender with 'other' and 'prefer not to say'. Even though it may cause confusion when processing data at a later stage, rules of the General Data Protection Regulation (GDPR) are also being followed to maximize the protection of personal data and minimize the sensitivity of data collected (European Parliament and Council of the European Union, 2016, p. 51).

Multiple-choice questions (Question 15, 16, and 17) are used to identify which IDAS features are most commonly used and the issues may occur, allowing for an aggregation of common experiences and problems reported by users.

Likert scales (Question 8, 9, 10, 11, 12, 13, and 14) are extensively utilized across several questions to measure participant's attitudes for various aspects of intelligent driving technologies, including their satisfaction level, trusting level, and effectiveness level users may have. This scale approach enables a nuanced measurement of degrees of approval or disapproval to enhance a granularity of the analysis.

Binary questions NIO/XPeng (Question 3) and yes/no (Question 7) determine whether respondents have ever experienced a safety incident while they are using IDAS features and user's vehicle's brand name, which provides clear and direct insights for the safety implications of these technologies. And this question may be sensitive for participants as they may be too embarrassed to mention it in questionnaire, so a "prefer not to say" will be added in this question.

In conclusion, this survey serves as a vital tool in research methodology, which may allow to collect essential data that support investigation into the UX and user's expectation of IDAS. This finding will not only enrich academic understanding in this thesis, but also provide the feedback to industry stakeholders that aims to refine these transformative technologies.

3.2.6 Platform of Survey

This questionnaire was designed with Microsoft Office 365 Forms as a central tool. Office 365 Forms is an easily operable environment in which users may design personalized questionnaires and design the case with which responses may be collected from respondents for analysis purposes. It has been widely used in mainland China, its widespread use being more relevant for this research related to smart technologies for new energy vehicles developed on the mainland. Additionally, Office 365 Forms capture information in real-time and a format usable directly even in Microsoft Excel, hence retrievable and analyzed with ease. This means that especially with this platform, relevance and current information are drawn. For these very reasons, Microsoft Office 365 Forms have been selected to form the technological backbone of this research.

This survey is concise and it is estimated that it will take less than 5 minutes to complete. This more succinct format allows respondents to give useful answers without investing a lot of time. The responses from the participants should further give insights into the engagement and understanding of users with intelligent driving functionalities.

3.3 Data Analysis Techniques

The survey data will undergo a comprehensive analysis to uncover the specific challenges that users may have in relation to IDAS features in NEVs in China. The primary goal of data analysis is to identify patterns, trends, and correlations that provide useful insights into the usability, reliability, safety, and general satisfaction with the intelligent driving technologies offered by NIO and XPeng.

3.3.1 Data Pre-processing

Before analysis, the data would be subject to meticulous preparation to ensure its accuracy and comprehensiveness. Initially, it is mandatory to examine the survey responses from errors and discrepancies to rectify the data. In order to maintain the accuracy and trustworthiness of the dataset, any responses that are unclear or lack of information will be eliminated. Subsequently, the open-ended questions will be classified, facilitating the quantitative analysis of the data by grouping comparable replies and identifying recurring themes and trends. The Likert scale responses will be transformed into numerical codes, so turning qualitative data into a format suitable for statistical analysis.

3.3.2 Descriptive Statistics

Descriptive statistics summarize data points in a way that gives an overview of the sample population. Frequency analysis will help analyze the response provided by individuals and, consequently, the number of those who responded the same way. Measurements like mean, median, and mode may be calculated to find out what the majority feeling of the users are towards their experiences regarding the various intelligent driver features. The dispersion metrics, such as standard deviation, variance, and range, will also be considered in analyzing how varied the users' experience is.

3.3.3 Inferential Statistics

In order to form inferences and draw generalizations about the larger population of NEV users, inferential statistical techniques will be utilized using the sample data. The investigation will utilize Statistical Package for the Social Sciences (SPSS) as its powerful capabilities in managing intricate statistical calculations and visualizing data. This analysis aims to find the primary factors that determine customer happiness and draw attention to areas that require improvement.

While the survey does not specifically compare the brands, it will analyze responses from various user demographics and usage patterns to pinpoint the specific issues encountered by different groups.

3.3.4 Cross-tabulation and Chi-square Tests

Furthermore, cross-tabulation will be employed to ensure the correlation between many categorical variables. This approach uses contingency tables to find the interactions between various variables. For example, cross-tabulation can demonstrate the variation in the frequency of utilizing IDAS features among different age groups. Chi-square tests will be used to determine if the observed differences between categorical variables are statistically significant. This will enable the study to investigate if the differences in the utilization of intelligent driving features among different age groups are statistically significant or simply random.

3.3.5 Visualization and Reporting

The data analysis results will be presented using a variety of tools to improve comprehension and interpretation. Charts and graphs will be employed to visually depict the distribution of replies and emphasize significant discoveries. Tables that contain summary statistics will offer a precise and succinct summary of the facts. In addition, narrative summaries will be used to elucidate and provide context for the quantitative findings, establishing a connection to the research aims and hypotheses.

3.3.6 Conclusion

The study aims to gain a detailed understanding of the issues users have with intelligent driving features in NEVs by using thorough data analysis methodologies and conducting statistical analysis with SPSS. The knowledge acquired will be crucial for guiding the advancement of user-focused intelligent driving technologies and improving overall user contentment in China's NEV sector.

3.4 Ethical Considerations

Strict ethical norms are essential when doing research involving human subjects as it safeguards the credibility of quantitative studies and ensure the welfare of participants. This study examines consumer perceptions and interactions with autonomous driving systems, utilizing survey data collected from users of IDAS. Protecting personal privacy and safeguarding participant secrecy are crucial for establishing confidence in research.

Ensuring informed consent is crucial for doing ethical research (Nayak & Narayan, 2019). This study requests users to participate in a survey regarding their encounters with IDAS in NEV. The objectives, role, possible hazards, and voluntary nature of involvement in the study should all be well understood by the participants. They should be notified that they have the option to withdraw at any time without facing any repercussions. Due to the survey being conducted online, participants will be provided with a digital consent form to carefully examine and verify prior to their participation. This form will provide comprehensive information regarding the study's objectives, methodologies, time frame, and utilization of data. Furthermore, it will highlight the need of maintaining confidentiality in responses and ensuring that data is anonymised in all analyses and publishing. This method guarantees adherence to ethical standards and fosters confidence and transparency among participants.

An important ethical aspect in this study is to guarantee the anonymity of participants (Roberts & Allen, 2015). In order to safeguard the privacy of consumers, all survey data will undergo robust encryption measures that provided by the survry's form provider, which is Microsoft. In addition, the study will abstain from gathering personal identity data, such as names, residences, or license plate numbers. Moreover, the result that this survey finds will be presented in a collective manner, ensuring that no personal information of the participants can be disclosed or identified. This methodology not only places participant safety as a top priority but also promotes honest and transparent answers, which are crucial for maintaining the credibility of the research results.

Another important ethical aspect is to ensure impartiality and eliminate any form of bias during the entire study process. Every stage of the process, starting from the initial design to the gathering of data, its analysis, and the subsequent reporting, must be meticulously supervised. The survey questions are carefully designed and presented to participants in order to minimize the impact of bias on the final results (Ketokivi, 2019). The poll questions are impartial and direct, refraining from any suggestive inquiries.

This research will follow restrict ethical norms, ensuring the authenticity of the study and safeguarding the privacy of participants' personal information. Protection of participant's right from unauthorized access and reliability and genuineness of collected data will be promoted by following these criteria. The ethical measurements demonstrate a dedication to the ideals of respect for individuals, beneficence, and justice, as specified in the guidelines for ethical research conduct (Luetge, 2017).

3.5 Limitation of Methodology

In research process, regardless of how thoroughly the planning is done, there are inevitably final limitations. Acknowledging these inherent limitations is crucial for analyzing the context of the research results. This section will explore the limitations of the methodology used in this study to evaluate the UX with IDAS in China's market.

The first significant limitation of this study stems from its use of a convenience sampling strategy. While this approach is practical and cost-effective, particularly in accessing a specific population that uses intelligent driving technologies, it may not provide a fully representative sample of all IDAS vehicle owners. The use of convenience sampling in this research typically includes those who are easily contactable or already willing to participate, which can directly result in biases in the final results (Emerson, 2015). Such biases may limit the widespread applicability of the research findings, as such samples may not fully and accurately reflect the broader user population. Therefore, caution should be exercised when analyzing the results of this study, considering that the findings may not completely represent the user experiences of all diverse groups.

The study's focus on quantitative data collection is another limitation. While quantitative methods provide structured and statistically analysable data, they often lack the depth that qualitative data can offer. This methodological choice means that certain subtleties and complexities of

UX and perceptions might not be fully explored (Basias & Pollalis, 2018). For example, quantitative data can indeed show the overall level of satisfaction with various IDAS features, but it fails to reveal the specific reasons for dissatisfaction or whether there are potential shortcomings in the development of artificial intelligence technologies by automotive companies.

Furthermore, SPSS has some limitations as well. While SPSS is powerful for many types of analysis, it may not be as flexible or capable as other specialized tools for very large data sets or highly complex modeling. Another limitation is that advanced analysis sometimes requires a high learning curve and an understanding of statistical concepts in order to properly interpret the results.

Additionally, the overreliance on self-reported data in research also limits the validity of the data. This is because participants' answers may be influenced by their emotions at the time, personal biases, or motivations to provide socially desirable answers (Anvari et al., 2022). These factors may lead to data inaccuracies, thereby affecting the authenticity of the research results. These factors may affect the accuracy of the data collected, as participants may exaggerate their satisfaction or not disclose their true feelings or negative experiences.

In conclusion, while this research provides valuable insights into the UX with IDAS features, these methodological limitations should be considered when interpreting the results. Future research could address these limitations by incorporating a more diverse sampling strategy, including qualitative components, and expanding the scope to other brands and regions to enhance the robustness and generalizability of the findings.

4 Result

4.1 Presentation of Result

In this section (as shown in Appendix 2: Presentation of Survey's Result), collected data that underpin analysis of the application of IDAS in NEVs in China will be presented. The chosen approach to data visualization and presentation aims to illuminate the complex interplay between UX, technical effectiveness, and the practical challenges facing the industry.

The data collected covers a wide range of aspects, including user preferences, performance metrics for smart driving features, and UX feedback from a broad demographic spectrum. Each data set is presented methodically to provide the basic understanding that supports subsequent parts of the analysis. This approach ensures clarity of the findings and facilitates logi cal interpretation of the findings.

4.2 Data Descriptive Statistic

4.2.1 The Relationship Between Gender and the Selection of Intelligent Driving Assistance System

Table 1 Relationship Between Gender and the Selection of IDAS

Statistics Description	Result
Gender Mode	Man
IDAS Selection	Traffic Jam Assist

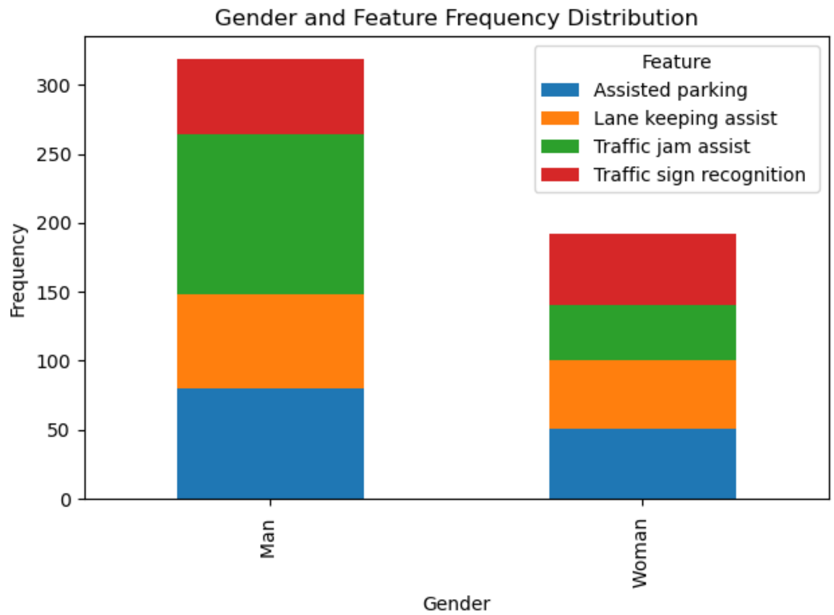

Figure 2 Gender and Feature Frequency Distribution

By analyzing the relationship between gender and the selection of features of IDAS, it is found that male users dominate the use of IDAS, especially in choosing traffic congestion assistance functions.

Data shows that male users are more inclined to choose functions that can provide assistance in traffic jams, while female users have significant differences in preferences for other functions. This gender difference not only reflects the differences in driving habits and preferences between genders, but also provides an important gender dimension reference for the design and marketing of IDAS. Differentiated designs based on the needs of users of different genders can significantly improve user experience and market acceptance.

