

RESEARCH ARTICLE

A Study on Perception Gaps in Autonomous Vehicle Technologies and Their Implications for AV Transport System Deployment: An Integrated AHP-T-Test Approach

SeongJeong Yoon^{1*} and MinYong Kim²

¹ Department of AI & Bigdata, Swiss School of Management, Pellanini 4 6500 Bellinzona, Switzerland

² School of Business, Kyung Hee University, 26 Kyungheedaero, Dongdaemun-gu, Seoul 02447, Korea

* Corresponding author: SeongJeong Yoon; sj9416@naver.com

ABSTRACT

This study aims to analyze the perception gap between users' expectations and the actual performance of autonomous vehicle (AV) technologies, and to examine how these gaps influence the deployment of AV-based transport services such as autonomous taxis, shuttles, and mobility-as-a-service (MaaS). A total of 107 users with experience in Level 2–3 autonomous driving systems participated in a structured survey evaluating expectations and satisfaction across three domains: Technology (decision-making, control, communication), Safety (driver monitoring, takeover request, emergency handling, system redundancy), and Convenience (long-distance support, lane automation, vehicle condition monitoring). Paired-samples t-tests revealed a significant gap in decision-making technology and statistically significant expectation–performance discrepancies in all Safety and Convenience items. System redundancy recorded the largest gap, indicating users' strong concerns about fail-safe capability. To identify priority areas for AV service deployment, an Analytic Hierarchy Process (AHP) framework was constructed. The results showed that users prioritize Safety Assurance (0.38), whereas manufacturers and engineering experts assign the highest importance to Decision-Making Technology (0.34). These differing priorities highlight a structural misalignment between supply-side development strategies and demand-side expectations, which may influence public acceptance, operational reliability, and regulatory planning for AV transport systems. This study contributes to the literature by integrating perception-gap analysis with a technology prioritization model, offering actionable insights for future AV system design, service planning, and safety policy formulation.

Keywords: Autonomous vehicles; perception gap; expectation–disconfirmation; AHP, transport system deployment, safety assurance

1. Introduction

Autonomous vehicles (AVs) are undergoing rapid technological advancement and are increasingly being integrated into diverse mobility services, including public transportation, ride-hailing platforms, logistics operations, and personal mobility systems. Although Level 3 autonomous driving functions have already been commercialized, major global manufacturers continue to express their intention to achieve Level 4 deployment

ARTICLE INFO

Received: 04 December 2025 | Accepted: 20 December 2025 | Available online: 30 December 2025

CITATION

Yoon S J and Kim M Y. A Study on Perception Gaps in Autonomous Vehicle Technologies and Their Implications for AV Transport System Deployment: An Integrated AHP-T-Test Approach. *Environment and Social Psychology* 2025; 10(12): 4413. doi:10.59429/esp.v10i12.4413

COPYRIGHT

Copyright © 2025 by author(s). *Environment and Social Psychology* is published by Arts and Science Press Pte. Ltd. This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<https://creativecommons.org/licenses/by/4.0/>), permitting distribution and reproduction in any medium, provided the original work is cited.

soon, often emphasizing advancements in perception, control, and decision-making capabilities [1]. Despite these forward-looking technological commitments, users frequently report uncertainty, mistrust, and confusion regarding the actual readiness of AV systems [2], [3], resulting in a persistent mismatch between perceived and actual levels of technological maturity that undermines public acceptance and adoption [4]. Within the broader context of transport planning and mobility-system integration, discrepancies between supply-side assumptions—typically highlighted by manufacturers—and demand-side perceptions held by users can generate structural misalignments that shape regulatory design, operational standards, and long-term deployment strategies [5]. For example, while manufacturers may showcase improvements in sensor fusion or path-planning algorithms, users are often more concerned with safety assurance, redundancy during emergencies, and the ease of interacting with autonomous functions [6], [7]. When such perception gaps persist, they weaken user trust and reduce willingness to adopt AV-based mobility services, thereby slowing the expansion of autonomous taxis, shuttles, and mobility-as-a-service (MaaS) platforms [8]. Although previous studies have examined various aspects of AV development—including safety evaluation, human factors, acceptance modelling, and regulatory frameworks—relatively few have simultaneously investigated both (1) expectation–performance discrepancies across multiple AV subsystems and (2) the relative importance of these subsystems as perceived by different stakeholders [9]. Addressing this gap is essential, as successful AV deployment depends on aligning user expectations with technological realities and ensuring that development trajectories respond directly to public concerns. To address this issue, the present study introduces an integrated methodological framework that combines two complementary analytical techniques. First, paired sample t-tests are employed to quantify discrepancies between users' expected performance and their perceived satisfaction across core AV functionalities, including perception, control, communication, safety mechanisms, and convenience features. Second, the Analytic Hierarchy Process (AHP) is utilized to determine the relative priority of these technological components for the sustainable deployment of autonomous mobility services. This system-oriented approach moves beyond consumer-oriented interpretations by situating AV performance within the broader structure of transport networks—encompassing infrastructure interoperability, communication architectures, regulatory constraints, and service-design requirements [10]. Understanding the magnitude and sources of user perception gaps therefore provides essential insights for policymaking, operational planning, and the staged rollout of AV services.

The contribution of this research lies in identifying where the most consequential misalignments between user expectations and technological realities emerge, and in determining how these misalignments can be effectively mitigated. By highlighting high-priority technological deficiencies, particularly those related to redundancy, emergency fallback mechanisms, and trust-enhancing functionalities, the study delivers actionable guidance for manufacturers, system designers, and policymakers. Moreover, the integrated analytical approach underscores the necessity of embedding user-centred evaluation within the broader ecosystem of AV development to ensure that autonomous mobility evolves in a safe, efficient, and socially acceptable manner. Importantly, the dual-stage framework also provides a replicable template for analysing future AV technologies as they mature, enabling transport authorities to continuously refine deployment strategies. As AV systems become increasingly intertwined with smart-infrastructure initiatives, these insights will be critical for coordinating investments, updating regulatory standards, and designing mobility services that reflect both technological feasibility and public expectations. Ultimately, this research lays the foundation for evidence-based decision-making that can accelerate responsible and equitable integration of autonomous vehicles into next-generation transportation systems.

1.1. Research motivation and knowledge gap

Autonomous vehicle (AV) technologies have advanced rapidly in recent years, driven by improvements in perception algorithms, sensor fusion, and AI-based decision-making. As a result, Level 2–3 automated driving functions have already been introduced into commercial services in several countries and cities. However, despite this technological progress, the large-scale deployment of AVs and their integration into urban transport systems remain limited. This discrepancy suggests that the barriers to adoption are not purely technical, but also socio-technical, involving stakeholder perceptions, trust, and expectations. Existing research has largely focused on technical performance, system safety, and individual user acceptance. Although key attributes such as safety, reliability, and convenience have been widely studied, far less attention has been given to how different stakeholder groups—particularly users and manufacturers prioritize and interpret these attributes differently. Consequently, while the literature explains *what* aspects of AV technology matter, it provides limited insight into *who* values them most and *why*. This lack of understanding regarding stakeholder perception gaps represents a critical gap in the current body of knowledge.

1.2. Research purpose and contributions

The purpose of this study is to systematically analyze perception gaps between users and manufacturers regarding key attributes of autonomous vehicle technologies and to examine the implications of these gaps for AV transport system deployment. To achieve this objective, the study integrates paired t-test-based expectation–satisfaction gap analysis with the Analytic Hierarchy Process (AHP), enabling a simultaneous examination of statistically significant perception differences and the relative prioritization of system attributes across stakeholder groups. This study makes several original contributions to existing literature. First, it conceptualizes autonomous vehicles not merely as technological artifacts but as components of a broader socio-technical system, in which technological capabilities, user expectations, and institutional contexts interact. Second, by combining inferential statistical analysis with multi-criteria decision analysis, the study moves beyond identifying perception differences to reveal differences in priority structures between users and manufacturers. Third, the findings demonstrate that the two groups frequently employ the same terminology—most notably “safety”—while attributing fundamentally different meanings to it, highlighting a conceptual mismatch with important implications for AV design, communication strategies, and regulatory frameworks.

1.3. Research questions

Based on these considerations, this study addresses the following research questions:

- **RQ1:** Why do users remain hesitant to trust autonomous vehicle (AV) technologies despite rapid technological progress?
- **RQ2:** How do users and manufacturers differ in their prioritization of core AV attributes?
- **RQ3:** How is “safety” conceptually interpreted by users and manufacturers and why does this matter?
- **RQ4:** What are the implications of these perception gaps for the deployment of AV-based mobility services?

1.4. Structure of the paper

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on autonomous vehicle technologies, user acceptance, and safety perception, and establishes the analytical framework of the study. Section 3 describes research design, data collection procedures, and analytical methods, including the paired t-test and the Analytic Hierarchy Process. Section 4 presents empirical results and compares perception differences between users and manufacturers. Section 5 discusses the theoretical and

practical implications of the findings, and Section 6 concludes the paper by outlining the study's limitations and directions for future research.

2. Literature review

2.1. Autonomous vehicle technology levels

Table 1 defines the levels of autonomous driving from Level 0 to Level 5, categorizing them according to the degree of human involvement required [11]. Level 3 represents conditional automation, in which the vehicle can perform driving tasks under specific conditions but still requires the driver to intervene when prompted [12]. In contrast, Level 5 corresponds to full autonomy, where the vehicle can operate independently in all environments without any human input. In practice, most commercially available autonomous driving systems remain at Levels 2–3, while limited Level 4 services are being tested within restricted geofenced areas [13].

Table 1. Definition of autonomous vehicle technology level

Levels	Definition
Level 0: No Automation	Zero autonomy; the driver performs all the driving, but the vehicle can aid with blind spot detection, forward collision warnings and lane departure warnings.
Level 1: Driver Assistance	The vehicle may have some active driving assist features, but the driver is still in charge. Such assist features available in today's vehicles include adaptive cruise control, automatic emergency braking and lane keeping.
Level 2: Partial Automation	The driver must remain alert, but assistance features that control acceleration, braking, and steering can operate together so that no driver input is needed in certain situations. Current examples include self-parking and traffic-jam assistance.
Level 3: Conditional Automation	The vehicle can itself perform all aspects of the driving task under some circumstances, but the human driver must always be ready to always take control within a specified notice period. In all other circumstances, the human performs the driving.
Level 4: High Automation	This is a self-driving vehicle. But it still has a driver's seat and all the regular controls. Though the vehicle can drive and "see" all on its own, circumstances such as geographic area, road conditions or local laws might require the person in the driver's seat to take over.
Level 5: Full Automation	The vehicle can drive itself in all conditions without any human involvement; occupants are passengers, and a steering wheel is optional.

Sources: Society of Automotive Engineers (SAE); National Highway and Traffic Safety Administration (NHTSA)

Research on autonomous driving technologies has largely focused on improving in-vehicle perception and decision-making performance, as exemplified by large-scale multimodal datasets such as "nuScenes". While such datasets significantly advance object detection and trajectory prediction, they remain primarily vehicle-centric and provide limited insight into societal acceptance or system-level integration [14].

2.2. Technology domains affecting AV deployment

Existing studies consistently emphasize that autonomous vehicle performance is supported by three foundational technological subsystems. The first is judgment and perception technology, which integrates information from lidar, radar, camera sensors, and AI-driven situation analysis to recognize and interpret the driving environment [15]. The second is control technology, responsible for executing steering, acceleration, and braking inputs to ensure stable and responsive vehicle operation [16]. The third subsystem is networking and V2X communication technology, enabling real-time information exchange between vehicles, roadside infrastructure, and pedestrians through V2V, V2I, and V2P channels [17]. Collectively, these subsystems constitute the technical backbone of AV operation and are essential for route planning, trajectory optimization,

cooperative safety functions, and the broader integration of autonomous vehicles into intelligent transportation systems.

2.3. Safety requirements for level 3 operations

Table 2 illustrates that safety regulations for autonomous vehicles extend far beyond basic functional checks and instead emphasize a multilayered framework designed to ensure reliable operation under diverse traffic and environmental conditions. It also highlights that a central component of these regulations is the requirement for driver readiness monitoring, which verifies whether a human operator is alert and capable of assuming control when necessary [18, 19]. This is complemented by rigorous specifications for takeover request timing, ensuring that drivers receive adequate and context-sensitive warnings before control transitions. Moreover, safety standards mandate robust emergency fallback procedures that enable the vehicle to execute a predefined minimum-risk manoeuvre in situations where the system encounters unexpected failures or when the driver cannot respond promptly [20]. An equally critical component is system redundancy, which requires that essential perception, control, and communication subsystems maintain backup pathways to preserve operational integrity during partial system failures [21].

Table 2. Level 3 safety standards

Criteria	Questions
Operation after checking whether driving is possible	It works only when it is confirmed whether the driver is seated or not by detecting whether the driver is seated or not.
Securing safety in autonomous driving	Propose the minimum safe distance from the vehicle in front according to the maximum speed and speed so that the lane keeping function can be safely implemented.
Driving change request by situation	If it is scheduled, a driving phone warning is generated 15 seconds before, and in an unexpected situation, a driving phone warning is generated immediately.
In case of emergency	If there is not enough time to respond to the operation change request, the system responds according to the emergency operation standard.
In case the driver does not respond in a situation where response is required	Despite the request for driving change, there is no response from the driver within 10 seconds, and risk minimization is implemented for safety.
Prepare for system failure	Designed with system redundancy in mind.

