DOI: 10.2507/37th.daaam.proceedings.xxx

APPLICATION OF ARTIFICIAL INTELLIGENCE IN AUTONOMOUS VEHICLES: TECHNICAL FOUNDATIONS AND USER PERCEPTIONS

Danijel Zelenika & Iva Lucija Borovac

Working Paper of 37th DAAAM Symposium

This Publication has to be referred as: Zelenika, D[anijel] & Borovac I[va] L[ucija] (2026). Application of Artificial Intelligence in Autonomous Vehicles: Technical Foundations and User Perceptions, Proceedings of the 37th DAAAM International Symposium, pp.xxxx-xxxx, B. Katalinic (Ed.), Published by DAAAM International, ISBN 978-3-902734-xx-x, ISSN 1726-9679, Vienna, Austria
DOI: 10.2507/37th.daaam.proceedings.xxx

Abstract

Autonomous vehicles are among the most challenging applications of artificial intelligence (AI). However, technical reviews of these systems seldom examine how they are perceived by potential users. This paper examines the role of machine learning and deep learning in the perception, decision-making, and control of autonomous vehicles. It reviews sensing systems and data processing, including cameras, radar, LiDAR, and sensor fusion, alongside functional safety, cybersecurity, privacy, and accountability in the context of relevant standards and regulations. The review is complemented by a survey (N = 55) examining self-assessed knowledge, trust, and attitudes toward AI and autonomous vehicles, using descriptive statistical analysis. Self-assessed knowledge was moderate for AI (3.29/5) and lower for autonomous vehicles (2.38/5), while average trust was relatively low (2.45/5). The most frequently recognized benefits were a reduction in traffic accidents (38.2%), greater accessibility of transportation (32.7%), and time savings (29.1%). However, only 25.5% indicated that they would use a fully autonomous vehicle, while many expressed concerns about cybersecurity (67.3%) and privacy (60.0%). Notably, only 9.1% of respondents expected autonomous vehicles to be safer than human-driven ones, suggesting that the perceived safety potential of AI does not translate into trust. Realizing this potential requires reliable technical solutions supported by clear ethical and regulatory frameworks. Given the small and non-representative sample, the findings should be considered indicative.

Keywords: artificial intelligence; autonomous vehicles; machine learning; deep learning; computer vision; LiDAR; radar

1. Introduction

The development of computer technologies has led to vehicles increasingly relying on sensors, communication systems, and software algorithms that support the driver or take over parts of the driving task. In this context, autonomous vehicles (AVs) represent one of the most demanding examples of artificial intelligence application, as the system must perceive the traffic environment in real time, assess possible situations, predict the behavior of other traffic participants, and select safe action. Such a system simultaneously integrates computer vision, machine learning, robotics, signal processing, localization, planning, and control.

The application of artificial intelligence in such a system is not limited to a single function. AI can participate in object recognition, traffic scene segmentation, depth estimation, trajectory prediction, action selection, and the optimization of

control commands. As a result, the quality of the final system depends on the entire processing chain, from data acquisition to decision execution. Literature frequently highlights a modular architecture that separates perception, localization, prediction, planning, and control, as well as approaches that integrate individual functions into end-to-end models.

Prior research provides a solid technical foundation for understanding AI in autonomous driving, with deep learning techniques being widely explored in both modular and end-to-end approaches [1], [2]. Modular architectures separate perception, localization, prediction, planning, and control, whereas end-to-end approaches learn a direct mapping from sensor inputs to control outputs. The trade-offs between interpretability, robustness, and performance remain an open research question. Computer vision challenges, datasets, and benchmarking methods for autonomous vehicles have been investigated in [3]. Additionally, studies on multi-modal sensor fusion [4], [5] highlight that combining camera, radar, and LiDAR data can improve system robustness while introducing additional challenges related to sensor calibration, temporal synchronization, and modality mismatch.

From a safety, cybersecurity, and regulatory perspective, the development of autonomous vehicles is framed by international standards and regulation, including SAE J3016 [6], ISO 26262 [7], ISO 21448 (SOTIF) [8], ISO/SAE 21434 [9], NHTSA report [10], and EU AI Act [11], which are discussed in Section 2. While the existing body of literature provides a comprehensive technical and regulatory understanding of autonomous vehicle systems, a substantial part of the existing research remains focused on technical aspects and does not fully incorporate user-centered empirical data. Previous systematic reviews have primarily examined factors influencing public acceptance, trust, perceived risk, and willingness or intention to use autonomous vehicles [12], [13]. Recent empirical research has highlighted the relevance of cybersecurity regulation, data sharing, data usage, and privacy concerns for individuals' intentions to use autonomous vehicles [14]. This study aims to investigate the role of artificial intelligence in the development of autonomous vehicles, with a particular focus on safety, cybersecurity, ethical and privacy concerns, as well as users' perceptions of autonomous vehicles. The study also examines whether artificial intelligence is perceived as contributing to improved safety and efficiency while identifying the main concerns and challenges associated with the adoption of AI-driven vehicles.