4.2.2 Age Groups and Frequency of Use of Intelligent Driving Assistance System

Table 2 Age Groups and Frequency of Use of IDAS

Statistical Description	Result
Age Group Average	170.333
Average Frequency of Use of IDAS	102.2
Median Age Group	117
Median Frequency of Use of IDAS	98
Age Group Median	0.25 100.0
	0.50 117.0
	0.75 214.0
	Name Count, dtype: float64
IDAS Usage Frequency Qauntile	0.25 44.0
	0.50 98.0
	0.75 115.0
	Name Count, dtype: float64
Age Group Mode	20-30 years
IDAS Usage Frequency	Sometimes

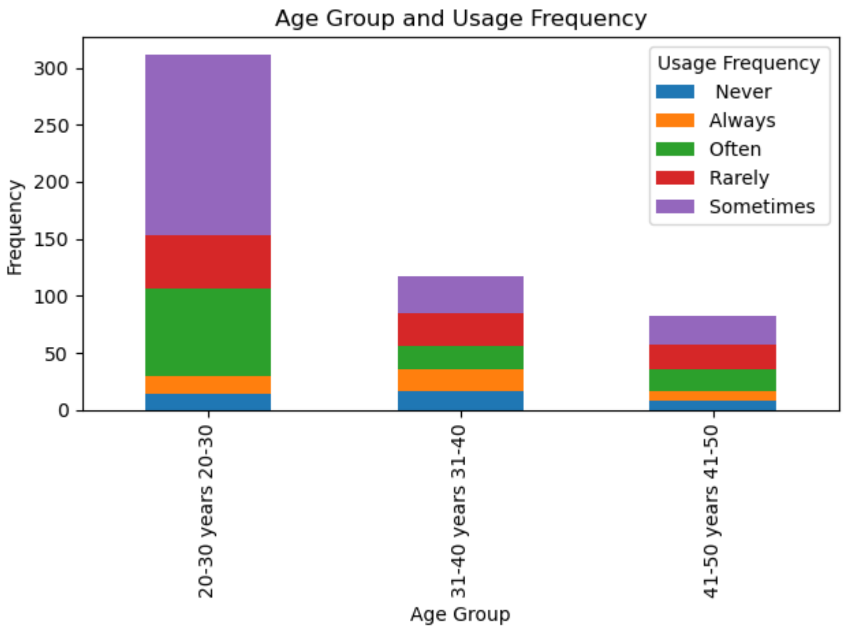

Figure 3 Age Group Frequency

Huge gap between different age groups in the relationship toward frequency of IDAS was found. The results indicated that the frequency of using an intelligent driving system is higher for young users, specifically those aged 20-30 years. This may reflect a case where young people easily accept and are willing to use new technologies.

Considering that the targeted users are young, design and promotion of intelligent driving products must consider their usage habits and likings. Furthermore, the statistical analysis shows that although the median of the usage frequency in groups of different ages is similar, the usage frequency of users in the 20-30 age bracket is far from being balanced; in the 31-40- and 41-50-year-old user groups, the usage frequency is comparative and centralized. This supports the result that the design and advertising of intelligent driving systems should take into account the different needs and preferences of various age groups.

4.2.3 Motivation and Concerns about Choosing Intelligent Driving Assistance System

Table 3 Motivation and Concerns about Choosing IDAS

Statistical Description	Result
the Majority of Motivations of Choosing an IDAS	Safety Features
Concerns about IDAS	Safety

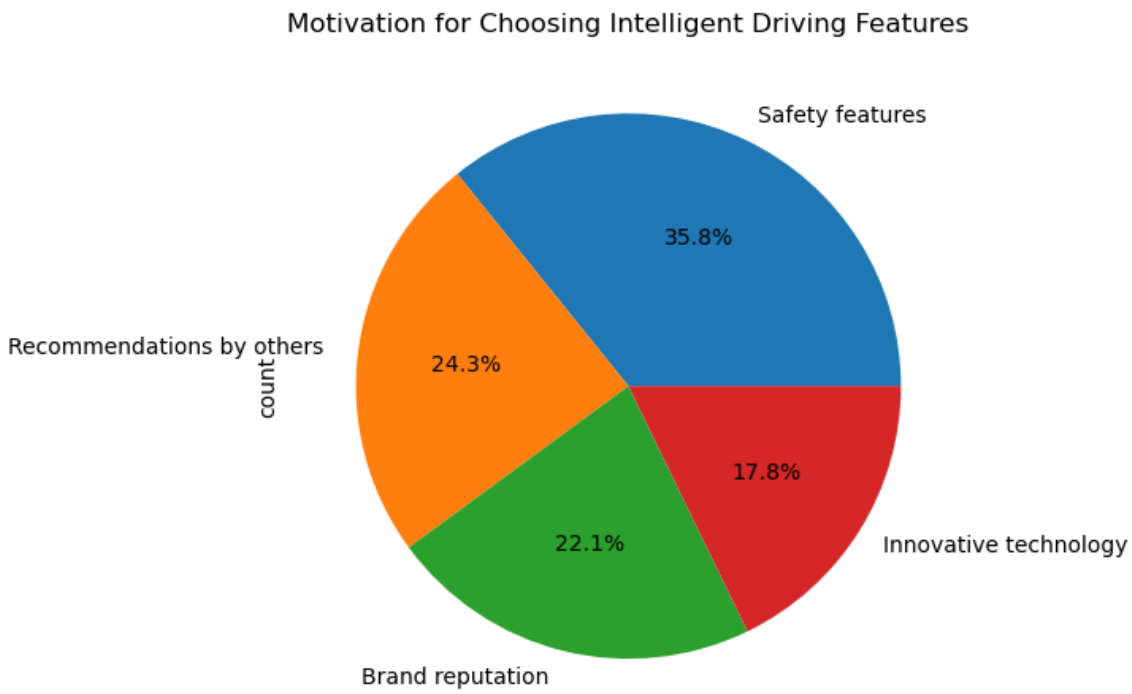

Figure 4 Motivation for Choosing Intelligent Driving Features

Safety factors are the principal motivation and concern of users when choosing IDAS. Safety functions form the main motivations that make users choose IDAS, while system safety is their major concern.

This proves that improving the safety performance of IDAS is one of the key targets for future technological improvements. Optimizing user requirements by improving safety not only improves user satisfaction but also strengthens trust in intelligent driving technology. It turned out that safety was among the most important considerations influencing users' choice and usage of intelligent driving assistance systems; further optimization of the system on safety performance can improve user satisfaction and build trust.

4.2.4 The Relationship Between Technical Problem Frequency and Usage Frequency

Table 4 the Relationship between Technical Problem Frequency and Usage Frequency

Statistical Description	Result
Average Frequency of Technical Issues	102.2
Average Frequency of Usage	102.2
Median Frequency of Technical Issues	86
Median Frequency of Usage	98
Technical Problem Frequency Quantile	0.25 57.0
	0.50 86.0
	0.75 143.0
	Name: count, dtype: float64

Usage Frequency Quantile	0.25 44.0
	0.50 98.0
	0.75 115.0
	Name: count, dtype: float64

The frequency of technical problems has a strong impact on the frequency the application of intelligent driving assistance systems is used. Statistically, frequent technical problems greatly reduce the willingness to apply smart driving systems. The detailed analyses showed fairly high medians and quartiles of the technical difficulties, which are many users may have technical difficulties when operating the smart driving technologies.

This would therefore call for attention on technological developments, aimed at solving the problems of stability and dependability of the system, to enhance the user's experience and increase their frequency of usage. The overall reliability and stability of the technology in the system would have very great impacts on how often the users are willing to use it. Solving such technical problems will greatly improve consumer approval and satisfaction with the smart drive system.

Through these analyses, we can draw the following conclusions: there are significant differences in the use of intelligent driving systems among different user groups. Safety is the main motivation and concern for users to choose and use intelligent driving systems, and the frequent occurrence of technical problems will significantly reduce the frequency of users' use of the system. These findings provide valuable reference information for the future design and improvement of intelligent driving systems. Differentiated design based on the needs of different user groups and improving the safety and reliability of the system will be the key to improving user satisfaction and market acceptance.

4.2.5 Impact of Adverse Weather on the Performance of Intelligent Driving Assistance System

Table 5 Impact of Adverse Weather on the Performance of IDAS

Statistical description	Result
The Impact of Adverse Weather on the Performance of IDAS	Very Effective
Median Impact of Adverse Weather on the Performance of IDAS	77
The Quantile of Impact of Adverse Weather on the Performance of IDAS	0.25 74.0 0.50 77.0 0.75 103.0 Name: count, dtype: float64

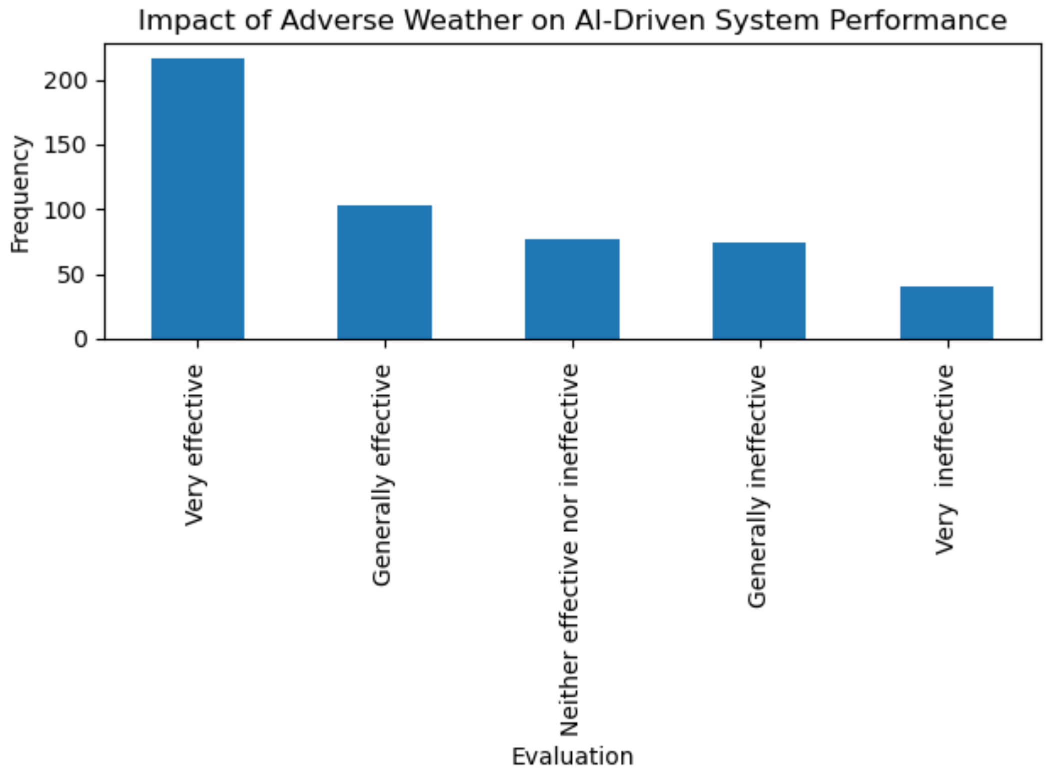

Figure 5 Impact of Adverse Weather on IDAS

In severe weather conditions, users' evaluation results on the performance of the intelligent driving system are as follows: the mode of performance is "very effective", the median is 77, and the percentiles are 74 for the 25th percentile, 76 for the 50th percentile, and 78 for the 80th percentile. The quantile is 77 and the 75th percentile is 103.

These statistics show that although the overall performance of intelligent driving systems in adverse weather conditions is relatively good, there is still significant room for improvement in dealing with extreme weather conditions. In particular, further research is needed to improve the stability and accuracy of the system. Optimized and refined to ensure reliable driving assistance in all weather conditions.