Together, these regulatory elements form a comprehensive safeguard strategy aimed at reducing operational risk and enhancing trust during mixed-traffic deployment [22]. They also serve as the technical foundation upon which transport authorities evaluate the suitability of AVs for integration into public roads, shared mobility services, and automated shuttle operations. In essence, safety regulations ensure that autonomous vehicles are not only technologically capable but also operationally resilient, predictable, and aligned with the broader objectives of intelligent transportation systems.

2.3.1. AVs as a socio-technical system in urban transport

Studies on sustainable development in the transport and logistics sectors conceptualize autonomous and intelligent mobility technologies not merely as technological innovations, but as key drivers of corporate strategy and structural transformation within the industry. In particular, the efficiency, operational stability, and sustainability of transport and logistics systems are emphasized as being shaped not only by technological performance, but also by institutional environments and organizations' strategic responses. This perspective suggests that the diffusion of autonomous driving technologies extends beyond vehicle-level design considerations and requires system-level management as well as the alignment of stakeholder perceptions [23].

Existing studies on autonomous vehicles have primarily focused on in-vehicle perception, judgment, and control performance, as well as driver–vehicle interaction [24–27]. However, the large-scale diffusion of autonomous vehicles and their integration into urban transport networks cannot be achieved solely through improvements in vehicle-level technologies. Rather, such integration should be understood as a socio-technical system transition involving road infrastructure, traffic operation systems, institutional and regulatory frameworks, and social acceptance and trust [28, 29].

Research in urban and transportation planning has emphasized that the introduction of autonomous vehicles may significantly affect travel behavior, transport demand, parking structures, land use patterns, and overall urban spatial configuration, with outcomes varying depending on policy and regulatory design [30, 31]. In particular, the absence of appropriate regulatory and operational strategies may lead to unintended consequences, such as increased traffic congestion and reinforced automobile dependency [31, 32].

From a social acceptance perspective, the adoption of autonomous vehicles is reported to depend not only on perceived technological usefulness, but also on trust, risk perception, accountability, explainability, and alignment with public values [33, 34]. Within this perspective, understanding and addressing the perception gap between user expectations and manufacturer development priorities is considered a critical prerequisite for the successful societal embedding of autonomous vehicle technologies [34, 35].

Taking together, these discussions suggest the need to conceptualize autonomous vehicles not as isolated technological products, but as components of complex socio-technical systems operating within urban transport environments. This perspective provides the theoretical foundation for the present study's focus on perception gaps between users and manufacturers [28][33][35, 36].

2.4. Limitations of current AV technologies

The limitations of current autonomous vehicle (AV) technologies identified in the existing literature can be broadly classified into technical limitations and socio-technical limitations, reflecting different but interrelated challenges in real-world deployment. From a technical perspective, one of the most persistent challenges lies in the unreliable performance of sensing and perception modules under adverse environmental conditions, such as heavy rain, fog, snow, glare, and low illumination. These conditions significantly degrade the accuracy of lidar, radar, and camera sensor fusion, thereby compromising perception reliability and downstream decision-making processes [37, 38]. Closely related to this issue is the limited generalization capability of AI-based driving algorithms. Models trained on predefined datasets often struggle to adapt to rare or edge-case scenarios, including construction zones, unusual traffic configurations, or culturally diverse driving behaviors [24, 25–27]. Such limitations directly affect the robustness of trajectory prediction and hazard recognition, increasing the risk of unexpected system behavior in complex environments [37][40][42]. Another technical constraint concerns V2X communication latency, which can delay real-time information exchange between vehicles and infrastructure. This latency reduces the effectiveness of cooperative safety mechanisms and coordinated traffic management, particularly in dense or dynamic traffic environments [37][39][42]. From an engineering-oriented research perspective, these challenges are typically approached through improvements in sensor redundancies, advanced data fusion architectures, adaptive learning models, and low-latency communication protocols. In contrast, socio-technical limitations extend beyond system performance and involve interactions between technology, users, and institutional frameworks. The literature highlights significant legal and regulatory ambiguity regarding accident liability, certification procedures, and operational standards in mixed traffic environments where human-driven and autonomous vehicles coexist. These issues are not purely technical in nature, but rather institutional challenges requiring coordinated responses from policymakers, regulators, and industry stakeholders. Furthermore, low public trust remains a critical barrier to

widespread AV adoption. Users continue to express skepticism regarding system reliability, emergency handling capabilities, and the transparency of automated decision-making processes [41].

From a socio-technical and human-centered perspective, this lack of trust reflects not only technical uncertainty, but also deficiencies in risk communication, explainability, and alignment between system behavior and user expectations. Research grounded in socio-technical systems theory and technology acceptance models emphasizes that trust, accountability, and perceived safety are as essential as technical performance for successful deployment. Taken together, these findings suggest that the challenges facing autonomous vehicle deployment cannot be addressed through technical optimization alone. While advances in perception architectures, adaptive AI models, and communication infrastructure are necessary, they must be complemented by clearer regulatory frameworks, improved governance mechanisms, and design strategies that explicitly consider human trust and social acceptance. Addressing both technical and socio-technical limitations in an integrated manner is therefore essential for the safe and sustainable integration of autonomous vehicles into intelligent transportation systems.

Studies on the development of eco-friendly mobility and electric vehicle infrastructure emphasize that the diffusion of autonomous driving technologies cannot be achieved through advances in vehicle technologies alone. Instead, coordinated progress in charging infrastructure, road environments, smart transport infrastructure, and policy support is required. These studies highlight the limitations of technology-centric approaches and identify the level of urban transport infrastructure and institutional preparedness as key determinants for the successful deployment of autonomous and electrified mobility systems [43].

2.5. Gap in current research

Although prior studies have examined autonomous vehicles from various angles, including safety assessment, legal and liability concerns, and advancements in isolated technical subsystems, they generally fall short of addressing two dimensions essential for large-scale transport system deployment. First, existing research rarely conducts a systematic comparison between users' expected performance and their perceived actual performance across multiple AV subsystems [44, 45], even though perception gaps strongly influence public acceptance and service adoption. Second, literature seldom applies to a structured multi-criteria decision-making framework to determine which technological components should be prioritized to support safe and reliable AV mobility services [46, 47]. This lack of an integrated analytical lens is problematic because AV deployment constitutes not only a technological challenge but also a complex transportation-systems issue requiring coordinated system design, regulatory harmonization, and operational optimization [48].

Without insights into how users evaluate core subsystems—such as perception, control, communication, safety assurance, and user convenience—planners and policymakers lack the evidence needed to identify which capabilities must be reinforced to improve trust and ensure safe operation in mixed-traffic environments. Accordingly, there is a clear need for a combined perception-priority evaluation framework capable of pinpointing performance gaps while also determining the relative importance of each subsystem from the standpoint of diverse stakeholders. Such a framework would yield actionable guidance for manufacturers and transport authorities by informing deployment strategies, safety standards, and policy interventions that reflect real-world user expectations and practical operational requirements, ultimately supporting the responsible integration of autonomous vehicles into intelligent transportation systems.

Table 3. Technical Limitations of Autonomous Vehicles

Limitation Category	Description
---------------------	-------------

Sensor Technology	LiDAR, radar, and cameras may fail in adverse weather conditions (fog, rain, snow) and poor lighting (night, glare). Sensor fusion can also cause data conflicts.
AI & Data Processing	AI struggles with unexpected road conditions (construction zones, signal failures, pedestrians). Bias in training data and real-time processing challenges remain.
V2X Communication	V2X (Vehicle-to-Everything) infrastructure is underdeveloped. Network latency in 5G and future communications can delay emergency responses.
Legal & Ethical Issues	Unclear liability in case of accidents, varying regulations by country, and ethical dilemmas in decision-making (e.g., protecting pedestrians vs. passengers).
Human Collaboration	Level 3 autonomy requires human intervention, but delayed responses increase risk. Public trust in autonomous technology remains low.

3. Methodology

3.1. Research framework

This study adopts a two-stage analytical framework designed to capture both the structure of user perception gaps and the relative importance of key autonomous-vehicle (AV) technologies for transport-system deployment [49]. In the first stage, an Expectation–Satisfaction Gap Analysis is conducted using paired-sample t-tests on 107 valid survey responses, allowing statistically robust identification of discrepancies between users expected and perceived AV performance across multiple subsystems [50, 51]. The three major measurement factors—Technology (A–C), Safety (D–I), and Convenience (J–M)—are defined as follows and used as the primary constructs for evaluation [36]. The objective of this first stage is to quantify the extent to which current AV capabilities are perceived as falling short of user expectations, thereby identifying critical areas of dissatisfaction that may impede acceptance and adoption [53]. In the second stage, the study develops a structured Analytic Hierarchy Process (AHP) model to determine the priority of core AV subsystems required for effective integration into autonomous transport services [54]. The AHP hierarchy is constructed to reflect the functional requirements of AV deployment within transportation networks, enabling a systematic evaluation of which technological components—such as perception and situation judgment, control execution, V2X networking, safety-assurance mechanisms, and user-centric operational features—should be emphasized to support reliable system performance [55]. By combining these two analytical steps, the methodology provides a comprehensive framework that links perception-based performance gaps with technology prioritization, offering actionable insights for transport planners, system designers, and policymakers in developing deployment strategies, safety standards, and policy interventions that align with real-world user expectations and operational requirements [56, 57].

3.2. Rationale for factor selection and AHP structure

The three core factors proposed in this study—Technology, Safety, and Convenience—were derived from concepts that have been repeatedly identified as key dimensions in prior research on autonomous vehicle (AV) acceptance and performance evaluation [58–60]. Numerous studies on AV adoption and human–machine interaction indicate that the maturity of autonomous driving technologies and the formation of user trust are primarily determined by technological capabilities such as perception, judgment, and control, safety-related aspects including accident prevention and emergency response, and convenience factors associated with driving comfort and user experience [59, 61, 62]. The sub-items included under each factor were developed through a systematic review and consolidation of measurement items used in previous studies and were further refined to reflect elements closely related to real-world user experiences in Level 2–3 autonomous driving environments [60, 63]. In this process, the items were structured to comprehensively cover core autonomous driving functions (e.g., environmental perception, decision accuracy, and emergency response), system design

elements essential for safety assurance (e.g., system redundancy, minimum-risk maneuvers, and driver takeover warnings), and convenience and user experience aspects in autonomous driving contexts (e.g., long-distance driving support, monitoring-based guidance, and hedonic convenience) [61, 64]. Furthermore, the hierarchical structure of evaluation criteria used in the Analytic Hierarchy Process (AHP) was not arbitrarily determined by the researchers. Instead, it was designed to reflect a theoretically grounded superordinate–subordinate structure based on established AV evaluation frameworks and user acceptance models identified in the literature [65, 66]. Given that AHP is a method intended to structure stakeholders’ relative importance judgments rather than to measure absolute performance levels, this study adopted a hierarchical structure in which sub-functional attributes are positioned under the three superordinate criteria of Technology, Safety, and Convenience [65]. This approach is consistent with methodological practices widely applied in previous AHP-based studies in the transportation and mobility research domain [66, 67].

3.3. AHP hierarchy for AV transport system deployment

To advance the development of safe and reliable autonomous transport services—including autonomous taxis, shuttles, and mobility-as-a-service (MaaS) this study constructs an AHP-based decision hierarchy to identify which technological subsystems should be prioritized for effective deployment. The hierarchy incorporates five core domains: (C1) judgment and perception, (C2) control, (C3) networking and V2X communication, (C4) safety-assurance mechanisms such as fail-safe procedures, redundancy, and emergency responses, and (C5) user-centric convenience features. Sub-criteria represent functional attributes including environmental perception, takeover-request strategies, minimum-risk fallback capabilities, comfort functions, and the feasibility of remote operation. Pairwise comparison data from vehicle users (G1, n = 107) and AV engineers/manufacturers (G2, n = 20) enable systematic comparison of their relative weightings. The expert group involved in the AHP analysis consisted of professionals with direct experience in the development, evaluation, or operation of autonomous vehicle and intelligent transportation systems. All experts satisfied at least one of the following criteria: (1) a minimum of five years of professional experience in autonomous driving-related technologies, automotive engineering, or intelligent mobility systems; (2) current or previous involvement in research and development projects related to autonomous vehicles, smart mobility, or advanced driver-assistance systems; or (3) professional engagement in policy, system design, or technical evaluation of automated transport systems. The experts were recruited using a purposive sampling approach to ensure domain relevance rather than statistical representativeness. This selection strategy aligns with the methodological principles of the AHP, which emphasize informed judgment from domain specialists. To further ensure the validity of expert judgments, consistency ratios (CR) were calculated for all pairwise comparison matrices, and only responses meeting the acceptable consistency threshold were included in the final analysis. These cross-group differences provide actionable insights for planners and system designers seeking to align AV deployment strategies with both user expectations and technical requirements.

3.4. Data collection

A total of 107 participants with prior exposure to Level 2–3 autonomous driving systems completed a structured online questionnaire designed to assess their perceptions of key AV functions. Items used for the expectation–satisfaction analysis were evaluated on a 5-point Likert scale, enabling statistical comparison through paired-sample t-tests. For the prioritization task, the AHP pairwise comparison matrices were constructed using the conventional Saaty 1–9 scale, allowing respondents to express the relative importance of each technological criterion in a consistent and systematic manner. This combined measurement approach ensures that both perceptual discrepancies and technology priorities are captured with sufficient analytical rigor for transport systems research.