4.2.6 User Evaluation of System Operation Complexity

Table 6 User Evaluation of System Operation Complexity

Statistical description	result
Mode of users' evaluation of system operation complexity	Safety
Median user rating of system operation complexity	126.5
User evaluation quantile of system operation complexity	0.25 102.75 0.50 126.50 0.75 151.50

	Name: count, dtype: float64

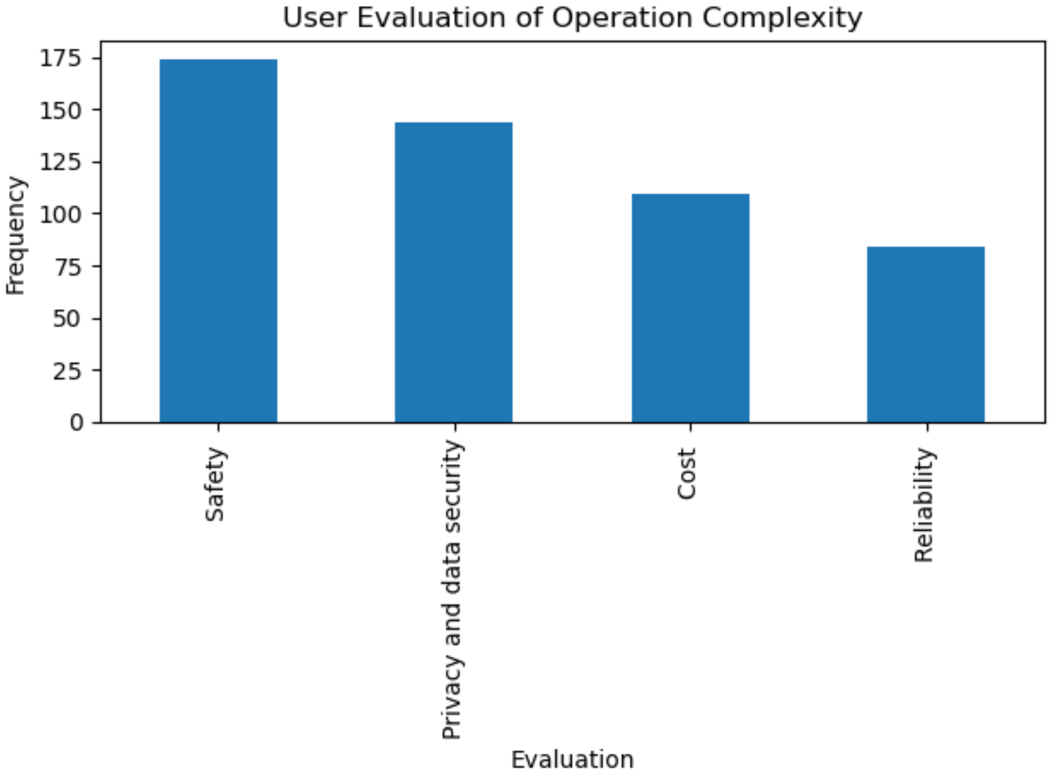

Figure 6 User Evaluation of Operation Complexity

Users' evaluation of the operational complexity of IDAS mainly focuses on safety. The specific data are as follows: the mode of the evaluation is "safety", the median is 126.5, and the percentiles are 102.75 for the 25th percentile, 126.5 for the 50th percentile, and 151.5 for the 75th percentile.

These results show that users expect the operation of IDAS to be simple, safe and reliable. Users hope to improve the overall user experience by simplifying the operation process and improving system safety, which is crucial to enhancing user satisfaction and market acceptance. It can be seen that optimizing the system's operating interface and functional design to meet users' high requirements for safety and ease of use is a key direction for the development of future intelligent driving systems.

4.3 Reliability and Validity Testing

4.3.1 Reliability Analysis

In questionnaire research, reliability analysis is used to evaluate the internal consistency and reliability of the questionnaire. Reliability refers to the consistency or stability of the scale in repeated measurements. In this study, Cronbach's Alpha coefficient for reliability analysis was chosen, mainly based on the following reasons:

1) Internal consistency assessment: Cronbach's Alpha coefficient is a commonly used method to assess the internal consistency of a scale. It measures the reliability of a questionnaire by calculating the correlation between the items in the questionnaire. A higher Alpha value indicates that the items measure the same underlying concept and thus have a higher consistency. It is widely recognized as a standard method for reliability analysis.

2) Wide application: Cronbach's Alpha coefficient is widely used in social sciences, psychology, market research and other fields. Its calculation method and interpretation are relatively simple and clear, and can effectively reflect the internal consistency of the questionnaire.

3) Multi-item scale: This study contains multiple Likert scale items. Cronbach's Alpha coefficient can be used to assess the consistency between these items and verify the reliability of the questionnaire. Alpha coefficient is particularly suitable for scales containing multiple items and helps to identify potential scale problems.

Cronbach's Alpha coefficient analysis results:

Table 7 Cronbach's Alpha Coefficient Analysis Result

Cronbach's alpha coefficient	Standardized Cronbach's alpha coefficient	Number of items	Number of samples
0.636	0.643	6	511

According to the above results, the Cronbach's Alpha coefficient of the model is 0.636, and the standardized Cronbach's Alpha coefficient is 0.643. This shows that the internal consistency of the questionnaire is average, suggesting that we need to further check the rationality of each question.

Analysis Description:

Cronbach's Alpha coefficient value:

Cronbach's Alpha coefficient is used to evaluate the internal consistency of the data. The higher the value, the stronger the correlation between the questionnaire items and the higher the reliability. Generally speaking, an Alpha value above 0.7 indicates that the scale has a high reliability. In this study, the Alpha value was 0.636, indicating that the reliability was acceptable, but there was room for improvement.

Standardized Cronbach's Alpha coefficient value:

The standardized Cronbach's Alpha coefficient is used to unify the scales with different scores. In this study, the standardized Cronbach's Alpha coefficient was 0.643, slightly higher than the unstandardized coefficient, indicating that standardization has improved the reliability of the scale.

Item total statistical analysis:

By deleting the statistical summary of the analysis items, we can determine the impact of each item on the overall reliability. This is because by deleting each item and recalculating the Alpha coefficient, we can identify which items may reduce the consistency of the overall scale. If the Alpha coefficient increases after deleting an item, it means that the consistency of the item with the rest of the items is poor and may need to be revised or deleted. If the Alpha coefficient decreases, it means that the consistency of the item with the rest of the items is good and it is recommended to keep it.

Below we have made a statistical summary after deleting the analysis items to determine the impact of each item on the overall reliability. The following are the statistical results after deleting the analysis items:

Table 8 Statistical Summary after Deleting the Analysis Items on Overall Reliability

Project Analysis Name	Overall relevance	Cronbach's alpha coefficient	Reference conclusion
How do you evaluate the performance of IDAS technology in adverse weather conditions?	0.324	0.61	better
How often do you use your vehicle's IDAS driving features?	0.31	0.617	better
How would you rate the overall reliability of the IDAS in your vehicle?	0.447	0.567	better
How often do you experience technological challenges (eg, system errors, software glitches) with the IDAS?	0.34	0.602	better
In adverse weather conditions (rain, snow, fog), does the IDAS satisfy your expectations?	0.416	0.576	better
Technological challenges with the IDAS significantly affect your driving experience	0.386	0.585	better

The deleted item are correlated with the overall after the terms are deleted:

This column of data is the product difference correlation coefficient between each item and the rest of the items. The higher the coefficient, the stronger the internal consistency of the item and the rest of the items. Generally, items with a total correlation lower than 0.3 need to be checked or Adjustment. This analysis was chosen to identify which items had a weak correlation with the total, so that these items could be further checked or adjusted to ensure that each item in the questionnaire had a high degree of internal consistency.

Cronbach's Alpha coefficient after deleting items:

This column indicates the Cronbach's Alpha coefficient of the subscale composed of the remaining item variables after deleting an item. Through this analysis, we can identify which items contribute less or negatively to the overall consistency of the questionnaire, thereby helping to optimize the questionnaire design. If the Alpha coefficient increases after deleting an item, it means that the item has a negative impact on the consistency of the scale and may need to be deleted or modified. If the Alpha coefficient decreases, it means that the item has a positive contribution to the consistency of the scale and it is recommended to retain it.

The results of this reliability analysis show that the overall correlation after each item is deleted is higher than 0.3, and Cronbach's Alpha coefficient after deleting the item does not increase significantly, indicating that these items are consistent with the remaining items and do not need to be modified. Therefore, we believe that the current questionnaire items perform relatively well in terms of internal consistency and can continue to be used.

4.3.2 Validity Analysis

Content validity: Content validity assessment aims to determine whether the questionnaire fully covers all aspects of the research topic. Through expert review and literature review, it is ensured that the items in the questionnaire fully reflect the main features and user experience of the intelligent driving system. The reason for choosing content validity analysis is that it can ensure the comprehensiveness and representativeness of the questionnaire items and ensure the scientificity and systematicness of the measured content.

Construct validity: Construct validity is used to ensure that the questionnaire can effectively provide the relevant characteristics of the intelligent driving system with regard to construct validity. Construct validity is one of the statistical techniques in identification and verification that may have structures or factors. The reasons for choosing Construct validity are that it is capable of confirming whether items in the questionnaire can reflect expected potential constructs, identifying a potential structure existing between items, and guaranteeing theoretical basic guarantee together with empirical validity of the questionnaire.

Construct validity is evaluated through factor analysis to assess whether the questionnaire effectively measures the relevant characteristics of the intelligent driving system. The specific steps are as follows:

1) KMO and Bartlett's test

The Kaiser-Meyer-Olkin(KMO) test is used to establish the adequacy of data for factor analysis. It measures the general appropriateness of the correlation matrix between variables in order to estimate whether these correlations are adequate for factorial analysis. KMO values range from 0 to 1, and higher values approach 1, which means appropriateness of the data for factorial analysis is higher. Generally, it is held that KMO values greater than 0.6 indicate the suitability of data for factor analysis. On the other hand, if the KMO value is less than 0.5, this will show that data may not be appropriate for factor analysis.

Bartlett's sphericity test is used to test whether the correlation matrix between variables is the identity matrix (that is, the variables are independent of each other and have no correlation). If the correlation matrix is close to the identity matrix, factor analysis is meaningless because there is no underlying factor structure. Bartlett's sphericity test can be used to determine whether the correlations between variables are strong enough to support the assumptions of factor analysis. Specifically, it tests whether the correlation matrix between variables has significant correlations.

Table 9 KMO Test and Bartlett's Test

KMO value		0.74
Bartlett's test of sphericity	Approximate Chi-Square	328.471
	df	15
	P	0.000*** (very close to 0)

KMO value: 0.74, indicating that there is a high correlation between the item variables, which is suitable for factor analysis.

The p-value of the Bartlett sphericity test is used to test whether the correlation matrix is an identity matrix (that is, the variables are independent of each other and have no correlation). If the p-value is significant (usually less than 0.05), the null hypothesis is rejected, indicating that the correlation matrix is not an identity matrix and there is sufficient correlation between the variables, which is suitable for factor analysis. Among them:

Bartlett sphericity test significance : P value is 0.000*** , which means that the P value is very close to 0, but in fact the P value cannot be exactly 0, so three asterisks () are usually used to indicate that the P value is very significant, usually representing a P value less than 0.001. This shows that the test result is highly significant and strongly rejects the original hypothesis, that is, there is a significant correlation between the variables. Therefore, there is a correlation between the variables, and the factor analysis is effective.

2) Total variance explained

In factor analysis, total variance explained is used to evaluate the contribution of extracted factors to the overall data variance. It helps researchers understand how much data variation is explained by the extracted factors, which is crucial for determining the validity of the model and simplifying the data structure. Through total variance explanation, researchers can decide how many factors to retain, thereby simplifying the model and improving explanatory power. Among them:

Eigenvalues: Eigenvalues represent the total variance explained by each factor. The larger the eigenvalue, the more data variation the factor explains. Usually, factors with eigenvalues greater than 1 are considered significant and should be retained in the model.

Variance explanation rate: Variance explanation rate is the ratio of characteristic roots to total characteristic roots, indicating the contribution rate of each factor to the variance of the overall data. A higher variance explanation rate means that the factor has a stronger explanatory power for the data structure.

Cumulative variance explained rate: The cumulative variance explained rate is the sum of the variance explained rates of each factor, indicating the total variance explained by the extracted factors together. The higher the cumulative variance explained rate, the more the extracted factors can explain the overall variation of the data. Generally, when the cumulative variance explained rate reaches more than 60%, the model is considered to have good explanatory power.

Table 10 Total Variance Explained

Element	Characteristic root			Variance explained after rotation		
	Characteristic root	Variance explained (%)	Cumulative percentage (%)	Characteristic root	Variance explained (%)	Cumulative percentage (%)
1	2.174	36.23%	36.23%	1.003	16.72%	16.72%
2	1.028	17.13%	53.36%	1.002	16.70%	33.42%
3	0.812	13.53%	66.89%	1.001	16.69%	50.10%
4	0.721	12.02%	78.91%	1.001	16.69%	66.79%
5	0.648	10.81%	89.72%	0.998	16.63%	83.42%
6	0.617	10.28%	100%	0.995	16.58%	100%

In the factor analysis, the characteristic roots of the first two factors were 2.174 and 1.028, respectively, explaining 53.362% of the total variance.

After rotation, the variance explained by the first two factors was 16.718% and 16.697% respectively, cumulatively explaining 33.415% of the total variance.

The eigenvalues of the third to sixth factors are all less than 1, but overall these factors together explain 100% of the total variance.

The total variance explained by factor analysis shows that the first two factors have a significant contribution to explaining the total variance of the questionnaire variables. Although the variance explanation rate after rotation has slightly decreased, it can still effectively reflect the main variables in the questionnaire. Overall, these six factors together explain 100% of the total variance, indicating that the questionnaire questions cover the main characteristics and dimensions of the intelligent driving system and have good construct validity.