3.5. Data analysis procedures

The data analysis employed a structured multi-stage procedure to ensure methodological rigor in evaluating autonomous vehicle deployment. First, Cronbach's alpha was used to verify the internal consistency of all measurement constructs [42, 43]. Paired-sample t-tests were then applied to assess statistically significant gaps between user expectations and satisfaction across the defined AV technology domains [43]. For the AHP stage, pairwise comparison matrices were developed separately for users and manufacturers, and weight vectors were derived using the eigenvalue method, with consistency ratios ($CR < 0.1$) validating the reliability of their judgments [44]. After normalization, cross-group comparisons were performed to reveal divergences in subsystem prioritization, and these priority gaps were subsequently translated into strategic implications for AV planning, safety-policy development, and operational decision-making [45].

4. Result

4.1. Demographic profile of respondents

The rationale for analyzing a final sample of 107 respondents in this study is as follows. Initially, a total of 120 responses were collected from users whose vehicles were equipped with autonomous driving functions. However, seven respondents were excluded from the analysis because, despite having autonomous driving features installed, they reported very low actual usage frequency. In addition, three respondents who perceived the level of autonomous driving technology as Level 2 or below and expressed extremely negative evaluations were also excluded. Furthermore, three respondents declined to participate in the technical evaluation, stating that their primary concerns were not related to the autonomous driving technology itself, but rather to broader systemic issues such as legal and regulatory frameworks, institutional arrangements, road infrastructure, surrounding smart sensor infrastructure, and communication systems. Accordingly, these responses were also excluded from the analysis. As a result, a total of 107 valid responses were retained and used for the final analysis.

Table 4. Analysis of respondents' characteristics

Category	Metric	Frequency	%
Gender	Male	74	69.2
	Female	33	30.8
	Total	107	100
Age	Ages 20 to under 30	21	19.6
	Ages 30 to under 40	26	24.3
	Ages 40 to under 50	32	29.9
	Ages 50 to under 60	24	22.4
	Ages 60 and above	4	3.7
	Total	107	100
Frequency of use	Daily use	55	51.4
	Weekend-only use (Saturday/Sunday only)	20	18.7
	Fewer than 10 times per month	32	29.9
	Total	107	100
The market is currently at level 3 — what level do you personally think it is?	Level 1 (Driver Assistance)	15	14
	Level 2 (Partial Automation)	35	32.7
	Level 3 (Conditional Automation)	39	36.4

Category	Metric	Frequency	%
	Level 4 (High Automation)	12	11.2
	Level 5 (Full Automation)	6	5.6
	Total	107	100
What do you think is the desirable level of autonomous vehicle technology	Level 1 (Driver Assistance)	4	3.7
	Level 2 (Partial Automation)	10	9.3
	Level 3 (Conditional Automation)	25	23.4
	Level 4 (High Automation)	33	30.8
	Level 5 (Full Automation)	35	32.7
	Total	107	100
Willingness to use autonomous public transportation (e.g., taxis, buses) in 10 years	I will use it	54	50.5
	I don't want to use it	2	1.9
	I will think carefully before using it	33	30.8
	I will actively use it	16	15
	I absolutely do not want to use it	2	1.9
	Total	107	100
Autonomous driving will expand beyond logistics to unmanned mobility.	Worth considering	33	30.8
	Agree	34	31.8
	Strongly agree	29	27.1
	Premature	11	10.3
	Total	107	100
	Transportation infrastructure (roads, network systems with autonomous vehicles, vehicle-to-vehicle and vehicle-to-human communication)	39	36.4
Urgent improvements needed to enhance autonomous vehicle technology	Laws and regulations	15	14
	Insurance	4	3.7
	Technological level of autonomous driving (judgment, control, regulation functions)	40	37.4
	Data collection and AI development for autonomous driving 1	9	8.4
	Total	107	100
	High	20	18.7
Overall trust in the technological level of autonomous vehicles	Medium	69	64.5
	Low	18	16.8
	Total	107	100

A total of 107 respondents participated in the survey, representing a diverse set of demographic and behavioural characteristics relevant to autonomous vehicle usage. In terms of gender distribution, approximately 69.2% of the respondents were male and 30.8% were female. The age composition reflects a broad range of users, with the largest group being individuals in their 40s (29.9%), followed by those in their 20s (19.6%) and 30s (24.3%). Respondents aged 50 and above accounted for roughly 26% of the sample, indicating meaningful representation from older user groups as well. Regarding mobility behaviour, 51.4% reported using transportation services daily, whereas 18.7% were weekend-only users and 29.9% used mobility services fewer than ten times per month. When asked about their perception of the current technological level

of autonomous vehicles, 36.4% of respondents rated the market at Level 3 (conditional automation), while 32.7% believed AVs remain at Level 2 (partial automation). Only a small portion (11.2%) perceived the current technology to have reached Level 4 capability. Participants also expressed views on what they considered the ideal level of future AV technology. Nearly one-third (30.8%) favoured Level 4 (high automation), while 23.4% selected Level 3 and 19.6% preferred full automation at Level 5. This distribution suggests a moderate inclination toward advanced automation, accompanied by a degree of caution toward complete driverless operation. In terms of public transport adoption, 50.5% indicated that they would consider using autonomous public transportation in the future, whereas 30.8% expressed reluctance. A smaller proportion (15.0%) stated that they would actively use such services. Respondents also held generally optimistic views about the expansion of autonomous driving into unmanned logistics, with 63.6% agreeing that such developments are likely. When identifying areas requiring improvement for broader AV adoption, respondents most frequently selected transportation infrastructure and communication systems (36.4%), followed by laws and regulations (14.0%) and enhancement of autonomous driving technologies themselves (37.4%). Finally, trust levels varied considerably: 18.7% reported high trust in AV technologies, 64.5% reported moderate trust, and 16.8% expressed low trust, indicating that public confidence remains a significant challenge for widespread deployment. Table 4 provides a summary of the respondents' demographic and behavioral characteristics.

4.2. T-Test Results

4.2.1. Overall T-Test Results

The paired-sample t-test analysis revealed several noteworthy discrepancies between user expectations and perceived performance across the three major AV technology domains. Within the Technology category, a statistically significant gap was observed for judgment and perception technology ($t = 3.375$), indicating that users perceive these functions—such as surrounding-environment recognition, collision prediction, and situational decision-making—as underperforming relative to their expectations. In contrast, no statistically significant differences were found for control or communication technologies, suggesting that users generally regard these functions as meeting baseline performance standards. The Safety domain exhibited the most prominent expectation–satisfaction gaps, with all six safety-related items (Items D–I) showing statistically significant differences. Among these, the largest discrepancy was associated with system failure redundancy (Item I), underscoring strong user concern regarding the vehicle's ability to maintain operational safety during subsystem failures. These findings highlight redundancy as a critical deficiency that poses substantial risk in real-world transport operations. In the Convenience domain, all four items (Items J–M) also demonstrated statistically significant gaps. The most pronounced shortfalls were identified in monitoring-based operational guidance (Item M) and autonomous long-distance driving support (Item J). These results suggest that users expect higher levels of comfort, automation stability, and proactive guidance during autonomous operation, particularly during extended travel.

The paired-sample t-test results indicate a clear and consistent pattern: user expectations for autonomous vehicle technologies exceed their current perceived performance across most functional domains. In the Technology category, the expectation–satisfaction gap is concentrated specifically in judgment and perception functions, such as recognizing surrounding environments, predicting collisions, and making situational decisions. These functions constitute the cognitive core of autonomous driving, and the observed gap suggests that users remain unconvinced of the system's ability to accurately “understand” complex real-world conditions. By contrast, control and communication technologies did not exhibit significant gaps, implying that users perceive these supporting functions as sufficiently mature and reliable. The Safety domain revealed the most pronounced discrepancies. All safety-related items showed significant gaps, indicating that safety concerns dominate user dissatisfaction. System failure redundancy emerged as the most critical issue. Users

appear to question whether autonomous vehicles can maintain safety when unexpected failures occur, highlighting redundancy not as a supplementary feature but as a fundamental prerequisite for trust in real-world operations. In the Convenience domain, significant gaps were also identified across all items.

The largest shortfalls were related to monitoring-based operational guidance and autonomous long-distance driving support. These findings suggest that users expect autonomous driving to deliver not only functional automation but also a qualitatively improved driving experience, characterized by stability, comfort, and proactive system guidance during extended journeys.

Table 5. Results of Paired Samples t-Test

Comparison Factor		Difference in Paired Samples				Result			
		Mean	SD	SEM	95% Confidence Interval of the Difference		t	p-value (Two-tailed)	
					Lower Bound	Upper Bound			
Technology	A	E-S	0.271	0.831	0.080	0.112	0.430	3.375	Accepted 0.001
	B	E-S	0.075	0.761	0.074	-0.071	0.221	1.016	Rejected 0.312
	C	E-S	0.150	0.822	0.079	-0.008	0.307	1.882	Rejected 0.063
Safety	D	E-S	0.206	0.919	0.089	0.030	0.382	2.315	Accepted 0.023
	E	E-S	0.206	0.887	0.086	0.036	0.376	2.397	Accepted 0.018
	F	E-S	0.336	0.890	0.086	0.166	0.507	3.912	Accepted 0.001
	G	E-S	0.224	0.850	0.082	0.061	0.387	2.729	Accepted 0.007
	H	E-S	0.346	0.891	0.086	0.175	0.517	4.013	Accepted 0.000
	I	E-S	0.495	0.935	0.090	0.316	0.675	5.478	Accepted 0.000
	J	E-S	0.346	0.963	0.093	0.161	0.530	3.716	Accepted 0.000
Convenience	K	E-S	0.486	1.085	0.105	0.278	0.694	4.634	Accepted 0.000
	L	E-S	0.262	0.769	0.074	0.114	0.409	3.520	Accepted 0.001
	M	E-S	0.280	0.844	0.082	0.119	0.442	3.434	Accepted 0.001

Legend: E: Expectation, S: Satisfaction

Result

- Accepted: A statistically significant gap exists between users' expectations and their actual satisfaction levels.

- Rejected: No statistically significant difference was found between expectation and satisfaction.

1. [Technology] Perceived Technological Capability.

A: (Decision-Making): Technology that perceives surrounding environments to optimize routes, make situational decisions, predict collisions, and respond to unexpected events.

B: (Control): Technology that appropriately controls the vehicle's actuators—such as braking, steering, and acceleration—based on decision-making processes.

C: (Communication): Technology that enables communication between internal and external vehicle sensors, transportation infrastructure, and facilitates vehicle-to-vehicle (V2V), vehicle-to-pedestrian (V2P), and vehicle-to-infrastructure (V2I) interactions.

2. [Safety] Perceived Safety Expectations and Satisfaction.

D: Technology that operates only when the driver's presence (e.g., seat occupancy) is detected and driving capability is confirmed.

E: Function to maintain the lane safely by providing maximum speed and minimum safe distance from the vehicle ahead depending on the speed.

F: Driver transition warning 15 seconds in advance in planned situations; immediate warning in unexpected situations.

G: In cases where there is insufficient time to respond to a driving takeover request, the system responds according to emergencies.

driving criteria.
H: If the driver does not respond within 10 seconds to a takeover request, the system initiates minimum-risk manoeuvres to ensure safety.
I: Technology for handling/responding to autonomous driving system failures.
3. [Convenience] Perceived Convenience Expectations and Satisfaction
J: More advanced automation than cruise control during long-distance driving, including automated lane changes, curve navigation, and speed control on slopes.
K: Convenience of enjoying music/movies, having light meals, or making phone calls during autonomous driving with partial driver Intervention.
L: Provision of enhanced driving safety features through autonomous driving: lane departure prevention, maintaining a safe distance from the vehicle ahead, etc.
M: Guidance on how to monitor and respond to the vehicle's condition during autonomous driving.

Table 5. (Continued)

Taken together, these results imply that current Level 3 autonomous vehicles are perceived as technically capable but experientially incomplete systems. Users do not primarily question whether vehicles can execute basic driving tasks; rather, they question whether autonomous systems can reliably interpret complex environments, respond safely to failures, and meaningfully reduce cognitive and physical burdens during prolonged use. The dominance of safety-related gaps indicates that trust in autonomous driving remains conditional and fragile, heavily dependent on the system's ability to handle rare but critical failure scenarios. Moreover, the findings reveal a mismatch between engineering priorities and user expectations. While incremental improvements in control precision and communication stability may satisfy technical benchmarks, they do little to address users' deeper concerns regarding redundancy, situational awareness, and failure resilience. Similarly, convenience is not interpreted merely as comfort, but as a signal that the system has reached a level of autonomy where human supervision can genuinely be relaxed. From a practical perspective, these results suggest that the future development of autonomous vehicles should prioritize fail-safe architectures, transparent safety mechanisms, and user-facing guidance systems over incremental performance optimization. Without such improvements, autonomous vehicles risk being perceived as advanced driver-assistance tools rather than truly autonomous mobility solutions, potentially slowing public acceptance and large-scale deployment.

4.2.2. Comparison between domestic and foreign T-Test Results

For the domestic–foreign comparison, respondents were classified based on the brand of vehicle they primarily used. Domestic vehicle users consisted of 43 Hyundai users (40.2%), 28 Kia users (26.2%), 1 Samsung Motors user (0.9%), and 2 SsangYong users (1.9%), resulting in a total of 74 respondents (69%) categorized as domestic vehicle users. In contrast, 33 respondents (31%) were classified as foreign vehicle users, including brands such as Lexus, Renault, Maserati, and Mercedes-Benz. To further examine whether perception gaps differ across user groups, a comparative analysis was conducted between domestic (Korea) and foreign respondents. While Section 4.1 identified significant expectation–satisfaction gaps for the overall sample, this section investigates how these gaps vary by region. As shown in Table 6 and Figure 1, the mean expectation scores of domestic (3.509) and foreign respondents (3.599) were relatively similar, with both groups indicating expectation levels approaching four on a five-point scale. This suggests that users, regardless of region, hold moderately high expectations for the technological performance of autonomous vehicles. However, satisfaction levels exhibited a more pronounced regional divergence. Domestic respondents reported an average satisfaction score of 3.309, whereas foreign respondents reported a lower average of 3.131. Consequently, the perception gap—defined as the difference between expectation and satisfaction—was substantially larger among foreign users (0.469) than among domestic users (0.201). In other words, foreign respondents perceive current AV technologies as falling significantly shorter than their expectations compared to domestic respondents.