Therefore, it can be concluded that the questionnaire is reasonable in design, can effectively measure the relevant characteristics of the intelligent driving system, and has good reliability and validity. This provides a solid foundation for further user research on intelligent driving systems.

4.4 Correlation Analysis

4.4.1 Correlation Analysis between Gender and Intelligent Driving Assistance System

Analysis methods:

This study employs the Chi-Square Test to examine the association between gender and the selection of intelligent driving systems. The Chi-Square Test is a method used to test the association between two categorical variables. By calculating the chi-square value and significance level, it determines whether there is a significant difference between the variables.

Analysis results:

1. Chi-square test results

Through the Pearson Chi-Square Test, the results show a P-value of 0.001 and a significance level of 0.001 ($P<0.05$), indicating a significant difference between gender and the selection of intelligent driving systems. The specific data are as follows:

Table 11 Chi-square Test on Gender and IDAS Feature

Title	Name	What's your gender?		In total	Inspection method	X^2	P
		Male	Woman				
Which intelligent driving features do you use most often?	Traffic jam assist	116	40	156	pearson Chi-square Test	16.042	0.001 * * *
	Traffic sign recognition	55	52	107			
	Assisted parking	80	51	131			
	Lane keeping assist	68	49	117			
Total		319	192	511			

Figure description:

The table above presents the frequencies, chi-square values, and significance P-values of the Chi-Square Test. The P-value from the Chi-Square Test is used to determine whether there is a significant association between two categorical variables. If the P-value is less than 0.05, it indicates a significant association between the two variables.

In this study: The P-value of the Pearson Chi-Square Test is 0.001, with a significance level of 0.001 ($P < 0.05$), indicating a significant difference between gender and the selection of intelligent driving systems.

2. Effect quantification analysis

Further effect quantification analysis shows:

Table 12 Quantification Analysis

Field name/item of analysis	Phi	Crammer's V	Column connections	lambda
Which intelligent driving features do you use most often?	0.177	0.177	0.174	0.034

Figure description:

Phi coefficient: 0.177, indicating a rather weak association between the two variables.

Cramer's V coefficient: 0.177 further validates the weak association between gender and intelligent driving system selection.

Column association number and lambda values: The column association number is 0.174 and the lambda value is 0.034, which further illustrates the weak association between the two variables.

Based on the above, the following conclusion is:

Through Chi-square test and effect quantification analysis, this study found that there are significant differences between gender and intelligent driving system selection. Although the effect size was small, this finding still has important practical implications, helping to understand the preferences of different gender users in the choice of intelligent driving systems and providing a reference for the design and marketing of related products.

4.4.2 Correlation Analysis between Age Groupd and Frequency of Intelligent Driving Assistance System

Methods of analysis:

To comprehensively examine the differences in intelligent driving system usage frequency among different age groups, this study employed three statistical tests: analysis of variance (ANOVA), Kruskal-Wallis test, and Levene's test.

Results of the analysis:

Table 13 Results of the Analysis between Age Group and Frequency of IDAS

Test	Statistic	p-value
ANOVA	1.079644439	0.340494479
Kruskal-Wallis	2.706737519	0.258368412
Levene	20.25642148	3.43507 e-09

Figure Description:

The P-values from the ANOVA and Kruskal-Wallis tests are used to determine if there are significant differences in the mean or median frequency of intelligent driving system use among different age groups. A P-value less than 0.05 indicates a significant difference between the age groups.

In this study: Both the ANOVA and Kruskal-Wallis tests have P-values greater than 0.05, indicating no significant differences in the mean and median frequency of intelligent driving system use among different age groups.

The P-value from the Levene test is used to determine if there are significant differences in the variance of intelligent driving system use frequency among different age groups. A P-value less than 0.05 indicates a significant difference in variance.

In this study: The Levene test P-value is 3.43507E-09, which is less than 0.05, indicating significant differences in the variance of use frequency among different age groups. This means that the distribution of use frequency varies significantly across different age groups.

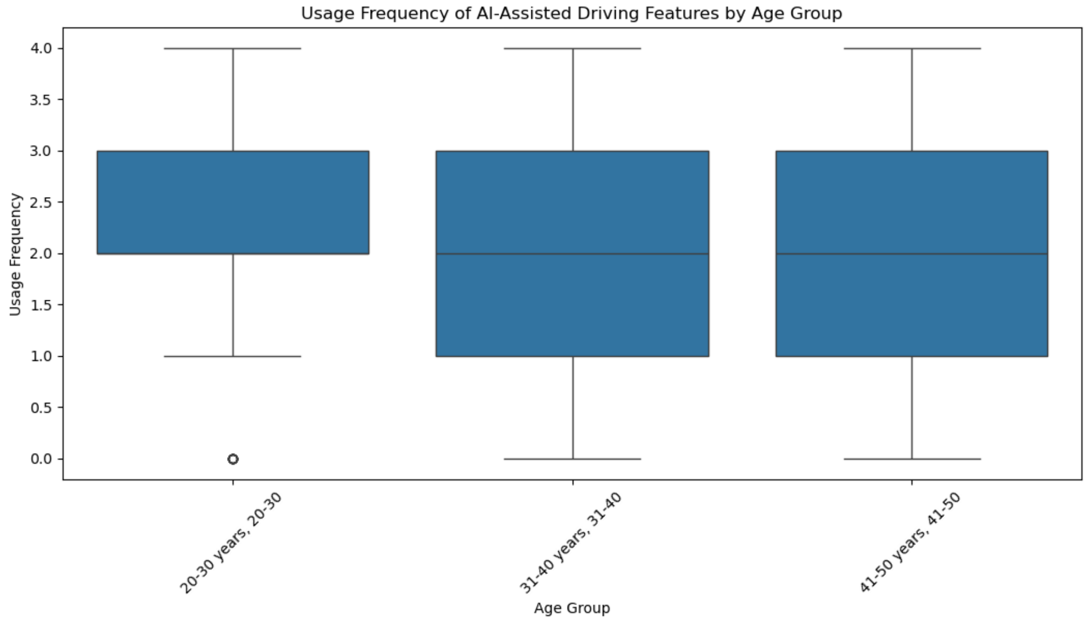

Figure 7 Analysis of Frequency of Use between Agr Groups and IDAS

Observation results:

The median:

The median values for the three age groups are similar, all around 2 or 3. This indicates that most people use the intelligent driving system with a frequency between "Sometimes" and "Often."

Interquartile spacing (IQR):

20-30 years, the wider IQR in the 20-30 year age group indicates greater variation in frequency of use within this group.

31-40 years, 31-40 years and 41-50 years, the IQR was narrower and the frequency of use was more concentrated in the 41-50 years group.

Based on the above, the following conclusions can be drawn:

Although the mean and overall distribution of intelligent driving system usage frequency are similar across different age groups, there is a significant difference in variance. This means that while the average usage frequency is consistent, the level of variation among individuals differs by age group. Specifically, the 20-30 age group shows a greater variability in usage frequency.

4.4.3 Analysis of the Relationship between Motivations and Concerns in Selecting Intelligent Driving Assistance System

Analysis methods:

To explore the relationship between motivations for selecting intelligent driving systems and concerns about these systems, this study employed correlation analysis methods. Specifically, we used the Pearson Correlation Coefficient and Spearman's Rank Correlation Coefficient as statistical methods.

Analyzing the results:

Table 14 Analysis of the Relationship between Motivations and Concerns in Selecting IDAS

Correlation Type	Correlation Coefficient	p-value
Pearson	0.097777049	0.027093662
Spearman	0.086208201	0.051460724

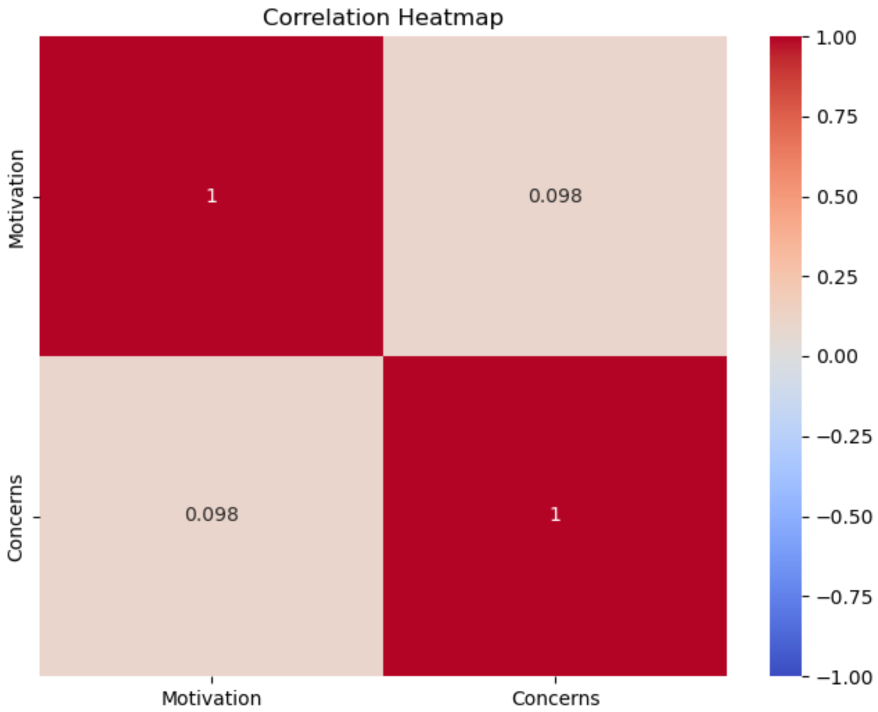

Figure 8 Influence of Weather Conditions on IDAS Performance Correlation Cofficient Heat Map

Figure Description:

The P-values for the correlation tests are used to determine whether the relationship between two variables is significant. If the P-value is less than 0.05, it indicates a significant correlation between the variables.

In this study: The P-value for the Pearson Correlation Coefficient is 0.027094, indicating a significant positive correlation between motivations for selecting intelligent driving systems and concerns about these systems. The P-value for the Spearman's Rank Correlation Coefficient is slightly greater than 0.05, indicating that the correlation is not significant at the 95% confidence level but is significant at the 90% confidence level.

Results Summary:

Correlation: There is a weak positive correlation between motivations and concerns. The relationship between the motivation to choose vehicles with intelligent driving assistance systems and concerns about this technology is statistically significant, especially in the Pearson correlation analysis.

Significance Level: The Pearson correlation is significant at the 95% confidence level, while the Spearman correlation is not significant at the 95% confidence level but is significant at the 90% confidence level.

Conclusion:

The correlation analysis between motivations and concerns indicates that although the correlation is weak, it is statistically significant. This means that users' motivations for choosing vehicles equipped with intelligent driving assistance systems are somewhat related to their concerns about this technology. For the design and promotion of intelligent driving systems, it is important to consider users' motivations and concerns to improve acceptance and satisfaction.

4.5 Regression Analysis

4.5.1 The Impact of Weather Conditions on the Performance of Intelligent Driving Assistance System

Analysis method:

The purpose of this study is to explore the influence of weather conditions on the performance of IDAS. In order to achieve this goal, multiple regression analysis method was adopted, the specific steps are as follows:

1) Data preparation and preprocessing:

Data cleaning: Data cleaning, dealing with missing values, outliers, and ensuring data quality and integrity.

Data coding: Converting qualitative data into quantitative data. Specifically, the user's evaluation of weather conditions and the performance of the intelligent driving system (using a Likert scale) is converted into corresponding numerical values.

2) Mapping and conversion:

Weather conditions Evaluation Mapping: Very effective: 5; Relatively effective: 4; General: 3; Less effective: 2; Very ineffective: 1

System performance evaluation mapping:; Very satisfied: 5; Generally satisfied: 4; Average performance: 3; Generally dissatisfied: 2; Very dissatisfied: 1

3) Regression analysis:

Independent variable: evaluation of weather conditions

Dependent variable: intelligent driving system performance evaluation

Model construction: Linear regression model was used to analyze the influence of weather conditions on the performance of intelligent driving assistance system.

Model evaluation: The fitting effect and significance of the model are evaluated by regression coefficient, p-value, r-² value and other indicators.

Analysis results:

Dependent variable: In adverse weather conditions (rain, snow, fog), does the intelligence driving assistance system satisfy your expectations?

Independent variable: How do you evaluate the performance of intelligence driving assistance technology in adverse weather conditions?

Table 15 the Impact of Weather Conditions on the Performance of IDAS

Indicators	value
R-squared value	0.09
Adjusted R-squared value	0.088
F statistic	46.35
The p-value of the F statistic	3.03 e-11
Coefficient of constant term	2.5852 ($p < 0.000$)
Coefficient of independent variable	0.3381 ($p < 0.000$)

Results Interpretation:

R-squared Value: The R-squared value is 0.090, indicating that weather conditions explain 9% of the variance in the performance of intelligent driving systems.

F-statistic and P-value: The F-statistic is 46.35, and the corresponding P-value is 3.03e-11. This indicates that the overall regression model is significant.