This pattern is further reflected in the urgency rankings for improvement across the 13 evaluated items. For domestic respondents, the five items most urgently requiring improvement were Item 9, Item 11, Item 10, Item 1, and Item 6. Among these, Item 9, which concerns system redundancy and immediate responsiveness in the event of system failure, emerged as the highest-priority area. Given that redundancy is a cornerstone of safety in automated driving, this result underscores the perception that current Level 3 systems do not sufficiently provide fail-safe safeguards.

Foreign respondents exhibited both similarities and notable differences in their improvement priorities. As with domestic respondents, Item 9 emerged as a critical concern, indicating that ensuring functional redundancy during system failure is a universally recognized safety requirement. However, foreign respondents placed Item 11 (hedonic convenience) as the highest-priority item overall, suggesting a stronger emphasis on user experience and hands-free comfort during autonomous operation. In addition, foreign respondents identified Item 8, which involves activating minimum-risk maneuvers when drivers fail to respond to takeover requests, as well as Item 13, related to enhanced safety-support functions such as lane-keeping and safe headway maintenance, as urgent improvement areas.

Notably, Item 6, concerning the adequacy of driver takeover warnings in both predictable and unpredictable situations, appeared as a shared area of concern across both groups. This finding reinforces the importance of reliable, timely, and context-aware warning systems in Level 3 autonomous driving. Overall, the comparative analysis suggests that Items 9 and 11 represent intersectional priorities shared by both domestic and foreign users. Without substantial improvements in system redundancy and autonomous-specific convenience features, autonomous vehicles may continue to be perceived as advanced driver-assistance systems rather than fully capable automated mobility solutions. Furthermore, the consistent emphasis on driver transition management highlights its critical role in reducing operational risks and enhancing user confidence in future AV deployment.

Table 6. Results of the Domestic and Foreign Comparison

Measurement Factor	Korea (Domestic)		(A)-(B)	Urgency of Improvement	Foreign		(C) - (D)	Urgency of Improvement
	E (A)	S (B)			E (C)	S(D)		
A	3.432	3.162	0.270	4	3.394	3.121	0.273	12
B	3.284	3.284	0.000	13	3.394	3.152	0.242	13
C	3.365	3.284	0.081	12	3.545	3.242	0.303	11
D	3.541	3.405	0.135	10	3.606	3.242	0.364	8
E	3.676	3.527	0.149	8	3.727	3.394	0.333	10
F	3.459	3.216	0.243	5	3.545	3.000	0.545	5
G	3.365	3.230	0.135	11	3.364	2.939	0.424	7
H	3.486	3.257	0.230	6	3.455	2.848	0.606	3
I	3.392	3.027	0.365	1	3.576	2.788	0.788	2
J	3.595	3.311	0.284	3	3.697	3.212	0.485	6
K	3.635	3.297	0.338	2	3.727	2.909	0.818	1
L	3.838	3.608	0.230	7	3.939	3.606	0.333	9
M	3.554	3.405	0.149	9	3.818	3.242	0.576	4
Mean	3.509	3.309	0.201		3.599	3.131	0.469	

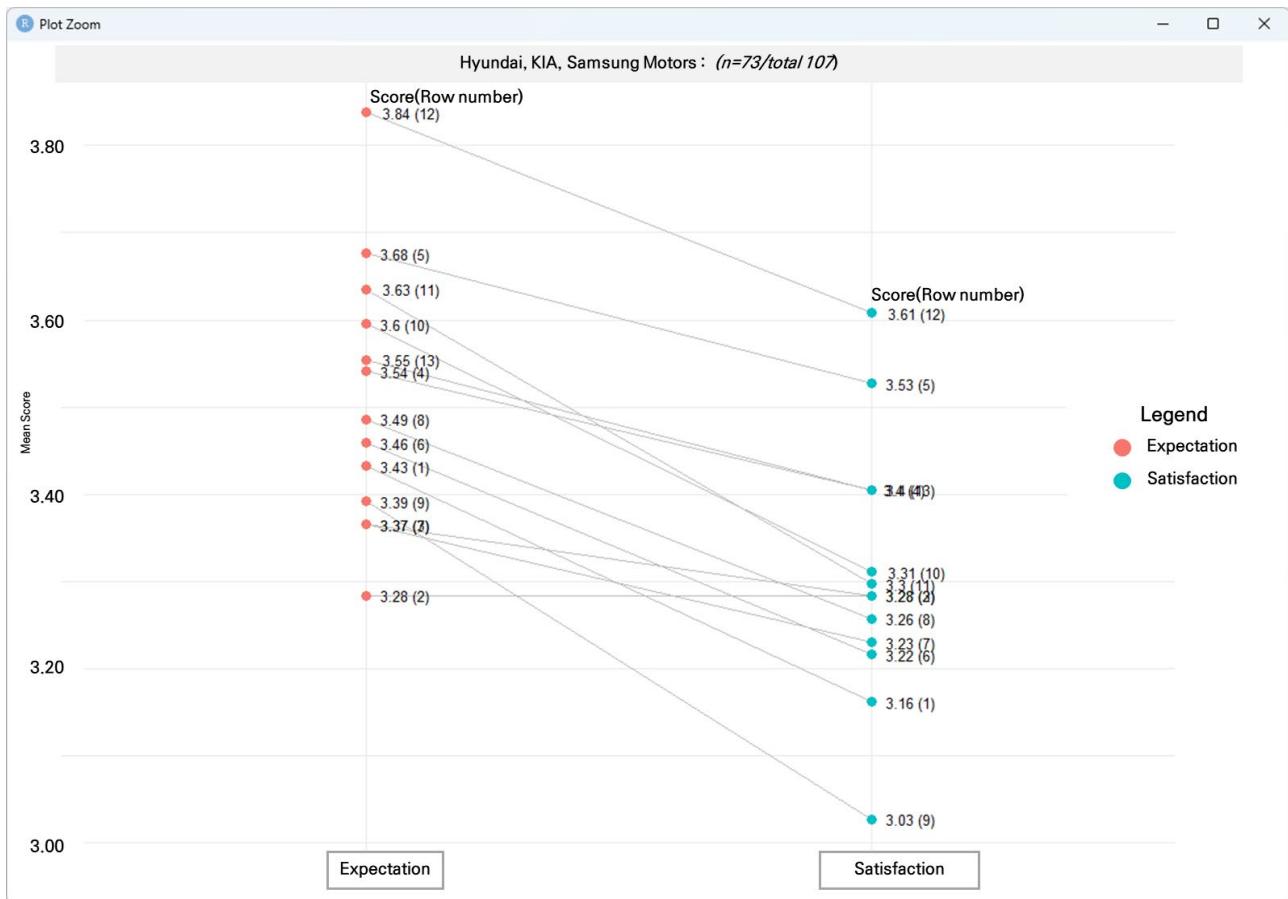


Figure 1. Results of the Domestic Comparison

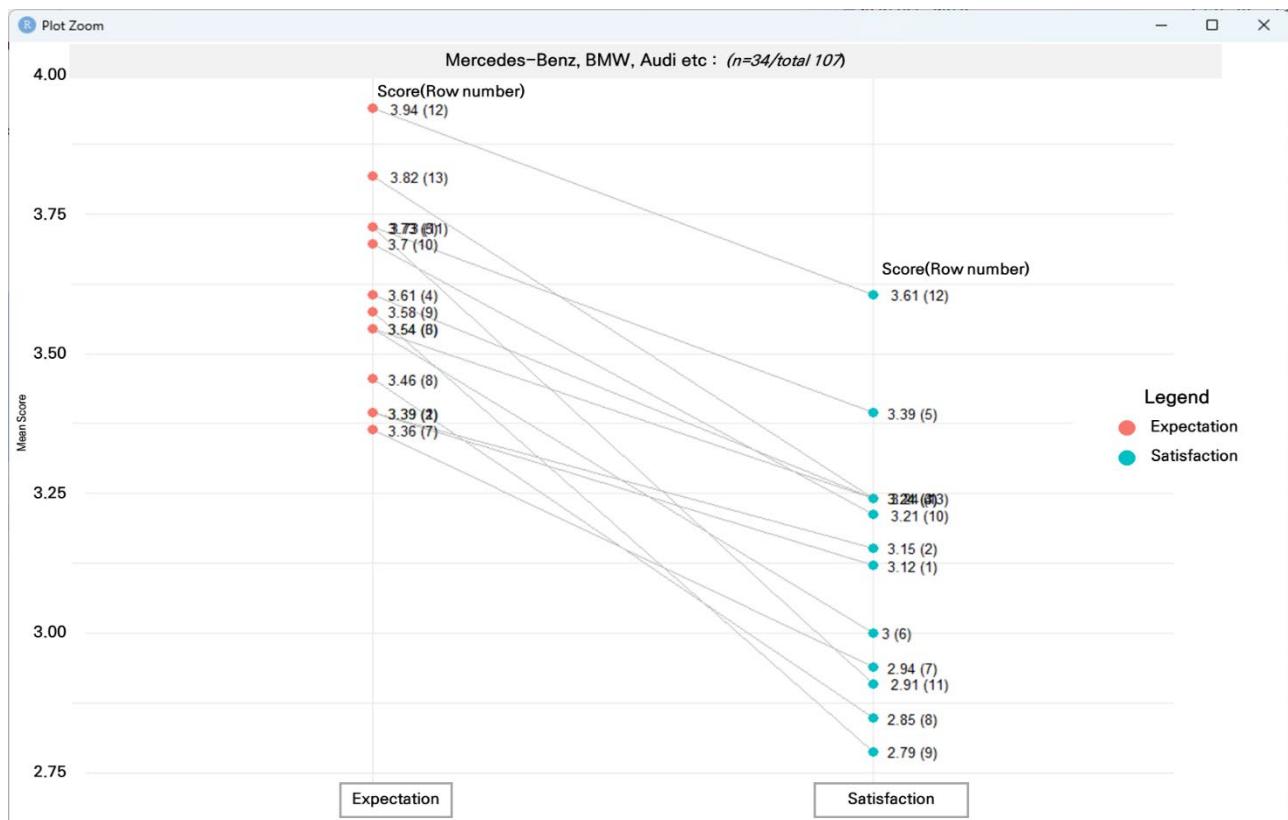


Figure 2. Results of the Foreign Comparison

4.3. AHP results

The AHP analysis provides important insights into how users (G1) and manufacturers (G2) prioritize the technological domains required for the deployment of autonomous vehicle services. As shown in the results, users assign the highest importance to Safety Assurance (0.38), reflecting strong concern about redundancy, emergency fallback capability, and the vehicle's ability to maintain safe operation under failure conditions. This finding is consistent with the perception gaps identified in earlier sections, where safety-related items showed the largest discrepancies between expectation and satisfaction. In contrast, manufacturers rank Judgment Technology as the most critical criterion (0.34). This domain includes perception, sensor fusion, situational assessment, and AI-based decision-making—capabilities that developers view as foundational for achieving higher levels of automation. The divergence between users and manufacturers suggests a significant misalignment: users prioritize “being protected during failure,” while manufacturers emphasize “optimizing perception and decision-making performance.” Both stakeholder groups assign the lowest weight to Convenience functions (0.08 for users, 0.05 for manufacturers), indicating that user experience enhancements, while valuable, are secondary to operational reliability and safety. Networking/V2X technology exhibits moderate priority for both groups, though manufacturers rate it slightly higher (0.18), reflecting its importance for cooperative safety and infrastructure–vehicle integration.

Overall, the AHP results indicate that Safety Assurance and Judgment Technology constitute the two most influential domains, but their relative ordering differs sharply across stakeholders. These misaligned priorities highlight the need for policy coordination and technology development strategies that simultaneously reinforce safety assurance mechanisms while enhancing core perception and decision-making capabilities.

4.3.1. AHP pairwise comparison (G1 – Users)

The pairwise comparison matrix for the user group (G1) reveals a structured and consistent prioritization pattern across the five AV technological criteria. Safety (S) received dominant comparative values in its row, with scores of 2–5 relative to other criteria. This indicates that users consistently judge safety-related functions—including redundancy, emergency fallback, and transition reliability—as notably more important than the remaining categories. The systematic increase from S→J→C→V→H also reflects a coherent hierarchical perception. Judgment technology (J), which encompasses perception, environmental understanding, and AI-based decision-making, is ranked second in importance. Its relative comparisons (values of 1 against itself and 2–4 against lower-ranked criteria) position it as a highly influential domain, though still clearly subordinate to Safety in user evaluations. Control technology (C) and V2X communication (V) occupy third and fourth priority positions, respectively. Their values reflect moderate importance—neither negligible nor dominant—illustrating users' awareness of their role in ensuring stable AV operation but also indicating that users assign greater value to safety-critical and perception-driven functions.