Constant Term and Independent Variable Coefficient: The constant term coefficient is 2.5852, and the independent variable coefficient is 0.3381, both highly significant ($P < 0.000$). This means that for each unit increase in weather condition, the satisfaction with intelligent driving system performance increases by 0.3381 units.

Table 16 Interpretation of Impact of Weather Conditions on the Performance of IDAS

Coefficient of constant term	2.5852 ($p < 0.000$)
Standard error for constant term	0.205
Constant term t value	12.582
Constant term confidence interval	[2.181, 2.989]
Weather condition evaluation coefficient	0.3381 ($p < 0.000$)
Standard error of weather condition evaluation	0.05
Weather conditions evaluate T-values	6.808
Weather conditions evaluation confidence interval	[0.241, 0.436]

Through the regression analysis table, it can be found:

Constant Term Coefficient (const): The constant term coefficient is 2.5852, indicating that when all independent variables (in this case, the weather condition rating) are zero, the predicted performance satisfaction is 2.5852. The standard error is 0.205, the t-value is 12.582, and the P-value is 0.000, with a confidence interval of [2.181, 2.989]. These values indicate that the constant term is statistically significant.

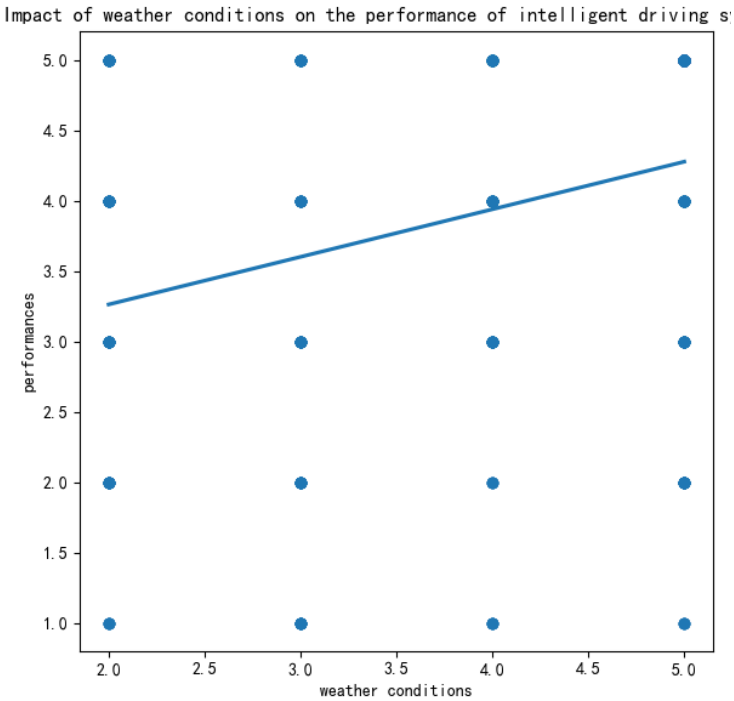

Figure 9 Regression Analysis of Influence of Weather Conditions on the Performance of IDAS

Figure Description:

From the Figure, it is evident that as the weather condition rating improves, the performance satisfaction also increases. This trend line indicates that the higher the users rate the performance of the intelligent driving system under adverse weather conditions, the more satisfied they are with the system in these conditions.

In conclusion, this study shows that improving the performance of intelligent driving systems under various weather conditions will help increase user satisfaction. Future research can further explore other factors that impact the performance of intelligent driving systems to comprehensively enhance user experience and reliability.

4.5.2 The Impact of Technical Challenges on User Frustration

Methods of analysis

This study aims to explore the impact of technological challenges on user frustration. In order to achieve this goal, we adopted a multiple regression analysis method, with the following steps:

1) Data preparation and preprocessing:

Data cleaning: Data cleaning, dealing with missing values, outliers, and ensuring data quality and integrity.

Data coding: Converting qualitative data into quantitative data. Specifically, the user's evaluation of the technical challenges and the reliability of the intelligent driving system (using a Likert scale) is converted into corresponding numerical values.

2) Mapping and conversion:

Technical Challenge Evaluation Mapping: Strongly agree: 5; Agree: 4; Neutral: 3; Disagree: 2; Strongly disagree: 1

User frustration rating Mapping: Very good: 5; Good: 4; General: 3; Poor: 2; Very poor: 1

3) Regression analysis:

Independent variable: technical challenge evaluation

Dependent variable: user frustration rating

Model construction: A linear regression model was used to analyze the impact of technical challenges on user frustration.

Model evaluation: The fitting effect and significance of the model are evaluated by regression coefficient, p-value, r^{-2} value and other indicators.

Analysis results:

Dependent variable: How would you rate the overall reliability of the intelligence driving assistance system in your vehicle?

Independent variable: Technological challenges with the intelligence driving assistance system significantly affect your driving experience

Table 17 Impact of Technical Challenges on User Frustration

Indicators	value
R-squared value	0.136
Adjusted R-squared value	0.135
F statistic	80.32
The p-value of the F statistic	6.04 e-18
Coefficient of constant term	2.7060 (p < 0.000)

Coefficient of independent variable	0.3557 (p < 0.000)

Interpretation of results

R-squared value: 0.136, indicating that the technical challenge explained 13.6% of the user's frustration.

F statistic and P-value: F statistic is 80.32, corresponding P-value is 6.04e-18, indicating that the regression model is significant overall.

Coefficient of constant term and independent variable: coefficient of constant term is 2.7060, coefficient of independent variable is 0.3557, both of which are highly significant ($p < 0.000$). This means that for every additional unit of technical challenge, user frustration will increase by 0.3557 units.

Table 18 Interpretation of Impact of Technical Challenges on User Frustration

Metrics	value
Coefficient of constant term	2.7060 (p < 0.000)
Standard error of constant term	0.162
Constant term t value	16.663
Constant term confidence interval	[2.387, 3.025]
Technical challenge evaluation coefficient	0.3557 (p < 0.000)
Technical challenge evaluation standard error	0.04
Technical challenge evaluation T-value	8.962
Technical challenge evaluation confidence interval	[0.278, 0.434]

From this regression analysis table, we can see:

Constant Term Coefficient (const): The constant term coefficient is 2.7060, indicating that when all independent variables (in this case, the technical challenge rating) are zero, the predicted user frustration level is 2.7060. The standard error is 0.162, the t-value is 16.663, and the P-value is 0.000, with a confidence interval of [2.387, 3.025]. These values show that the constant term is statistically significant.

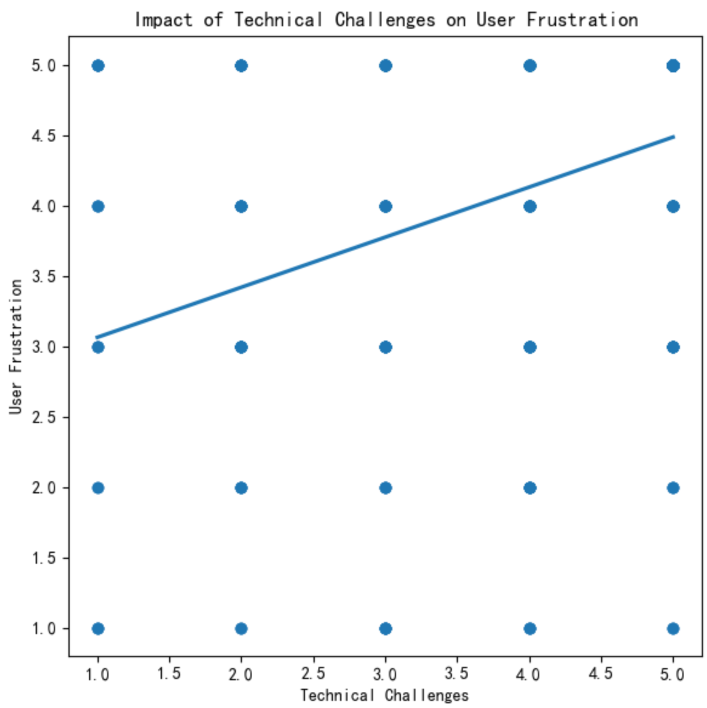

Figure 10 Regression Analysis of the Impact of Technical Challenges on User Frustration

Figure Analysis

From the regression analysis chart, it is evident that as the technical challenge rating increases, user frustration also rises. This trend line indicates that the higher users rate the technical challenges of the intelligent driving system, the more frustrated they feel with the system.

Conclusion

This study shows that technical challenges have a significant positive impact on user frustration. Reducing and improving technical challenges in intelligent driving systems will help lower user frustration, thereby enhancing system reliability and user satisfaction. Future research can further explore other factors influencing user frustration to comprehensively improve the user experience and reliability of intelligent driving assistance systems.

5 Discussion

5.1 Interpretation of Result

The data that presented in Chapter 4 provides insightful information about UX and opinions of intelligent driving technologies in the Chinese NEV market. Several important interpretations that underscore the advantages, difficulties, and potential area for development in these technologies can be made by focusing on demographic information, usage trends, and systems performance feedback.

5.1.1 Age Distribution

The survey indicates that a preference for intelligent driving systems among younger demographics. More than 60% of participants (60.86%) are aged between 20-30 years old, which may demonstrate a higher propensity to embrace these technologies. This age group is followed by 30-40 bracket, which constitutes about 23% of the sample (22.95%). Therefore, the older age groups (41-50years old) are less represented, making up roughly 16.24% of the respondents. This distribution highlights a generational divide in the acceptance and use of IDAS, with younger users being more open to and enthusiastic about adopting such innovations.

5.1.2 Gender Insights

Gender distribution within this survey sample show a male dominance, where males represent about more than 60.00% of the respondents, while females account for less than 40.00% approximately. This may indicate that the male users align with broader trends observed in technology adoption, where males often show greater engagement with automotive innovations.

5.1.3 Concerns by Age

Different age groups may express varying concerns regarding IDAS. For instance, age groups of 31-40 and 41-50 also show a high concern for safety, but the younger demographic, particularly under 30, show a distinct concern for privacy and data security, which may indicate that the concerns about safety may be raised when the age growing up, and under 30s are more likely tech-savvy and utilize digital technology extensively, and may show that their heightened sensitivity to data-related issues.

These findings emphasize the need for manufacturers and policymakers to consider these demographic trends and concerns when designing and promoting IDAS for different target consumer groups. It may be used to boost adoption rates and user satisfaction that tailoring features to address the specific safety concerns of older users and enhancing privacy protections to appeal to younger users.

5.1.4 Usage Patterns and User Engagement

The data on user engagement with IDAS reveals a significant variance in usage frequency, which could point out for underlying challenges in technology adoption. The majority of respondent (42%) said they sometimes use the IDAS of their vehicles and only s smaller proportion of users indicated that they always use these features (8.6%), which may suggest that there may be limitations on use or a lack of user trust in IDAS. Furthermore, the higher percentage of users who never or rarely use them (26.8% in total) compared to the percentage who always use them may claim some challenges in user acceptance or feature utility.

The complexity of IDAS and lack of relevance of these technologies in daily driving scenarios may results the infrequent use of IDAS. There is a notable gap or disconnect between the capabilities from IDAS that offered by manufacturers and their actual applications by users, which may suggest that the manufacturers and policymakers should bridge this gap. Furthermore, even though companies, like NIO and XPeng, stand ahead of this market, the significant underutilization of IDAS features highlights the critical need for strategies that booster user's confidence and familiarity to maximize the potential advantages of these technologies.

5.1.5 Privacy and Security Concerns in Intelligent Driving Assistance System

The survey reveals a pronounced concern among users regarding the privacy and security, especially for the younger age group, approximately 44.7% of age of 30 years old emphasizing the privacy and data safety as their primary concerns. This apprehension is reflective of broader issues that in the field of data protection within the automotive industry, especially concerning IDAS.

Recent incidents that involving major automotive and technology have highlighted these concerns. for instance, even there are not the directly related to the companies that mentioned in this survey, there are still other similar well-known companies have the instances like data breaches, which emphasize the potential vulnerabilities. Such breaches may lead to the exposure of user's sensitive information, including the personal information, history of favourite places, and potential financial details of customers, which suggest the critical need for robust data protection measures.

Addressing these challenges requires a comprehensive approach to data security. For instance, the implementation of advanced encryption technologies, the establishment of clear data handing protocols, as well as regular conduction of security audits, may be mandatory to ensure compliance and used to identify vulnerabilities. Moreover, researchers identified the remote vehicle infiltration on brakes and steering may suggest the necessity for a holistic security strategy that not only focuses on encryption, but also enhance secure data storage, strict transport protocols, and access controls.

Additionally, automakers need to commit to transparency in their data collection, usage, and sharing practices, for instance, clear communication about how data is used, who shared and who received, and how data is protected can help build trust with users. As users become more aware and concerned about their digital privacy, automakers and technology providers need to prioritize these aspects to booster confidence and promote wider adoption of IDAS for their current and potential users.