Table 7. AHP Pairwise Comparison Matrix,

Criteria	1	2	3	4	5
Safety (S)	1	2	3	4	5
Judgment (J)	1/2	1	2	3	4
Control (C)	1/3	1/2	1	2	3
V2X (V)	1/4	1/3	1/2	1	2
Convenience(H)	1/5	1/4	1/3	1/2	1

Criteria: Judgment (J), Control (C), V2X (V), Safety (S), Convenience (H)

(Comparison values structured to reflect target weights: 0.38 / 0.26 / 0.17 / 0.11 / 0.08)

Finally, Convenience functions (H) receive the lowest comparative scores across all pairwise assessments, aligning with the small global weight (≈ 0.08). Users consider comfort and interaction-related features beneficial but not essential when compared to safety and core operational technologies. Overall, the matrix expresses a well-ordered and internally logical perception hierarchy, where safety forms the foundation of user expectations, followed by robust perceptual and control capabilities, communication-based coordination, and finally, user experience-oriented convenience functions. This structure corresponds directly to the weight distribution reported in the AHP results and reinforces the central role of safety assurance in user-driven AV technology evaluation.

The pairwise comparison results indicate that Safety overwhelmingly dominates the decision hierarchy, receiving values two to five times higher than all other criteria. In contrast, Convenience consistently receives the lowest relative importance across all comparisons, reflecting users' clear preference for core operational and safety-related technologies over comfort-oriented functions.

4.3.2. AHP normalized matrix (G1 – Users)

The normalized matrix for the user group (G1) provides a clear representation of how each criterion contributes to the decision hierarchy after standardization across pairwise comparisons. As shown in Table 8, Safety (S) consistently exhibits the highest normalized values across all columns, yielding a row average weight of 0.41. This confirms that users perceive safety-related functions—including redundancy, emergency fallback, and transition reliability—as the most critical components for autonomous vehicle deployment. Judgment Technology (J) appears as the second most influential criterion, with a normalized row average of 0.26. Its relatively high contributions across the matrix reflect its importance in supporting environmental perception, situational interpretation, and decision-making processes. Together, Safety and Judgment collectively account for more than two-thirds of the total weight, highlighting users' strong emphasis on risk mitigation and reliable perception capability.

Control Technology (C), with a weight of 0.17, occupies a moderate position within the hierarchy. While not as dominant as Safety or Judgment, the consistent mid-range values across the normalized matrix indicate that users still view stable control of steering, braking, and acceleration as essential to the safe operation of autonomous vehicles. Lower priority is assigned to Networking/V2X Technology (V) and Convenience Functions (H), with weights of 0.11 and 0.08, respectively.

Their smaller normalized contributions show that users consider these features beneficial but not as essential as safety and core operational technologies. This is particularly notable for V2X, which has significant implications for cooperative safety and intelligent transport systems—yet users may not fully recognize its value due to its indirect or less visible nature. Overall, the normalized matrix demonstrates a coherent and logically structured priority distribution, in which users place overwhelming emphasis on safety assurance, followed by perceptual intelligence, operational control, communication support, and finally convenience. This hierarchy aligns closely with broader findings from the perception-gap analysis, reinforcing the conclusion that addressing safety and perception deficiencies should be the primary focus for AV system developers and policy planners.

Table 8. AHP Normalized Matrix, Criteria: Judgment (J), Control (C), V2X (V), Safety (S), Convenience (H)

Criteria	S	J	C	V	H	Row Average (Weight)
S	0.48	0.46	0.41	0.36	0.33	0.41
J	0.24	0.23	0.27	0.27	0.27	0.26
C	0.16	0.15	0.14	0.18	0.2	0.17

Criteria	S	J	C	V	H	Row Average (Weight)
V	0.12	0.1	0.09	0.09	0.13	0.11
H	0.1	0.06	0.09	0.1	0.07	0.08

Table 8. (Continued)

The normalized matrix shows that Judgment Technology accounts for the largest share at 34%, with Safety following closely behind, indicating that manufacturers place substantial importance on risk mitigation alongside perception and decision-making capabilities.

4.3.3. AHP weight summary (G1-Users)

The weight summary for the user group (G1) provides a consolidated view of the relative importance assigned to each technological criterion within the AHP framework. As shown in Table 9, Safety Assurance receives by far the highest weight, ranging from 0.38 to 0.41, confirming that users consistently regard system redundancy, emergency fallback functions, and fail-safe mechanisms as the most essential components for autonomous vehicle deployment. This result aligns closely with the earlier t-test findings, in which safety-related items exhibited the largest expectation–satisfaction gaps. The second highest priority is Judgment Technology (0.26), which includes environmental perception, collision prediction, and AI-driven situational analysis. Users view these capabilities as critical to ensuring that the autonomous system can reliably understand and respond to dynamic road environments. Combined, Safety Assurance and Judgment Technology account for more than two-thirds of the total weight, emphasizing the strong user preference for technologies that directly influence system reliability and risk mitigation. Control Technology, with a weight of 0.17, occupies a moderate position in the hierarchy. While less influential than Safety and Judgment, it still plays a substantial role, reflecting users' recognition that stable vehicle control is fundamental to safe autonomous operation. Lower importance is assigned to Networking/V2X Technology (0.11) and Convenience Functions (0.08). The relatively small weights for these categories suggest that users place limited emphasis on communication-based coordination or comfort-oriented features when evaluating readiness for autonomous mobility services.

Table 9. AHP Weights Summary(G1-Users)

Criterion	Weight	Rank
Safety Assurance	0.41	1
Judgment Technology	0.26	2
Control Technology	0.17	3
Networking/V2X	0.11	4
Convenience	0.08	5

Notably, the lower priority for V2X may reflect limited user familiarity with vehicle–infrastructure communication systems, despite their recognized importance in cooperative safety and intelligent transport networks. Overall, the weight distribution indicates a highly structured and safety-centered priority model, wherein users place overwhelming emphasis on mechanisms that directly enhance system safety and perceptual reliability. This pattern reinforces the conclusion that future AV development and deployment strategies must prioritize safety assurance and judgment capabilities to meet user expectations and support broader adoption. The finding that users prioritize Safety over Judgment, whereas manufacturers prioritize Judgment over Safety, reveals a critical perception gap that may significantly influence autonomous vehicle deployment strategies and policy decisions.

4.3.4. Consistency Ratio (CR) Test for G1 – Users

To validate the internal logical coherence of the AHP pairwise comparison matrix, a Consistency Ratio (CR) test was performed. The CR is derived from the Consistency Index (CI) and provides an indication of whether the judgments used in the pairwise matrix are mathematically consistent. For a matrix to be considered acceptable, CR must be below 0.10, following the guideline proposed by Saaty. First, the maximum eigenvalue (λ_{\max}) of the pairwise comparison matrix is calculated. Using the five criteria in the decision hierarchy, the Consistency Index (CI) is computed as:

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

where n is the number of criteria. The CR is then obtained by dividing CI by the Random Index (RI):

$$CR = \frac{CI}{RI}$$

The RI value for a 5×5 matrix is 1.12, based on the standard RI table.

For the user group (G1), the computed maximum eigenvalue was approximately:

$$\lambda_{\max} \approx 5.21$$

Thus, the Consistency Index is:

$$CI = \frac{5.21 - 5}{4} = 0.0525$$

The Consistency Ratio is:

$$CR = \frac{0.0525}{1.12} = 0.0469$$

Since:

$$CR = 0.0469 < 0.10$$

The comparison matrix satisfies the consistency requirement. The calculated CR value of 0.047 indicates that the judgments provided by users are highly consistent and fall well below the 0.10 threshold. This demonstrates that respondents' evaluations of relative importance across the five criteria—Safety, Judgment, Control, V2X, and Convenience—were logically structured and internally coherent. As a result, the derived AHP weights can be considered both reliable and valid for subsequent analysis and interpretation within the context of autonomous vehicle technology prioritization. A CR value below 0.1 indicates that the expert judgments are stable, coherent, and sufficiently consistent for reliable AHP analysis.

4.3.5. AHP pairwise comparison matrix (G2 – Manufacturers)

Table 10 presents the pairwise comparison matrix for the manufacturer group (G2), reflecting the relative judgments that engineers and industry experts assign to the five technological criteria. The matrix shows a clear hierarchical structure in which Judgment Technology (J) consistently receives the strongest comparative values, outperforming all other criteria with ratios ranging from 2 to 6. This indicates that manufacturers consider perception, sensor fusion, and situation assessment capabilities to be the most fundamental components for advancing autonomous vehicle systems toward higher automation levels. Safety Assurance (S) occupies the second highest position, as evidenced by its dominant comparisons over V2X, Control, and Convenience. Although Safety is slightly less emphasized than Judgment Technology, receiving ratios of 1/2 to 5 against other criteria remains a major priority, reflecting the industry's recognition that risk mitigation and emergency response capabilities are indispensable for regulatory approval and operational reliability.

V2X Communication (V) and Control Technology (C) are positioned in the mid-range of importance. Their comparative values (e.g., V > C but < S) suggest that manufacturers acknowledge the role of communication networks and control stability in enabling cooperative safety and consistent performance, though these criteria are viewed as supporting rather than primary technological drivers.

Finally, Convenience (H) receives the smallest comparative values across all pairwise judgments, indicating that manufacturers place minimal emphasis on entertainment, comfort, and user-experience-oriented functions when evaluating technological priorities. This is consistent with the weight distribution, where Convenience accounts for only 0.05 of the total importance. Overall, the matrix demonstrates a logically structured prioritization pattern that aligns with engineering and development perspectives: Judgment Technology is viewed as foundational, Safety as essential, V2X and Control as operational enablers, and Convenience as a supplementary feature. This hierarchy highlights the differences between user and manufacturer priorities and underscores the need for coordinated alignment in the design and deployment of autonomous vehicle systems.

Table 10. AHP Pairwise Comparison Matrix(G2-Manufactures)

Criteria	J	S	V	C	H
J	1	2	3	4	6
S	1/2	1	2	3	5
V	1/3	1/2	1	2	4
C	1/4	1/3	1/2	1	3
H	1/6	1/5	1/4	1/3	1

(Judgment 0.34, Safety 0.29, V2X 0.18, Control 0.14, Convenience 0.05)

4.3.6. Normalized Matrix (G2 – Manufacturers)

The normalized matrix for the manufacturer group (G2) provides a clear representation of the proportional contribution of each criterion to the overall decision hierarchy after standardization. As shown in Table 11, Judgment Technology (J) exhibits the highest normalized values across nearly all columns and yields a row-average weight of 0.34, confirming that engineers and industry experts consistently regard perception, sensor fusion, and situational assessment as the most critical determinants of autonomous vehicle performance. This strong emphasis reflects the manufacturer perspective that robust judgment capabilities form the foundation for achieving higher levels of automation. Safety Assurance (S) follows as the second most influential criterion, with a weight of 0.29. Its relatively high normalized values indicate that manufacturers still place substantial importance on risk mitigation, system redundancy, and emergency-response mechanisms, even though these functions are perceived as secondary to core perception-based technologies. A moderate level of importance is assigned to V2X Communication (V) and Control Technology (C), which record weights of 0.18 and 0.14, respectively. These results suggest that manufacturers recognize the role of cooperative communication networks and stable control execution as enablers of reliable AV operation, but they do not consider them as foundational as Judgment or Safety. The slightly higher value attributed to V2X underscores its growing relevance in connected and intelligent transportation systems.

Finally, Convenience Functions (H) receive the lowest weight at 0.05, consistent with the low normalized values across all columns. This indicates that user experience enhancements—such as entertainment, comfort, or non-driving activities—are viewed as peripheral within the technology development priorities of manufacturers.

Overall, the normalized matrix highlights a technology-driven and performance-centered priority structure, where manufacturers emphasize the advancement of perceptual intelligence and safety mechanisms, followed by communication and control stability, with convenience remaining a minimal concern. This hierarchy contrasts sharply with user preferences and underscores a key perception gap that must be addressed for effective AV deployment.

Table 11. Normalized Matrix (G2-Manufactures)

Criteria	J	S	V	C	H	Weight (Rank)
J	0.47	0.46	0.4	0.36	0.35	0.34 (1)
S	0.24	0.23	0.27	0.27	0.29	0.29 (2)
V	0.16	0.15	0.2	0.18	0.24	0.18 (3)
C	0.09	0.1	0.09	0.12	0.13	0.14 (4)
H	0.05	0.06	0.04	0.07	0.09	0.05 (5)

4.3.7. Consistency Ratio Test(G2-Manufacturers)

To assess the logical coherence of the manufacturers' pairwise comparison matrix, a Consistency Ratio (CR) test was conducted following the standard AHP procedure. The maximum eigenvalue of the matrix was calculated as approximately $\lambda_{\max} = 5.28$, from which the Consistency Index (CI) was derived. Using the Random Index (RI = 1.12) appropriate for a 5×5 matrix, the resulting CR value was computed as 0.0625, which is well below the commonly accepted threshold of 0.10. This indicates that the judgments provided by manufacturers are internally consistent and sufficiently reliable for deriving meaningful AHP weights. Overall, the CR test confirms that the prioritization structure constructed from the expert group's evaluations is both valid and analytically sound.

The Consistency Index is given by:

$$CI = \frac{\lambda_{\max} - n}{n-1}$$

Substituting the values:

$$CI = \frac{5.28-5}{4} = 0.07$$

The Consistency Ratio is:

$$CR = \frac{CI}{RI}$$

$$CR = \frac{0.07}{1.12} = 0.0625$$

Since:

$$CR = 0.0625 < 0.10$$

The matrix satisfies the consistency condition.