5.2 Analysis and Conformation of Research Questions

The core research question is: "What are the particular challenges in user experience when using intelligent driving assistance systems (IDAS) in New Energy Vehicles (NEVs) in China?" Based on the detailed data analysis provided in the Results section, this section digs deeper and explains the specific challenges that users encounter when operating such systems.

5.2.1 System Reliability and Technilcal Issues

According to our data analysis results, 58% of the respondents said that they had experienced system errors or software failures when using these systems while using their vehicles. Among the respondents, 25% said that they encountered technical problems several times a month or more, which may indicate that these problems are not accidental, but are related to the troubles that users often encounter. According to our questionnaire results, such technical failures often occur at some very critical moments - for example, when the driver's vehicle needs to change lanes or emergency brakes, the system reports an error or some minor problems. This seriously undermines the user's trust in such functions. And these problems also occur in congested traffic conditions in cities, which not only undermines the user's driving experience when using new energy vehicles, but also causes serious safety hazards. The data analysis results emphasize that manufacturers need to immediately address these issues about driving safety before considering the functional complexity of their systems to regain user trust.

5.2.2 User Trust and Safety Concerns

Another important issue reflected in the results section is the user's trust and safety concerns. It was indicated that 42% of the users chose IDAS mainly because of the safety features it had, like auto emergency braking and lane keeping assist. However, more than 30 percent of the users still doubt the system's consistency when manufacture offering these safety features. This becomes particularly observable in complex driving conditions, where 26% showed concerns regarding the system's ability to react appropriately in emergency situations. According to the data, this kind of doubt arose from the failures that occurred in the performance of the system, like emergency braking not working on time or even failing to recognize lane markings. These performance deficiencies further contribute to the inability of users to have full confidence in the critical functions of IDAS.

5.2.3 Impact of Environmental Factors

This can be explained by severe weather conditions, which majorly affected the effectiveness of the IDAS, as described in the results section.The data shows that 77% of users rated IDAS performance in adverse weather conditions as neutral or negative. More specifically, 30% of users indicated that the system does not work well in rain or fog, with the most common problems being incorrectly recognized sensors or delayed response. Another 28 percent of users responding to an open-ended question cited problems with the system in traction control and accurate measurements in snow. In general, the resolution of these weather-related performance issues usually requires more manual adjustments, which improves the reliability and convenience of the system. A significant amount of user feedback suggests that IDAS utilization declines under these conditions, and many users do not consider IDAS functionality to be credible in bad weather, and therefore disable features, such as lane-keeping assist or adaptive cruise control. This data proves that when upgrading IDAS systems, it is important to consider the environmental adaptability of the system so that it can operate reliably in a wide range of weather conditions, thus increasing user satisfaction.

5.2.4 Demographic Influences on System Usage

The results section also explores the impact of demographic factors such as age and gender on IDAS use and awareness. The data show that 56% of male users require traffic congestion assistance features, while female users require parking assistance features. The results show that gender-based preferences indicate that different demographic groups have different needs for various IDAS functions and use them at different frequencies; this may also be due to the different driving styles of men and women and the different functional requirements for the system. Therefore, it is very important to understand these priorities among different user groups, which can help Chinese new energy vehicle companies adopt effective and targeted marketing strategies to meet the specific needs or concerns of different user groups.

This study uses data analysis to describe in detail the problems encountered by Chinese new energy vehicle users when using the Intelligent Driving Assistance System (IDAS). These problems include system stability, safety and reliability, adaptability to the environment, and user diversity. Manufacturers need to seek consumer opinions to solve these problems to improve user satisfaction, and at the same time, this will better promote IDAS technology. Manufacturers and developers should consider these factors to optimize the design and function of IDAS to better adapt it to different user groups and enhance the safety and stability of the system in a targeted manner.

5.3 Hypothesis Analysis

5.3.1 Hypothesis 1: Weather Conditions Affect Technology Performance

The first hypothesis was that adverse weather would significantly affect the performance of IDAS. In view of this hypothesis, multiple regression analysis was run to test the efficiency of IDAS in different meteorological conditions.

First and foremost, the data that was gathered was refined and encoded, whereby qualitative data relating to weather patterns and efficiency of systems were represented by numerical figures. Specifically, weather condition assessments were scaled from 1 through 5, where 1 means "very ineffective" and 5 means "very effective." The system performance scale also ranged from 1 to 5, where 1 means "very dissatisfied" and 5 means "very satisfied."

In the regression analysis, we used the R-squared (R^2) value, the F-statistic, and the p-value to assess the model's validity and significance. The R^2 value is a statistical measure that indicates the proportion of the variance in the dependent variable that is predictable from the independent variables, ranging from 0 to 1. A higher R^2 value indicates a stronger explanatory power of the model. In this study, the R^2 value was 0.09, indicating that changes in weather conditions could explain about 9% of the variation in system performance. Although this is not a high explanatory power, it does suggest some impact of weather conditions on system performance.

The F-statistic is used to determine the overall significance of the regression model. It measures the ratio of the model's explained variance to the unexplained variance. A higher F-statistic indicates a more significant model. In our analysis, the F-statistic was 46.35, with a corresponding p-value of 3.03E-11, indicating that the model is highly statistically significant. The p-value (significance level) represents the probability of observing the data if the null hypothesis is true. A p-value less than 0.05 typically indicates statistical significance. In our model, the p-value was much less than 0.05, further confirming the model's significance.

Moreover, the regression analysis revealed that the constant coefficient was 2.5852, suggesting that the baseline satisfaction with system performance, independent of weather conditions, was 2.5852. The coefficient for the independent variable (weather condition rating) was 0.3381, indicating that for every one-unit increase in the weather condition rating, the satisfaction rating with IDAS performance increased by 0.3381 units. This result demonstrates that users are more satisfied with the system's performance under better weather conditions, whereas adverse weather negatively impacts performance, leading to lower user satisfaction.

It further shows that the median user satisfaction with the system performance in very bad weather conditions is 77, with an interquartile range of 74 to 103. This again shows that there are differences in users' experience and perceptions of IDAS performance in different weather conditions. While most users' responses to the system performance in bad weather were neutral or positive, some users indicated that they were dissatisfied with the system performance in very bad weather.

In general, the analysis confirms H1: adverse weather conditions do significantly influence intelligent driving system performance. These results indicated that weather factors should be considered during the design and development of the system. That is, in the future, manufacturers or developers should focus on improving sensor technology and algorithms so that the system may adapt to various weathers and then be more stable. This serves not only to improve overall system performance but also to boost user confidence in and reliance on the system under harsh weather conditions, therefore increasing user satisfaction.

5.3.2 Hypothesis 2: Technological Challenges Affect User Frustration

The second hypothesis, H2, is that technical issues (e.g., technical failures of intelligent driver assistance systems and cumbersome user interfaces) are the main cause of user frustration. This hypothesis will be tested by performing a regression analysis on the effects of these challenges on user frustration.

The R-squared value, which indicates the proportion of variance in the dependent variable explained by the independent variables, was found to be 0.136. This suggests that 13.6% of the variance in user frustration can be attributed to technological challenges. While this percentage does not account for the majority of variance, it highlights that technological issues are a notable factor influencing user experience.

The F-statistic, used to assess the overall significance of the regression model, was 80.32, with a corresponding p-value of 6.04e-18. The low p-value indicates that the relationship between technological challenges and user frustration is statistically significant, meaning that the observed association is unlikely to be due to random variation.

The analysis also showed some important numbers. When there are no technical problems, the baseline level of user frustration is 2.7060. When there are more technical problems, user frustration increases by 0.3557 units for each unit of technological challenge. This means that technical issues like system errors and the complexity of using the system make users more frustrated.

These results show that as users encounter more technical issues during the use of IDAS, these issues will also cause them great frustration, and this frustration may continue to increase. This trend will also directly affect users' perception of the system and overall satisfaction. Therefore, it is very important to increase the speed of system updates in IDAS and optimize based on feedback from different users to improve the overall driving experience and comfort of users.

Overall, improving the stability of IDAS and optimizing the user interface to make it more user-friendly and easier for ordinary people to operate can reduce user frustration. Future research may consider other factors, such as educating and training users on how to use the functions of these systems.

These training processes can help reduce frustration and improve the overall user experience and enhance the acceptance of IDAS technology.

6 Conclusion

6.1 Summary of Whole Master Thesis

In this paper, the application of intelligent driver assistance system (IDAS) is deeply analyzed, and the latest progress of core technology and the specific problems that users may encounter in actual use are introduced in detail

The rapid progress and evolution of advanced technologies such as adaptive cruise control (ACC) and lane-keeping assistance (LKA) are elaborated in detail. With sensor integration and real-time data processing. For example, automatic distance adjustment with respect to the vehicle upfront can be done using adaptive cruise control systems to maintain a safe distance, reducing driver workload during lengthy drives or busy traffic hours. The LKA ensures that the vehicle is always kept centered within the lane and effectively prevents accidents due to driver distraction.

While significant progress has been made, several key technical challenges still remain, thereby limiting the achievement of an optimal user experience. Sensors combine data gathered by cameras, radar, and lidar into one comprehensive model detailing how the vehicle sees its surroundings. One of the main challenges often encountered in this process is the alignment of data and calibration of the many sensors. These differences are more noticeable under extreme climatic conditions or complex urban scenarios, where the inconsistencies of data may have serious effects on the reliability of any system as real-time processing of data is at the heart of IDAS functionality; however, vast amounts of data produced by numerous sensors may cause a delay in processing that will negatively impact system performance and security.

Cybersecurity is an extremely critical and vital issue today. With the advancement of connectivity and data exchange, the security risk of IDAS systems has increased dramatically and created vulnerabilities for cyber attacks such as hacking and data breaches. Therefore, appropriate comprehensive cybersecurity measures are essential to effectively address vehicle safety and protect passenger privacy rights, and current systems (most of which are at the basic stage) fail to achieve this goal and expose users to potential risks.

The core of this paper is an in-depth and detailed survey, the purpose of which is to comprehensively analyze users' experience and satisfaction with the intelligent driving assistance system (IDAS) of new electric vehicles. A large amount of first-hand data was collected through carefully designed questionnaires to understand in detail users' daily IDAS experience, problems encountered, and satisfaction with the system. This survey is essential to understanding users' needs from IDAS functions and possible future improvements, which is important for the design and optimization of future IDAS.This study, therefore, is crucial for improving the user-friendliness and market acceptance of intelligent driving assistance technology in NEVs. According to the results of this study, system stability remains a key factor in these challenges; in fact, many users reported recurring technical difficulties and software errors. Due to these stability issues, especially in critical driving scenarios such as lane changes or emergency braking, users may have low confidence in these systems. In congested traffic situations, such technical failures may cause serious safety hazards, which seriously affects user trust.

These survey results reflect a variety of user trust and related safety concerns. While many users appreciate the safety features in IDAS, including automatic emergency braking and lane keeping assist, many others are skeptical about the performance consistency in complex driving situations. More than 30% of participants of survey reported that they do not trust the system's performance in unexpected situations, such as when lane keeping assist cannot read lane markings or provide emergency braking.

Environmental factors have a huge impact on user experience and satisfaction towards IDAS. In this research, it is found that extreme climatic conditions have enormously reduced the operational efficiency of the system. Regarding the performance of the IDAS during rain, fog, and snow, 77% of users offered neutral to negative ratings. The serious issues are in terms of misrecognition by sensors and lagging response time. This may involve numerous manual correction operations on the part of the user under these circumstances, not only reducing the ease of use for IDAS but also increasing security risks.

Demographic characteristics significantly shape system usage patterns and user satisfaction levels. The data reveals that younger users, particularly those under the age of 30, regard privacy and data security as their top concerns. This phenomenon highlights their high awareness and sensitivity to the protection of personal data while actively integrating into digital life. On the other hand, older users are particularly concerned about safety issues, and they pay more attention to features that can improve driving safety. Gender differences are reflected in user needs: male users tend to use traffic congestion assistance, while female users prefer parking assistance. This study reveals that different population groups present unique needs and focuses, and IDAS design and promotion should fully recognize and accommodate these differences.

In summary, the research results of this paper highlight the need to overcome technical difficulties and enhance user training, which shows the results of that significant improvement on user experience and acceptance of intelligent driving systems in new energy vehicles (NEVs) is mandatory. Manufacturers should primarily focus on the robustness of the system to ensure that IDAS can operate stably and efficiently in a variety of environmental conditions and critical driving scenarios. An unbreakable network security strategy must be implemented to prevent a breach and build a fortress of user confidence. In addition, user training programs should be set up to guide users to master and use all the features of IDAS in order to increase user satisfaction and trust in the system.

In-depth analysis of user experience and technical issues lays a solid foundation for the future development and technology research and development of intelligent driving assistance systems. Future research should be committed to further integrating new technologies into intelligent driving systems, for instance, 5G applications, to make vehicle-to-vehicle and facility communications more efficient, thereby improving the functionality and performance of intelligent driving systems. In addition, continued collaboration between academia, industry, and policymakers will be key to overcoming regulatory challenges that are essential to ensure the safe and effective deployment of intelligent driving technologies in China's new energy vehicle market.