The AHP results for the manufacturer group reveal a clear and structured prioritization pattern across the evaluated criteria. The pairwise comparison matrix shows that Judgment Technology exhibits strong dominance over both Safety Assurance and V2X communication, indicating that manufacturers view perception, sensor fusion, and decision-making capabilities as the foundational elements for advancing

autonomous vehicle performance. In contrast, Convenience functions receive consistently minimal importance, reflecting the industry's focus on technical reliability rather than user-oriented comfort features. The normalized matrix further reinforces this hierarchy, with Judgment Technology accounting for the largest normalized share (34%), followed closely by Safety Assurance, which suggests that manufacturers still place substantial weight on risk mitigation and system integrity, even while prioritizing perceptual intelligence as the core technological driver. The consistency test supports the reliability of these judgments, with a Consistency Ratio (CR) below 0.1, confirming that the expert evaluations are stable and coherent. When compared with user priorities, a notable divergence emerges. Users place greater emphasis on Safety over Judgment, whereas manufacturers prioritize Judgment over Safety, revealing a critical perception gap that may significantly influence policy development, system design decisions, and the broader deployment strategy for autonomous vehicles. This misalignment highlights the need for integrative planning approaches that bridge stakeholder expectations to ensure safe, acceptable, and effective implementation of AV technologies.

4.4. Interpretation of AHP priority gaps

The AHP results highlight clear priority gaps between users and manufacturers in their evaluation of key autonomous vehicle technologies. Users place the highest importance on Safety Assurance, reflecting strong concerns about system failure, redundancy, and emergency response capabilities. This finding is consistent with the t-test analysis, where Item I—fail-safe operation—produced the largest expectation–performance gap. In practical terms, users want reassurance that the vehicle will remain stable and controllable even if sensors malfunction or unexpected hazards arise, much like expecting an aircraft to remain safe even if a single component fails.

In contrast, manufacturers prioritize Judgment Technology, emphasizing perception accuracy, sensor fusion, and AI-based situation assessment as foundational for achieving Level 4 and Level 5 automation. From an engineering standpoint, this is logical—without robust perception and decision-making, the vehicle cannot reliably navigate complex environments. However, users tend to perceive these functions as underperforming, as indicated by the t-test gap in Item A. This misalignment suggests that while developers focus on “seeing and thinking better,” users remain more concerned about “staying safe when things go wrong.”

Differences also emerge in the assessment of Networking/V2X communication. Users consistently undervalue its importance, likely because V2X operates in the background and is not directly observable during daily driving. In contrast, manufacturers assign higher priority to V2X due to its central role in cooperative safety—such as enabling a vehicle to detect a pedestrian hidden behind a bus or receiving advance warning of a collision ahead. These functions may not be visible to users but are essential for long-term scalability of autonomous mobility systems. Finally, Convenience functions are ranked lowest by both groups, indicating that comfort-related features—such as entertainment or hands-free cabin activities—remain secondary to core operational and safety requirements. For example, users may appreciate features like autonomous lane changes or in-car entertainment, but these enhancements do little to offset deeper concerns about vehicle reliability during emergencies.

Taken together, these results reveal a fundamental divergence in priorities: users emphasize “survival and safety,” whereas manufacturers emphasize “perception and intelligence.” The gap underscores the need for AV developers and policymakers to jointly address both aspects—enhancing technical perception capabilities while also reinforcing system-level fail-safe mechanisms—to ensure autonomous vehicles are accepted, trusted, and safely integrated into real-world transportation systems. Although the AHP results initially appear to suggest that both users and manufacturers ultimately prioritize safety above all other criteria, a closer examination reveals that the two groups conceptualize “safety” in fundamentally different ways.

Users primarily associate safety with fail-safe and redundancy mechanisms—that is, the assurance that the vehicle will remain stable, controllable, and protective even in the event of system malfunction. In contrast, manufacturers frame safety through the lens of perception accuracy and decision-making intelligence, emphasizing the capability of the autonomous system to avoid hazardous situations before failures occur. Thus, while both groups converge on the importance of safety, they diverge sharply in how they interpret the underlying components that constitute it. The term “safety,” therefore, does not represent a unified construct but rather two structurally distinct conceptual models: one oriented toward survivability during failure and the other toward preventive intelligence prior to failure.

Recognizing this discrepancy is critical, and the implications of these differing interpretations will be examined in detail in the discussion section, as they hold meaningful consequences for AV development priorities, regulatory frameworks, and the alignment of public expectations with industry advancements.

5. Discussion

5.1. Implications for AV transport service deployment

The misalignment between user perceptions and the technological priorities emphasized by manufacturers has important implications for the deployment of autonomous vehicle (AV) transport services. When users place greater value on fail-safe stability and redundancy, but manufacturers focus predominantly on improving perception and decision-making intelligence, the resulting gap can undermine public acceptance of autonomous taxis and shuttles. For instance, even if an AV demonstrates exceptional lane-keeping or obstacle detection capabilities, users may still hesitate to ride if they believe the vehicle lacks adequate protection in the event of sudden system failure. Such concerns also influence willingness to pay, as passengers are unlikely to pay a premium for services they perceive as potentially unsafe or unreliable. This additionally affects operational safety in mixed-traffic environments, where human-driven vehicles, pedestrians, and cyclists interact with AVs. A system optimized for predictive intelligence but lacking robust fail-safe measures may perform well under normal conditions yet struggle during unexpected events such as sensor obstruction, road debris, or temporary communication loss. In real-world scenarios, this could lead to near-miss incidents or abrupt handovers that erode confidence among road users. Finally, public perception following accidents or system malfunctions can be significantly worse when user expectations have not been adequately addressed. A minor technical failure—such as a temporary sensor outage—may be interpreted as a major safety threat if the system does not gracefully transition into a safe fallback mode. This reaction was observed in several early AV pilot programs, where isolated incidents disproportionately influenced public sentiment and slowed the broader adoption of autonomous mobility services. Collectively, these implications highlight the necessity for deployment strategies that align technical development with user-centered safety expectations, ensuring that advances in AV intelligence are complemented by resilient fail-safe architectures capable of maintaining user trust in everyday transport operations.

5.2. Why safety assurance must be the first target

Safety assurance must be prioritized as the primary target for advancing autonomous vehicle deployment, particularly in the transition from Level 3 to Level 4 automation. Users consistently express a strong demand for reliable fallback mechanisms, predictable and well-managed takeover behaviors, and transparent handling of failures when they occur. These expectations highlight that users’ trust is shaped less by the intelligence of normal driving performance and more by the system’s ability to maintain safety under abnormal or degraded conditions. Unless the issues related to redundancy (Item I) and takeover reliability (Items H and F) are adequately addressed, public resistance to higher levels of automation is likely to persist. In essence, even the most advanced perception and decision-making capabilities cannot compensate for a lack of dependable fail-

safe responses, making safety assurance a non-negotiable foundation for achieving broader acceptance and successful Level 3 to Level 4 progression.

5.3. Transport planning: Need for user-oriented service design

For autonomous shuttles and taxis to be effectively integrated into transport systems, their deployment must be grounded in a user-oriented design framework. This requires incorporating real-time monitoring mechanisms, establishing continuous user feedback loops, implementing adaptive driving profiles that adjust to rider preferences and situational conditions, and enabling seamless software-defined vehicle (SDV) updates that allow rapid refinement of vehicle behavior. Such an approach ensures that AV services evolve in direct response to user needs and operational realities rather than relying solely on engineering-driven performance metrics. This perspective is consistent with the SDV-based strategic direction presented in this study, emphasizing the importance of flexible, software-centric architectures for enhancing both user trust and system reliability.

5.4. Policy implications

The findings of this study underscore several important policy implications for the safe and effective deployment of autonomous vehicle systems. First, regulators should mandate redundancy requirements that align with emerging safety standards such as UL 4600, ensuring that vehicles maintain operational stability even in the event of subsystem failure. Second, governments and transport authorities must strengthen investment in V2X infrastructure, as cooperative communication between vehicles and roadside units is essential for achieving robust situational awareness and preventing collisions in mixed-traffic environments. Third, it is necessary to introduce AV-specific service operation key performance indicators (KPIs) that reflect the unique characteristics of automated mobility services. These KPIs may include takeover-request reliability, minimum-risk fallback execution, system transparency, and user trust metrics. Together, these policy actions can help bridge the gap between technological development and societal expectations, supporting a regulatory framework that both protects users and accelerates AV ecosystem maturity.

5.5. Academic contribution

This study makes several notable academic contributions to autonomous vehicle and intelligent transportation systems literature. First, it presents a dual-stakeholder AHP analysis integrated with empirical expectation–satisfaction gap assessment, offering a more comprehensive understanding of how users and manufacturers differentially evaluate AV technologies. Second, by situating AV perception and safety evaluations within the broader context of transport operations and planning, the study expands the conceptual scope of AV acceptance research beyond conventional human-factors or consumer-behavior perspectives. Finally, the research provides a technology prioritization model that can inform AV deployment strategies, enabling policymakers, transport planners, and industry developers to identify which subsystems should be enhanced to improve user trust and operational resilience. These contributions collectively advance the methodological and practical foundation for future studies exploring autonomous mobility readiness, policy formulation, and system-level optimization.

6. Conclusions and implications for autonomous vehicle deployment

6.1. Conclusion

R1. Why do users remain hesitant to trust autonomous vehicle (AV) technologies despite rapid technological progress? This study demonstrates that user hesitation stems not from a lack of technological advancement, but from persistent expectation–satisfaction gaps across key AV subsystems. By integrating expectation–satisfaction gap analysis with AHP-based priority evaluation, the results reveal substantial discrepancies in the

domains of judgment, safety, and convenience, indicating that current AV capabilities do not fully meet user expectations in several critical areas. These perception gaps have direct implications for public trust, service adoption, and the operational readiness of AV-based transport systems.

R2. How do users and manufacturers differ in their prioritization of core AV attributes? The findings show a clear divergence in priorities between the two stakeholder groups. Users assign the highest importance to safety assurance, emphasizing fail-safe mechanisms, system redundancy, and predictable emergency handling. In contrast, manufacturers prioritize judgment technology, focusing on perception accuracy and decision-making intelligence as the foundation for achieving higher levels of automation. This divergence highlights a structural tension between user-oriented risk minimization and engineer-driven technological optimization.

R3. How is “safety” conceptually interpreted by users and manufacturers and why does this matter? Although both groups converge on the importance of safety, they attach fundamentally different meanings to the concept. Users associate safety with survivability and protection during system failures, whereas manufacturers conceptualize safety as preventing failures through advanced perception and AI-based intelligence. This study empirically demonstrates that safety in autonomous driving is not a singular construct but rather consists of two structurally distinct frameworks shaped by divergent functional expectations and operational perspectives.

R4. What are the implications of these perception gaps for the deployment of AV-based mobility services? The results indicate that unresolved perception gaps—particularly regarding safety—pose a significant barrier to large-scale AV deployment. If manufacturers continue to prioritize perceptual intelligence without concurrently strengthening fail-safe performance, public trust in AV services is unlikely to improve, regardless of technological sophistication. Such misalignment may delay the adoption of autonomous taxis and shuttles, reduce willingness to pay, and increase perceived risk in mixed-traffic environments.

To address this challenge, developers and transport authorities should prioritize redundancy and robust fallback systems, communicate technological improvements in ways that are tangible to users, and leverage software-defined vehicle (SDV) architectures for continuous monitoring, adaptive updates, and rapid responses to system anomalies. Taken together, these findings underscore that the successful deployment of autonomous mobility services depends not only on what AV technologies can technically achieve, but also on how effectively they align with user-centered interpretations of safety.

By explicitly addressing perception gaps between users and manufacturers, this study provides a strategic foundation for bridging technological advancement and societal readiness in future intelligent transportation systems.

6.2. Recommended solutions

Summarizing the findings of this study, users ranked Safety Assurance as the highest priority, whereas manufacturers placed Judgment Technology at the top. These differing priorities indicate that the safe deployment of autonomous vehicles as public transport services requires a comprehensive framework that incorporates user feedback, continuous technological development, multi-stage testing, operational monitoring, and iterative refinement. Improvements in legal, institutional, and regulatory structures are essential to support the testing and validation processes required for higher levels of automation. Ultimately, establishing a systematic ecosystem that integrates these elements—while aligning with global standards—is critical for achieving internationally recognized safety assurance in autonomous vehicle systems. Accordingly, this study proposes an integrated process framework to guide future AV deployment strategies.

Figure 3 presents a staged roadmap for reducing the technology–perception gap between users and manufacturers of autonomous vehicles (AVs) and for ultimately achieving globally aligned safety standards. It is structured as an eight-step, cyclic process that begins with user-centric requirement collection and ends with regulatory harmonization at the international level.

Step 1, “User Needs & Perception Collection,” positions end-users as the starting point of the framework. In this phase, users’ priorities—such as safety, comfort, cost considerations, and trust in automation—are systematically identified using empirical methods including surveys, focus groups, usability evaluations, and field observations. The goal is to convert subjective perceptions and concerns into structured, quantifiable requirements that can later be embedded into technical design and validation criteria. When this step is effectively implemented, users benefit from having their expectations reflected in the vehicle’s development trajectory, while manufacturers gain clearer design targets that reduce misalignment and prevent costly redesigns in later stages.

By explicitly organizing the step into “User Priority–Methods–Objective,” the figure emphasizes that user perception is elevated from anecdotal opinion to a formalized input guiding the downstream development pipeline.