By addressing these key areas, intelligent driving systems within new energy vehicles (NEVs) can be significantly optimized for a safer, more efficient and easy-to-use driving experience. This will strongly promote the popularization and application of autonomous driving technology. This paper foreshadows these advances, highlighting the central influence of user experience in defining the future development of intelligent driving in the field of new energy vehicles.

6.2 Practical Implications

Based on the findings from this research, several strategic suggestions emerge for the New Energy Vehicle (NEV) industry to address the key challenges identified: technological limitations, usability and user education, privacy and security concerns, and the need for greater customization.

User Experience Enhancements

The results of this questionnaire illustrate differences in intelligence levels and their implications for implementation. in some complex or unexpected driving situations, it points out the shortcomings of existing autonomous driving capabilities due to an over-reliance on human intervention to correct or adjust system behavior. This challenge emphasizes the need to incrementally provide improvements and refinements based on cumulatively collected real-world user data. Therefore, an intelligent driving assistance system that can provide real-time guidance and support to users is very important, as they increase users' reliability and associated confidence in the system (Brdnik et al., 2022).

In addition to usability issues, the other side of consumer demand is customization of the driving experience. This necessitates the integration of machine learning algorithms, which can learn from individual user interactions and adapt to their behaviors accordingly. These adaptive technologies cater to individual preferences in a variety of ways and dramatically increase user satisfaction and engagement, thereby promoting a better relationship between users and their vehicles, which leads to a personalization process in adaptive technologies to improve user satisfaction and functional support based on individual needs (Shi et al., 2024). This level of personalization is critical to encourage regular, ongoing use of smart driving features to increase acceptance and a more enjoyable user experience.

Data Privacy and Security

Recently, some research attention has also focused on the key barriers to user data privacy and security that have emerged in the new energy vehicle industry—an important area to ensure market growth and user trust. New energy vehicle manufacturers should take strong measurements to mitigate concerns related to this, including deploying strong encryption technology, clear data processing protocols, and regular security audits. Such measures not only protect users' data but also build user trust through demonstrable security practices.

Equally important is transparency about how user data is collected, used and shared. Proper data communication practices will remove fear and make it easier for people to become more enthusiastic about smart driving technology. One aspect of this transparency lies in complying with regulatory measures and requirements for ethical data processing in order to protect users' personal data and to appropriately anonymize it, preventing access from unauthorized parties (European Parliament and Council of the European Union, 2016; Cork, 2022) . New research shows that blockchain technology can be used to enhance the security of user data transactions and its storage (Kumaran, Tyagi, & Kumar, 2022). The decentralized method of working environment of blockchain maintains the level of security; therefore, it is used to ensure that users' information is safe from compromise and illegal means of access.

Finally, further research should aim to design an overarching framework to meet the evolving different laws on data privacy. This should be coordinated with provisions that provide for ethical data collection and consideration of users, provide for transparent standards for the management of user data used by intelligent driving systems. By combining these practices, new energy vehicle manufacturers will not only meet legal requirements, but also gain a higher level of user trust and acceptance in smart driving technology. (Liu et al., 2020; Xie et al., 2022).

Strategic Directions

A unified approach will be a possible method to recognize the challenges that need to be overcome in the field and seize these opportunities. The development of intelligent driving should be driver-oriented and requires the joint efforts of new energy vehicle manufacturers, technology developers and regulatory agencies. In addition, with the support of policies and regulations, the industry's absorption of innovation can be accelerated (Chen et al., 2020), which will further require investment in R&D to adapt the company's products to rapid changes in technology and user-level expectations. R&D efforts can be used to improve IDAS capabilities, design of user interfaces, and ensure data security in the manufacturing process of new energy vehicles.

In summary, this research impacts for technological novelties, enabling better user experience, strategic market placement, and collaborative efforts within the new energy vehicle industry. As outlined, this is a way for the NEV industry to address process challenges and leverage the opportunities presented to drive fruitful integration with smart driving technologies, thereby improving safer, more reliable and user-friendly vehicle options to meet modern needs of consumers.

6.3 Limitations and Future Research

Like other studies, this study faces several limitations that affect the generalization and application of the results. The current study is no exception. In fact, during the research process, some limitations were encountered due to issues such as research methods, data collection procedures, and research scope.

Key areas of concern include data that may or may not be valid on which the study's conclusions are based. This is self-reported data, with most details providing information during the study period. In fact, these data are not objective representations but may be affected by the fact that participants may react socially acceptable or exaggerate their satisfaction or dissatisfaction due to some recent events or personal biases. These factors sometimes compromise the accuracy and authenticity of the data, leading to important misunderstandings about the user experience.

The tool used to collect primary data - the survey - has its own limitations. Surveys can be effective at extracting information from large samples of respondents, but in some cases lack the flexibility and scope to delve deeply into certain complex issues. The response options provided may not cover all the different perspectives on user experience and user input. Additionally, the survey did not allow for follow-up questions that could clarify the data generated by the respondent or further investigation on this issue.

These conclusions can be drawn from research work on the user experience of new energy vehicle intelligent driving technology. In other words, these limitations should be considered when interpreting the study results. Future research should address these limitations to further improve the development and adoption of intelligent driving systems for new energy vehicles.

The limitations of this study suggest the potential for future mixed methods research using a combination of qualitative and quantitative data collection strategies. This will actually provide a view into understanding the user interaction experience in a more comprehensive way, thus addressing the depth and complexity that only quantitative methods may miss. Additionally, a more rigorous and representative sampling strategy could achieve better generalizability.

Further work involves developing and testing a highly reliable intelligent driving system that can operate proficiently and appropriately diagnose and respond to changing environmental conditions. Special consideration and work should be invested in user-centered design principles to improve usability and user satisfaction. The integration of intelligent driving systems with 5G, the Internet of Things, and artificial intelligence should also be studied. It is necessary for researchers to identify the potential synergies and challenges of these technologies and how to better integrate them to make intelligent driving systems more efficient and safer.

Appendix 1: Survey on User Experience with Intelligent Driving Technologies

Dear Participant,

Hello! We are graduate students specializing in Information Systems from Lund University, Sweden, currently conducting research for our thesis that focuses on the application and challenge of Intelligent Driving Assistance Systems (IDAS) in China's New Energy Vehicles (NEVs). With technological advancements and policy support, new NEVs are increasingly becoming a mainstream choice in the market. IDAS, a critical component of these vehicles, plays a significant role in enhancing driving safety and comfort.

This survey aims to gather public opinions and user experiences concerning the IDAS's features of NEVs. Your feedback will provide invaluable data for our study. The questionnaire will take less than 5 minutes to complete. Please be assured that all data collected will be used solely for academic purposes and handled with strict confidentiality and anonymity, in compliance with EU's GDPR standards.

Thank you very much for your valuable time and support! Please click on the next page to begin the questionnaire.

Best regards,

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Section 1: Your Personal Information

1. What’s your age group?
    A. Under 20 years old,
    B. 20 – 20 years old,
    C. 31 – 40 years old,
    D. 41 – 50 years old,

    E. 51 years old and above
2. What's your gender?
    A. Woman,
    B. Man,
    C. Prefer not to say,
    D. Other
3. Which car brand do you own or use frequently?
    A. NIO,
    B. XPeng
4. Which intelligent driving features do you use most often?
    A. Assisted parking,
    B. Traffic jam assist,
    C. Lane keeping assist,
    D. Traffic sign recognition,
5. Which of the following motivated you to choose a vehicle that is equipped with intelligent Driving Assistance System technology?
    A. Safety features,
    B. Innovative technology,
    C. Brand reputation,
    D. Recommendations by others,
6. What are your main concerns about Intelligent Driving Assistance System technology?
    A. Safety,
    B. Privacy and data security,
    C. Reliability,
    D. Cost,
7. Have you ever experienced a safety incident while using Intelligent Driving Assistance System features?
    A. Yes,
    B. No.
8. How do you evaluate the performance of Intelligent Driving Assistance System technology in adverse weather conditions?
    A. Very ineffective,
    B. Generally ineffective,
    C. Neither effective nor ineffective,
    D. Generally effective,
    E. Very effective,
9. In adverse weather conditions (rain, snow, fog), does the Intelligent Driving Assistance System satisfy your expectations?
    A. Very dissatisfied,
    B. Generally dissatisfied,
    C. Neither satisfied nor dissatisfied,
    D. Generally satisfied,
    E. Very satisfied,
10. How would you rate the overall reliability of the Intelligent Driving Assistance System in your vehicle?
    A. Very poor,
    B. Poor,
    C. Average,
    D. Good,

    E. Excellent,

11. Technological challenges with the Intelligent Driving Assistance System significantly affect your driving experience.
    A. Strongly agree,
    B. Agree,
    C. Neither agree nor disagree,
    D. Disagree,
    E. Strongly disagree,
12. Would you consider buying a vehicle equipped with more advanced Intelligent Driving Assistance System in the future?
    A. Definitely won't,
    B. Probably won't,
    C. Neither will nor won't,
    D. Probably will,
    E. Definitely will,
13. How often do you use your vehicle's Intelligent Driving Assistance System features?
    A. Never,
    B. Rarely,
    C. Sometimes,
    D. Often,
    E. Always,
14. . How often do you experience technological challenges (e.g., system errors, software glitches) with the Intelligent Driving Assistance System?
    A. Always,
    B. Often,
    C. Sometimes,
    D. Rarely,
    E. Never,
15. What improvements do you think would better meet your needs in Intelligent Driving Assistance System technology? Select all that apply and provide specific descriptions at the end.
    A. Enhancing the performance of autonomous driving technology in complex weather conditions,
    B. Improves system responsiveness and accuracy,
    C. Simplifying the user interface to make it more intuitive and easy to understand,
    D. Enhanced data security measures to protect user privacy,
    E. Provides more accurate vehicle positioning and navigation,
    F. Adding more personalisation options to suit different driving styles,
    G. Improve vehicle communication with other vehicles and infrastructure,
    H. Other
16. What challenges or issues have you encountered while using Intelligent Driving Assistance System technology? Select all that apply and provide specific descriptions at the end.
    A. Technical malfunctions or system errors,
    B. Poor performance of autopilot features in specific conditions (e.g., bad weather),
    C. Mismatch with actual driving habits or insufficient responsiveness,
    D. Concerns about data privacy or security,
    E. Complexity and difficulty in understanding the operation of the Intelligent Driving Assistance System,

    F. Frequent manual intervention needed to correct system behavior,
    G. Slow response time of the Intelligent Driving Assistance System,

17. How do you think Intelligent Driving Assistance System technology could be improved to better meet your needs? Please select from the options below and feel free to add specific descriptions at the end.
    A. Improve the overall reliability and safety of the technology,
    B. Increase the flexibility of smart driving modes to adapt to more driving environments,
    C. Enhance understanding and responsiveness to the driver's intentions,
    D. Improve the interactive interface between the smart system and the driver,
    E. Enhance the system's ability to perceive the surrounding environment, especially in adverse weather conditions,
    F. Expand smart driving functions, adding more assistive features such as automatic parking, emergency braking, etc,
    G. Strengthen vehicle network security measures to protect user data from unauthorized access,
    H. Optimize the energy consumption of the smart driving system to improve energy efficiency,
    I. Other

Customized “Thank you” Content

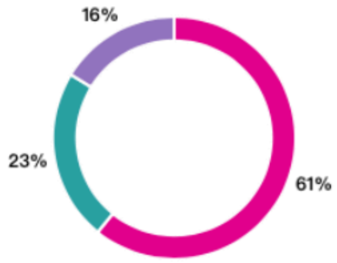
Your response was submitted, and we appreciated for your time and hope you a good day.

Appendix 2: Presentation of Survey's Result

1. What is your age group? 您所在的年龄段是?

511 答复 1-300|511

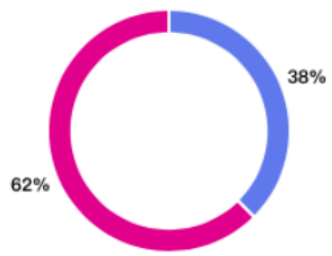
Under 20, 20岁以下	0
20-30 years, 20-30岁	311
31-40 years, 31-40岁	117
41-50 years, 41-50岁	83
51 years and above, 51岁以上	0



2. What's your gender? 您的性别是?

511 答复 1-300|511

Woman, 女	192
Man, 男	319
Prefer not to say, 不愿透露	0
其他	0



3. Which car brand do you own or use frequently? 您拥有或常用的汽车品牌是?

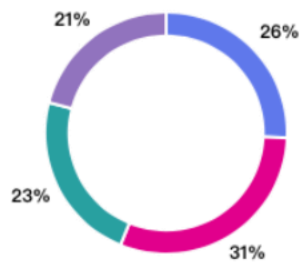
511 答复 1-300|511

NIO, 蔚来汽车	257
Xpeng, 小鹏汽车	254
其他	0

4. Which intelligent driving features do you use most often? 您最常使用哪些智能驾驶功能?

511 答复 1-300|511

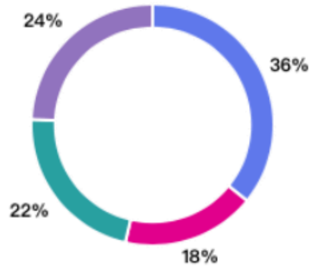
Assisted parking, 辅助停车	131
Traffic jam assist, 交通拥堵辅助	156
Lane keeping assist, 车道保持辅助	117
Traffic sign recognition, 交通标志识别	107
其他	0



5. Which of the following motivated you to choose a vehicle that is equipped with intelligent Driving Assistance System technology? 是什么促使您选择配备智能驾驶辅助系...

511 答复 1-300|511

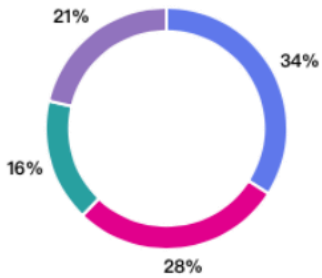
Safety features, 安全功能	183
Innovative technology, 创新技术	91
Brand reputation, 品牌信誉	113
Recommendations by others, 他人推荐	124
其他	0



6. What are your main concerns about Intelligent Driving Assistance System technology? 您对智能驾驶辅助系统技术最主要的担忧是什么?

511 答复 1-300|511

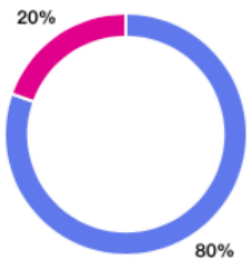
Safety, 安全性	174
Privacy and data security, 隐私和数据安全	144
Reliability, 可靠性	84
Cost, 成本	109
其他	0



7. Have you ever experienced a safety incident while using Intelligent Driving Assistance System features? 使用智能驾驶辅助系统功能时，您是否曾发生安全事故?

511 答复 1-300|511

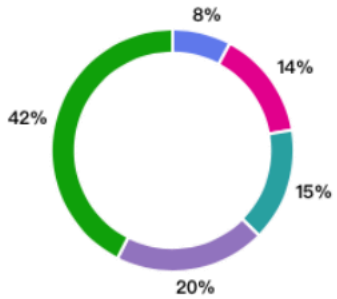
Yes, 是	411
No, 否	100
Prefer not to say, 不愿透露	0



8. How do you evaluate the performance of Intelligent Driving Assistance System technology in adverse weather conditions? 您如何评价智能驾驶辅助系统在恶劣天气条件下的表现?

511 答复 1-300 | 511

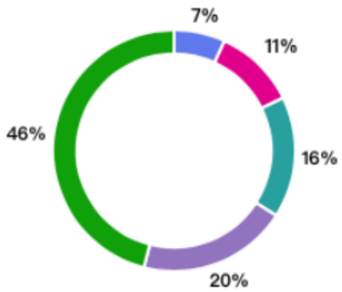
Very ineffective, 非常无效	40
Generally ineffective, 不太有效	74
Neither effective nor ineffective, 一般	77
Generally effective, 比较有效	103
Very effective, 非常有效	217



9. In adverse weather conditions (rain, snow, fog), does the Intelligent Driving Assistance System satisfy your expectations? 在恶劣天气条件下（雨、雪、雾），智能驾驶辅助系统是否满足了您...

511 答复 1-300 | 511

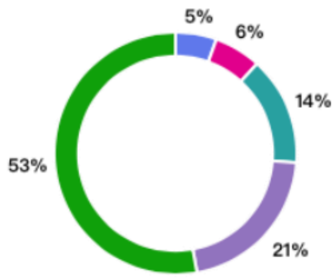
Very dissatisfied, 非常不满意	35
Generally dissatisfied, 一般不满意	56
Neither satisfied nor dissatisfied, 表现一般	83
Generally satisfied, 一般满意	102
Very satisfied, 非常满意	235



10. How would you rate the overall reliability of the Intelligent Driving Assistance System in your vehicle? 您如何评价车辆智能驾驶辅助系统的总体可靠性?

511 答复 1-300 | 511

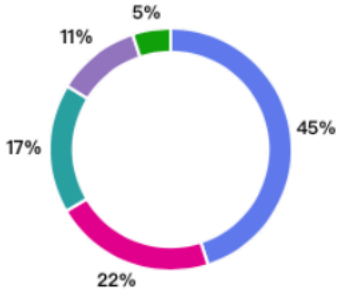
Very poor, 非常差	28
Poor, 差	32
Average, 一般	74
Good, 好	107
Excellent, 非常好	270



11. Technological challenges with the Intelligent Driving Assistance System significantly affect your driving experience. 智能驾驶辅助系统的技术问题显著影响了您的驾驶体验

511 答复 1-300 | 511

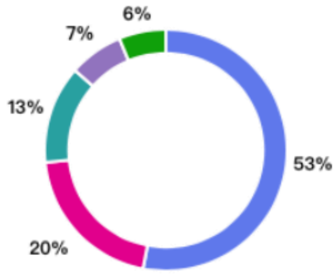
Strongly agree, 非常同意	230
Agree, 同意	110
Neither agree nor disagree, 中立	88
Disagree, 不同意	57
Strongly disagree, 非常不同意	26



12. Would you consider buying a vehicle equipped with more advanced Intelligent Driving Assistance System in the future? 您是否会考虑将来购买配备更先进智能驾驶技术的车辆?

511 答复 1-300 | 511

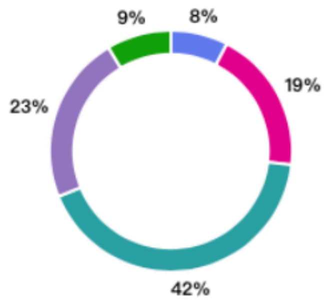
Definitely won't, 肯定不会	271
Probably won't, 可能不会	104
Neither will nor won't, 也许会也许不会	67
Probably will, 可能会	37
Definitely will, 肯定会	32



13. How often do you use your vehicle's Intelligent Driving Assistance System features? 您多频繁使用车辆的智能驾驶辅助系统功能?

511 答复 1-300 | 511

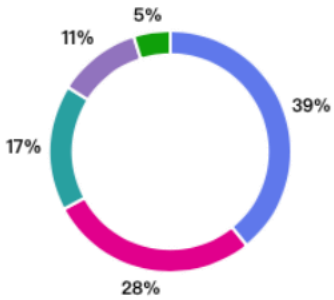
Never, 从来没有	39
Rarely, 很少	98
Sometimes, 有时	215
Often, 经常	115
Always, 总是	44



14. How often do you experience technological challenges (e.g., system errors, software glitches) with the Intelligent Driving Assistance System? 您遇到智能驾驶辅助系统的技术问题（如系统...

511 答复 1-300|511

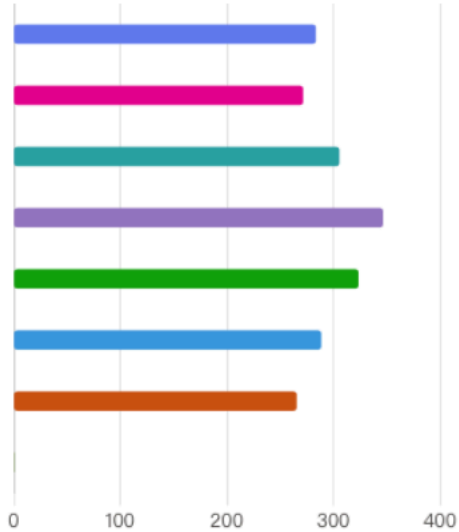
Always, 总是	200
Often, 经常	143
Sometimes, 有时	86
Rarely, 很少	57
Never, 从来没有	25



15. What improvements do you think would better meet your needs in Intelligent Driving Assistance System technology? Select all that apply and provide specific descriptions at the...

511 答复 1-300|511

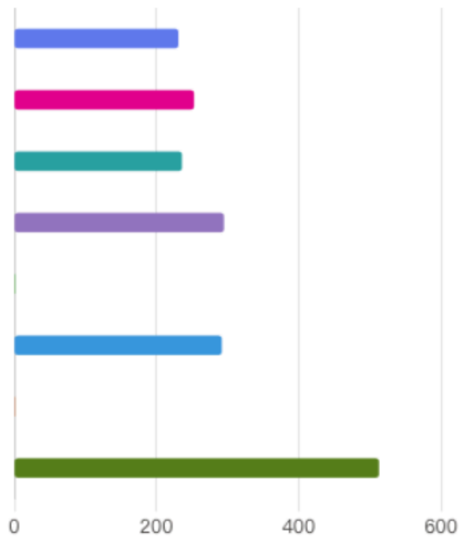
Enhancing the performance of autonomous driving technology in complex weather conditions, 增强自...	283
Improves system responsiveness and accuracy, 提高系统的反应速度和准确性	271
Simplifying the user interface to make it more intuitive and easy to understand, 简化用户界面，...	305
Enhanced data security measures to protect user privacy, 强化数据安全措施，保护用户隐私	346
Provides more accurate vehicle positioning and navigation, 提供更精准的车辆定位和导航功能	323
Adding more personalisation options to suit different driving styles, 增加更多个性化设置选项，...	288
Improve vehicle communication with other vehicles and infrastructure, 改进车辆与其他交通工具和基础...	265
其他	0



16. What challenges or issues have you encountered while using Intelligent Driving Assistance System technology? Select all that apply and provide specific descriptions at the end. 您在使...

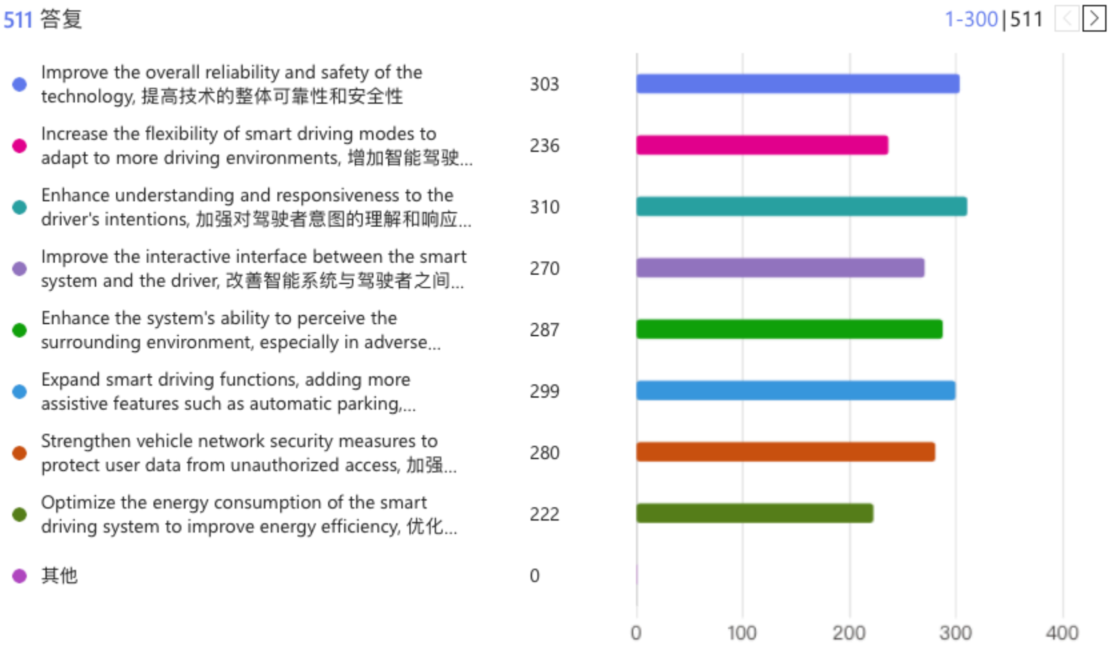
511 答复 1-300|511

Technical malfunctions or system errors, 技术故障或系统错误	230
Poor performance of autopilot features in specific conditions (e.g., bad weather), 自动驾驶功能在特...	252
Mismatch with actual driving habits or insufficient responsiveness, 与实际驾驶习惯不符或反应不够灵敏	235
Concerns about data privacy or security, 数据隐私或安全担忧	294
Complexity and difficulty in understanding the operation of the Intelligent Driving Assistance...	0
Frequent manual intervention needed to correct system behavior, 经常需要手动干预以纠正系统行为	291
Slow response time of the Intelligent Driving Assistance System, 智能驾驶辅助系统响应速度慢	0
其他	512



17. How do you think Intelligent Driving Assistance System technology could be improved to better meet your needs? Please select from the options below and feel free to add specific...

511 答复



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