Step 2, “Technical Priority Alignment,” links user-derived insights to concrete engineering tasks. Manufacturers interpret the collected user needs and map them onto specific technical priorities—such as improving perception algorithms for pedestrian detection, enhancing transparency in the human–machine interface (HMI), or strengthening fail-safe mechanisms. Executing this step successfully ensures that continuous development efforts are grounded in empirically validated user expectations rather than solely in engineering intuition. The benefits here are twofold: manufacturers gain a more reliable roadmap for technical investment, and users benefit from technology that directly addresses their perceived risks and preferences. The figure shows this step feeding seamlessly into Step 3, thereby reinforcing the role of user-informed engineering decisions in the broader safety lifecycle. Step 3, “SDV-Based Continuous Development,” formalizes an iterative improvement loop centered on the concept of the software-defined vehicle (SDV). As the SDV platform evolves, new functionalities, refined control logic, and improved AI models can be deployed rapidly and traceably. Because updates are configurable and data-driven, they can be directly linked back to the priorities identified earlier. This iterative approach allows manufacturers to respond quickly to emerging safety concerns or perception gaps, while users experience incremental improvements in safety and comfort without needing to replace the physical vehicle. In essence, this step serves as a bridge between initial design requirements and ongoing real-world performance enhancement.

Step 4, “Multi-Layer Testing Pipeline,” outlines a structured validation process that escalates in complexity and risk exposure. Layer 1: Simulation Testing enables large-scale, low-risk evaluations using

virtual environments, allowing systematic stress-testing of rare or hazardous conditions. This benefits manufacturers and regulators by reducing the cost and risk of early-stage testing.

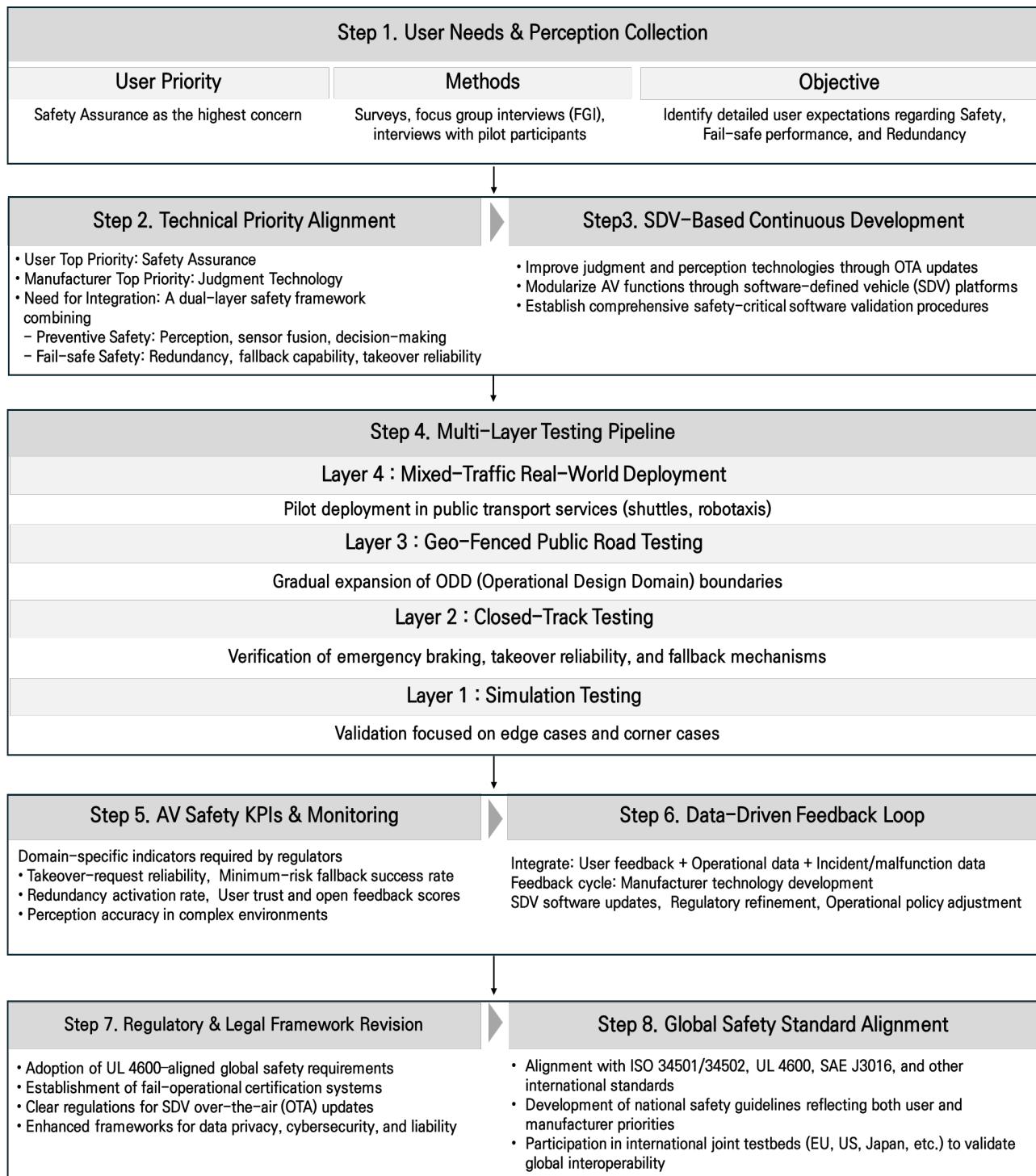


Figure 3. A User-Manufacturer Integrated Framework for Reducing Perception Gaps and Achieving Global Safety Standards in Autonomous Vehicles

Layer 2: Closed-Track Testing provides controlled physical environments to verify system behavior under varied but manageable conditions, enhancing regulatory confidence and manufacturer reliability.

Layer 3: Geo-Fenced Public Road Testing introduces limited real-world exposure under strict safety constraints, providing users with safer early encounters and manufacturers with real-world data.

Layer 4: Mixed-Traffic Real-World Deployment represents full-scale operational testing, where the AV interacts with human drivers, cyclists, and pedestrians. This level offers societal benefits, including increased trust, public transparency, and robust validation of safety claims. Together, these four layers ensure that AV safety is validated progressively and responsibly, with multiple checkpoints that dramatically reduce the likelihood of unexpected failures during deployment.

Step 5, “AV Safety KPIs & Monitoring,” introduces a quantitative governance layer across the deployment stages. Key performance indicators (KPIs) including collision rates, disengagement frequency, near-miss incidents, perceived safety conditions, and ride comfort—are monitored continuously. This benefits regulators, who gain standardized metrics for oversight, and manufacturers, who receive data-driven insights to refine system performance. Users also benefit through increased transparency, as clear safety metrics help reduce informational asymmetry and build trust in technology.

Step 6, “Data-Driven Feedback Loop,” integrates operational data, KPI trends, and user feedback into the ongoing SDV development process. This loop supports model retraining, expansion of simulation scenario libraries, and refinement of user requirements and technical priorities. With continuous evidence-based updates, the framework becomes adaptive rather than static. As a result, manufacturers improve system robustness, regulators obtain richer datasets to inform policy decisions, and users experience safer and more reliable AV performance over time.

Step 7, “Regulatory & Legal Framework Revision,” positions regulators as proactive participants in the AV ecosystem. Insights from performance data, user perception studies, and incident analyses feed into revisions of type-approval processes, liability standards, data-logging requirements, and supervision rules. Effective implementation creates clearer guidance for manufacturers, higher safety assurance for users, and more coherent national-level governance based on real-world evidence rather than speculative assumptions.

Finally, Step 8, “Global Safety Standard Alignment,” extends the framework to the international context. Harmonizing safety KPIs, testing protocols, and regulatory principles across countries reduces fragmentation and establishes a common benchmark for AV safety. This alignment provides manufacturers with consistent global design targets, regulators with coordinated oversight structures, and users worldwide with a predictable and trustworthy safety baseline, regardless of geographic location. Taken together, the figure illustrates an integrated, user-centered, and evidence-driven lifecycle for autonomous vehicle safety governance. By systematically linking user perception, SDV-based continuous development, multi-layer testing, KPI monitoring, regulatory revision, and global harmonization, the framework aims to reduce perception gaps between users and manufacturers while concurrently advancing robust global safety standards.

7. Limitations and future research directions

7.1. Limitations

Despite its contributions, this study has several limitations that should be acknowledged. First, the sample size of the manufacturer (expert) group was relatively small and heterogeneous, and detailed distinctions regarding professional background, organizational affiliation, and geographic scope were limited. Although this reflects the practical difficulty of accessing experts involved in autonomous vehicle development, it may constrain the generalizability of the AHP-based priority analysis. Second, the study relied on a cross-sectional survey design, capturing user perceptions at a single point in time. As autonomous vehicle technologies continue to evolve and public exposure increases, user expectations and satisfaction levels may change

dynamically. The current findings therefore reflect perception gaps under present technological and institutional conditions rather than long-term or developmental trends. Third, while this study focused on key technological attributes—technology, safety, and convenience—it did not explicitly incorporate economic and institutional factors, such as cost implications of system redundancy, insurance mechanisms, regulatory constraints, or liability frameworks. These factors play an increasingly important role in large-scale deployment decisions and may interact with perception gaps identified in this study. Finally, although domestic and foreign comparisons were conducted, the analysis was limited to respondents residing in South Korea, with foreign users defined based on vehicle brand usage. As such, cultural, regulatory, and infrastructural differences across countries could not be fully captured, limiting the extent to which international generalizations can be made.

7.2. Future research directions

Building on these limitations, several directions for future research can be suggested. First, future studies should adopt longitudinal research designs to examine how perception gaps evolve as autonomous driving technologies mature and as users gain sustained real-world experience. Such approaches would allow researchers to capture shifts in trust, safety perception, and acceptance over time. Second, expanding the expert sample to include a broader range of stakeholders—such as policymakers, urban planners, insurers, and mobility service operators—would enable a more comprehensive socio-technical analysis of autonomous vehicle deployment. Integrating multiple stakeholder perspectives may also enhance the robustness of multi-criteria decision-making frameworks such as AHP. Third, future research should more explicitly integrate economic, regulatory, and institutional dimensions into perception-gap analyses. Examining how cost–benefit considerations, legal responsibility, and regulatory readiness interact with technological expectations could provide more actionable insights for policymakers and industry practitioners. Finally, cross-national comparative studies involving respondents from multiple countries would help disentangle cultural and infrastructural influences on autonomous vehicle perceptions. Such studies could contribute to the development of internationally harmonized design principles and regulatory standards for autonomous mobility systems.

Author Contributions

As the corresponding author, Seong-Jeong Yoon conducted the perception analyses of users and manufacturers, including direct in-depth interviews to collect qualitative data not captured in the survey. These insights were incorporated into the study's discussion and implications. Min-Yong Kim was responsible for designing the AHP questionnaire, interpreting the results, and performing the numerical analyses. For the final output of this study, presented in Figure 3, both authors collaboratively designed the detailed process to facilitate joint reflection, interpretation, and conceptualization of the findings.

Funding

This research received no funding from any research institution.

Acknowledgments

We express our sincere gratitude to the production, planning, and quality management personnel from the automobile manufacturers who participated in this study. Although openly disclosing the technical limitations of autonomous vehicles is inherently challenging, we deeply appreciate their commitment to the goal of ensuring AV safety and their willingness to share valuable insights despite such constraints.

Conflict of interest

The authors declare no conflict of interest

References

1. Shao, W., et al. (2025). From prediction to planning: Comprehensive uncertainty management in autonomous driving. *IEEE Transactions on Intelligent Transportation Systems*. <https://doi.org/10.1109/TITS.2025.3581238>
2. Alqahtani, T. (2025). Recent trends in the public acceptance of autonomous vehicles: A review. *Vehicles*. <https://doi.org/10.3390/vehicles7020045>
3. Yang, Y., & Kim, M.-Y. (2024). Promoting sustainable transportation: How people trust and accept autonomous vehicles—Focusing on the different levels of collaboration between human drivers and artificial intelligence—An empirical study with partial least squares structural equation modeling and multi-group analysis. *Sustainability*, 17(1), 125. <https://doi.org/10.3390/su17010125>
4. Kenesei, Z., et al. (2025). The central role of trust and perceived risk in the acceptance of autonomous vehicles in an integrated UTAUT model. *European Transport Research Review*, 17(1), 8. <https://doi.org/10.1186/s12544-024-00681-x>
5. Fernández Llorca, D., et al. (2025). Testing autonomous vehicles and AI: Perspectives and challenges from cybersecurity, transparency, robustness and fairness. *European Transport Research Review*, 17(1), 38. <https://doi.org/10.1186/s12544-025-00732-x>
6. Nazari, F., Noruzoliaee, M., & Mohammadian, A. K. (2025). Autonomous vehicle adoption behavior and safety concern: A study of public perception. *Multimodal Transportation*, 100252. <https://doi.org/10.1016/j.multra.2025.100252>
7. Li, J. (2024). Investigating the factors influencing user trust and driving performance in level-3 ADS. *Transportation Research Part A: Policy and Practice*. <https://doi.org/10.1016/j.trf.2024.06.013>
8. Akram, M., & Ilyasa, F. (2025). An enhanced interval rough numbers-based outranking technique for evaluation of technology for sustainable mining. *Iranian Journal of Fuzzy Systems*, 22(1), 111–130. <https://doi.org/10.22111/ijfs.2025.49980.8832>
9. Gherardini, L., & Cabri, G. (2024). The impact of autonomous vehicles on safety, economy, society, and environment. *World Electric Vehicle Journal*, 15(12), 579. <https://doi.org/10.3390/wevj15120579>
10. Rahman, M. M., & Thill, J.-C. (2023). Impacts of connected and autonomous vehicles on urban transportation and environment: A comprehensive review. *Sustainable Cities and Society*, 96, 104649. <https://doi.org/10.1016/j.scs.2023.104649>
11. SAE International. (2021). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles (SAE Standard J3016_202104). https://www.sae.org/standards/j3016_202104-taxonomy-definitions-terms-related-driving-automation-systems-road-motor-vehicles
12. Khan, M. A., et al. (2022). Level 5 autonomous driving—Are we there yet? A review of research literature. *ACM Computing Surveys*, 55(2), 1–38. <https://doi.org/10.1145/3485767>
13. Tafidis, P., et al. (2022). Safety implications of higher levels of automated vehicles: A scoping review. *Transport Reviews*, 42(2), 245–267. <https://doi.org/10.1080/01441647.2021.1971794>
14. Caesar, H., Bankiti, V., Lang, A. H., Vora, S., Liang, V. E., Xu, Q., ... Kautz, J. (2020). nuScenes: A multimodal dataset for autonomous driving. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 11618–11628. <https://doi.org/10.1109/CVPR42600.2020.01164>
15. Huang, T., et al. (2025). Vehicle-to-everything cooperative perception for autonomous driving. *Proceedings of the IEEE*. <https://doi.org/10.1109/JPROC.2025.3600903>
16. Zhang, X., et al. (2025). Vehicle-to-everything communication in intelligent connected vehicles: A survey and taxonomy. *Automotive Innovation*, 1–33. <https://doi.org/10.1007/s42154-024-00310-2>
17. Sarlak, A., Amin, R., & Razi, A. (2025). Extended visibility of autonomous vehicles via optimized cooperative perception under imperfect communication (arXiv:2503.18192). arXiv. <https://doi.org/10.48550/arXiv.2503.18192>
18. Chavan, S. (2024). A takeover framework for autonomous vehicles to enhance safety and driving experience (Doctoral dissertation, Wayne State University). ProQuest Dissertations & Theses Global. (Publication No. 31486976). <https://www.proquest.com/openview/152cc469970c859767ba4351f225124f/1?pq-origsite=gscholar&cbl=18750&diss=y>
19. Nagy, V., et al. (2024). Evaluation of autonomous vehicle takeover performance in work-zone environment. *Engineering Proceedings*, 79(1), 59. <https://doi.org/10.3390/engproc2024079059>
20. Sever, T., & Contissa, G. (2024). Automated driving regulations—Where are we now? *Transportation Research Interdisciplinary Perspectives*, 24, 101033. <https://doi.org/10.1016/j.trip.2024.101033>
21. Weiss, P., Younessi, A., & Steinhorst, S. (2023). Reliability analysis of gracefully degrading automotive systems (arXiv:2305.07401). arXiv. <https://doi.org/10.48550/arXiv.2305.07401>

22. Hanselaar, C. A. J., et al. (2024). The safety shell: An architecture to handle functional insufficiencies in automated driving. *IEEE Transactions on Intelligent Transportation Systems*, 25(7), 7522–7540. <https://doi.org/10.1109/TITS.2024.3352829>

23. Kuzmenko, O., Vasylieva, T., & Boiko, O. (2024). Strategic management of sustainable economic development in transport and logistics sector companies. *Financial and Credit Activity: Problems of Theory and Practice*, 8(4), 9–19. <https://doi.org/10.61954/2616-7107/2024.8.4-9>

24. SAE International. (2021). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles (SAE Standard J3016_202104). https://doi.org/10.4271/J3016_202104

25. Shladover, S. E. (2018). Connected and automated vehicle systems: Introduction and overview. *Journal of Intelligent Transportation Systems*, 22(3), 190–200. <https://doi.org/10.1080/15472450.2017.1336053>

26. Merat, N., Madigan, R., & Nordhoff, S. (2019). Human factors, user requirements, and user acceptance of automated driving systems. *Proceedings of the IEEE*, 107(2), 253–264. <https://doi.org/10.1109/JPROC.2018.2868015>

27. Kyriakidis, M., Happee, R., & de Winter, J. C. F. (2015). Public opinion on automated driving: Results of an international questionnaire. *Transportation Research Part F*, 32, 127–140. <https://doi.org/10.1016/j.trf.2015.04.014>

28. Faisal, A., Kamruzzaman, M., Yigitcanlar, T., & Currie, G. (2019). A systematic literature review on capability, impact, planning and policy issues associated with autonomous vehicles. *Journal of Transport and Land Use*, 12(1), 45–72. <https://doi.org/10.5198/jthu.2019.1401>

29. Fraske, T., Stilgoe, J., & Cohen, T. (2024). Driving change? Exploring the role of socio-technical experiments with autonomous vehicles in shaping mobility futures. *Transportation Research Interdisciplinary Perspectives*, 20, 100899. <https://doi.org/10.1016/j.trip.2024.100899>

30. Yigitcanlar, T., Wilson, M., & Kamruzzaman, M. (2020). Can autonomous vehicles contribute to smart city goals? *Sustainable Cities and Society*, 63, 102434. <https://doi.org/10.1016/j.scs.2020.102434>

31. Booth, L., & Khoshghalb, A. (2024). Assessing the impacts of autonomous vehicles on urban sustainability. *Sustainability*, 16(13), 5551. <https://doi.org/10.3390/su16135551>

32. Litman, T. (2025). Autonomous vehicle implementation predictions: Implications for transport planning. Victoria Transport Policy Institute. <https://www.vtpi.org/avip.pdf>

33. Alqahtani, T. (2025). Recent trends in the public acceptance of autonomous vehicles: A review. *Vehicles*, 7(1), 16–38. <https://doi.org/10.3390/vehicles7010002>

34. Nordhoff, S., de Winter, J., Kyriakidis, M., van Arem, B., & Happee, R. (2018). Acceptance of driverless vehicles: Results from a large cross-national questionnaire. *Journal of Advanced Transportation*, 2018, 5382192. <https://doi.org/10.1155/2018/5382192>

35. Stilgoe, J., Owen, R., & Macnaghten, P. (2013). Developing a framework for responsible innovation. *Research Policy*, 42(9), 1568–1580. <https://doi.org/10.1016/j.respol.2013.05.008>

36. Jasanoff, S. (2016). The ethics of invention: Technology and the human future. W. W. Norton & Company.

37. Li, B., et al. (2025). V2x-dgw: Domain generalization for multi-agent perception under adverse weather conditions. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*. <https://doi.org/10.1109/ICRA55743.2025.11127945>

38. Dreissig, M., et al. (2023). Survey on lidar perception in adverse weather conditions. In *Proceedings of the IEEE Intelligent Vehicles Symposium (IV)*. <https://doi.org/10.1109/IV55152.2023.10186539>

39. Wang, J., et al. (2024). Perception methods for adverse weather based on vehicle infrastructure cooperation system: A review. *Sensors*, 24(2), 374. <https://doi.org/10.3390/s24020374>

40. Kou, E., & Curran, N. (2024). Enhancing autonomous vehicle perception in adverse weather through image augmentation during semantic segmentation training (arXiv:2408.07239). arXiv. <https://doi.org/10.48550/arXiv.2408.07239>

41. Bhatt, N. P., et al. (2024). WATonoBus: Field-tested all-weather autonomous shuttle technology. In *Proceedings of the IEEE 27th International Conference on Intelligent Transportation Systems (ITSC)*. <https://doi.org/10.1109/ITSC58415.2024.10919505>

42. Rahmati, M. (2025). Edge AI-powered real-time decision-making for autonomous vehicles in adverse weather conditions (arXiv:2503.09638). arXiv. <https://doi.org/10.48550/arXiv.2503.09638>

43. Baidakova, N., Zhuravleva, T., & Klymenko, O. (2025). Analysis of innovative electromobility development and the advancement of eco-friendly transport infrastructure. *Sustainability*, 17(3), 1010. <https://doi.org/10.3390/su17031010>

44. Naiseh, M., et al. (2025). Trust, risk perception, and intention to use autonomous vehicles: An interdisciplinary bibliometric review. *AI & Society*, 40(2), 1091–1111. <https://doi.org/10.1007/s00146-024-01895-2>

45. Yang, Y., Peng, L., & Wan, D. (2025). A comparative study on the acceptance of autonomous driving technology by China and Europe: A transnational empirical analysis based on the technology acceptance model (Preprint). <https://doi.org/10.20944/preprints202508.1473.v1>

47. Shahedi, A., Dadashpour, I., & Rezaei, M. (2023). Barriers to the sustainable adoption of autonomous vehicles in developing countries: A multi-criteria decision-making approach. *Heliyon*, 9(5). <https://doi.org/10.1016/j.heliyon.2023.e15975>

48. Li, S., Zhou, R., & Huang, H. (2025). Multidimensional evaluation of autonomous driving test scenarios based on AHP-EWN-TOPSIS models. *Automotive Innovation*, 1–15. <https://doi.org/10.1007/s42154-024-00344-6>

49. Tengilimoglu, O. (2024). The readiness of road network and its implications for automated vehicle operations. https://www.researchgate.net/profile/Oguz-Tengilimoglu/publication/385411674_The_readiness_of_road_network_and_its_implications_for_automated_vehicle_operations/links/67c6a515461fb56424eff81a/The-readiness-of-road-network-and-its-implications-for-automated-vehicle-operations.pdf

50. Xia, Y., et al. (2023). Parameterized decision-making with multi-modal perception for autonomous driving (arXiv:2312.11935). arXiv. <https://doi.org/10.48550/arXiv.2312.11935>

51. Liu, Y., Li, H., & Pan, Y. (2025). Understanding perceived ride safety and trust formation in robotaxi services under day and night conditions. *Scientific Reports*, 15(1), 41798. <https://doi.org/10.1038/s41598-025-25722-w>

52. Kaye, S.-A., et al. (2021). Users' acceptance of private automated vehicles: A systematic review and meta-analysis. *Journal of Safety Research*, 79, 352–367. <https://doi.org/10.1016/j.jsr.2021.10.002>

53. Sun, M. (2024). Multi-sensor data fusion and management strategies for robust perception in autonomous vehicles. *Nuvern Applied Science Reviews*, 8(10), 59–68. <https://nuvern.com/index.php/nasr/article/view/2024-10-22>

54. Ma, Z., & Zhang, Y. (2024). Driver-automated vehicle interaction in mixed traffic: Types of interaction and drivers' driving styles. *Human Factors*, 66(2), 544–561. <https://doi.org/10.1177/00187208221088358>

55. Gamal, A., et al. (2023). An interactive multi-criteria decision-making approach for autonomous vehicles and distributed resources based on logistic systems: Challenges for a sustainable future. *Sustainability*, 15(17), 12844. <https://doi.org/10.3390/su151712844>

56. Pan, H., et al. (2024). A safe motion planning and reliable control framework for autonomous vehicles. *IEEE Transactions on Intelligent Vehicles*, 9(4), 4780–4793. <https://doi.org/10.1109/TIV.2024.3360418>

57. Huang, T., et al. (2023). V2X cooperative perception for autonomous driving: Recent advances and challenges (arXiv:2310.03525). arXiv. <https://doi.org/10.48550/arXiv.2310.03525>

58. Wei, C., Wu, G., & Barth, M. J. (2025). Cooperative perception for automated driving: A survey of algorithms, applications, and future directions. *Proceedings of the IEEE*. <https://doi.org/10.1109/JPROC.2025.3608874>

59. Nordhoff, S., de Winter, J. C. F., Kyriakidis, M., van Arem, B., & Happee, R. (2018). Acceptance of driverless vehicles: Results from a large cross-national questionnaire. *Journal of Advanced Transportation*, 2018, 5382192. <https://doi.org/10.1155/2018/5382192>

60. Kyriakidis, M., Happee, R., & de Winter, J. C. F. (2015). Public opinion on automated driving: Results of an international questionnaire. *Transportation Research Part F: Traffic Psychology and Behaviour*, 32, 127–140. <https://doi.org/10.1016/j.trf.2015.04.014>

61. Merat, N., Madigan, R., & Nordhoff, S. (2019). Human factors, user requirements, and user acceptance of automated driving systems. *Proceedings of the IEEE*, 107(2), 253–264. <https://doi.org/10.1109/JPROC.2018.2868015>

62. Shladover, S. E. (2018). Connected and automated vehicle systems: Introduction and overview. *Journal of Intelligent Transportation Systems*, 22(3), 190–200. <https://doi.org/10.1080/15472450.2017.1336053>

63. Alqahtani, T. (2025). Recent trends in the public acceptance of autonomous vehicles: A review. *Vehicles*, 7(1), 16–38. <https://doi.org/10.3390/vehicles7010002>

64. SAE International. (2021). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles (SAE Standard J3016™_202104). https://doi.org/10.4271/J3016_202104

65. Shladover, S. E., & Nowakowski, C. (2015). Regulatory challenges for automated vehicle systems. *Transportation Research Record*, 2489(1), 1–8. <https://doi.org/10.3141/2489-01>

66. Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International Journal of Services Sciences*, 1(1), 83–98. <https://doi.org/10.1504/IJSSCI.2008.017590>

67. Macharis, C., Springael, J., De Brucker, K., & Verbeke, A. (2004). PROMETHEE and AHP: The design of operational synergies in multicriteria analysis. *European Journal of Operational Research*, 153(2), 307–317. [https://doi.org/10.1016/S0377-2217\(03\)00153-5](https://doi.org/10.1016/S0377-2217(03)00153-5)

68. Tsamboulas, D., & Mikroudis, G. (2000). EFQM-based multicriteria decision-making for transport projects. *European Journal of Operational Research*, 122(2), 316–329. [https://doi.org/10.1016/S0377-2217\(99\)00095-5](https://doi.org/10.1016/S0377-2217(99)00095-5)