To address the problem outlined above, this paper combines two complementary approaches. First, an overview of the scientific and technical literature is provided to explain the fundamental concepts of artificial intelligence, machine learning, and deep learning, and to describe how these methods are applied within the sensor and data-processing pipeline of autonomous vehicles (cameras, radar, LiDAR, and sensor fusion), as well as the associated functional safety, cybersecurity, privacy, and accountability frameworks. The second approach is based on a survey examining respondents' self-assessed knowledge, trust, and attitudes toward artificial intelligence and autonomous vehicles. The data collected was analyzed using descriptive statistics. By combining theoretical analysis with survey-based evidence, this study examines the hypothesis that respondents perceive artificial intelligence as improving the safety and efficiency of autonomous vehicles, while also recognizing technical and ethical challenges that must be addressed for the technology to gain broader public trust and acceptance.

2. Artificial Intelligence in Autonomous Vehicles

Artificial intelligence can be viewed as a field of computer science that develops methods and systems capable of performing tasks that, in their usual form, require certain abilities associated with human intelligent behavior, such as reasoning, pattern recognition, learning, and decision-making [15]. An important characteristic of the application of AI in vehicles is the requirement for real-time operation. The model must not only be sufficiently accurate but must also produce a result within a sufficiently short time to allow the vehicle to respond to changes in the surrounding situation. In addition, the output must be sufficiently stable and predictable to be integrated into the vehicle's safety concept. For this reason, the development of autonomous systems differs from that of many conventional artificial intelligence applications: while a classifier error in an internet application may be inconvenient, an incorrect object assessment during driving can have immediate safety consequences.

Machine learning represents a set of methods in which a model learns patterns from data rather than having all rules explicitly defined manually. In supervised learning, the model is trained on examples for which the target values are known, such as images labelled with object classes. In unsupervised learning, the goal is to identify the underlying structure of the data without explicitly provided labels, while reinforcement learning methods optimize an agent's behavior based on rewards and penalties. Deep learning involves the use of multilayer neural networks to learn complex patterns and features from data. Convolutional neural networks are particularly important for image processing, while recurrent architectures and newer models based on attention mechanisms can be used for time-series and sequential processing. The main advantage of deep learning in autonomous driving is its ability to automatically extract useful features from large amounts of data. Computer vision uses deep models for object detection, semantic and instance segmentation, depth estimation, object tracking, and traffic scene understanding. For example, a camera can provide detailed information about the color and texture of a traffic sign, while a deep learning model can use a sequence of images to determine whether a particular object is a pedestrian and estimate its position relative to the road. In practice, these models are often complemented by additional sensors, as a single image does not provide equally reliable information under all conditions.

A typical autonomous driving architecture can be described as a sequence in which sensors collect data, the perception module extracts objects and scene structure, localization determines the vehicle's position, prediction estimates the future behavior of other road users, planning selects the trajectory and action, and control converts the selected trajectory into

Working Paper of 37th DAAAM Symposium

commands for the vehicle. Cameras are among the most widely used sensors in autonomous driving systems because they provide rich visual information about color, texture, traffic signs, traffic lights, and the shape of objects. Multi-camera configurations enable a wider field of view and the creation of spatial representation by combining projections from different viewing angles. Deep learning-based computer vision models are frequently used to process camera data. Radar uses radio-frequency waves to detect objects and estimate their position and relative velocity. Compared with cameras, radar has the advantage of directly measuring the Doppler shift and providing greater reliability under certain reduced-visibility conditions. Reviews of contemporary methods show that radar can be particularly useful for estimating object dynamics, although its data are often sparser, less precise, and less spatially detailed than images or LiDAR point clouds. LiDAR (Light Detection and Ranging) measures distances using laser pulses and generates a three-dimensional point cloud. This type of data provides direct information about the three-dimensional structure of the scene, which is useful for localization, object detection, and environmental reconstruction. LiDAR is particularly valuable when precise estimation of the geometry of the space surrounding the vehicle is required. Sensor fusion refers to the combination of information from different sensors to obtain a more reliable representation of the surrounding environment. The basic idea is that the limitations of one sensor can be mitigated by information provided by another. Cameras provide semantically rich visual information, radar provides reliable information about relative velocity, while LiDAR offers a geometrically precise 3D representation. Multimodal approaches therefore represent an important direction in the development of autonomous vehicle perception systems.

Beyond the perception and planning algorithms themselves, the use of AI in vehicles is shaped by safety, cybersecurity, and accountability requirements that govern how these algorithms are developed, validated, and approved. SAE J3016 [6] defines six levels of driving automation, from Level 0 to Level 5, and distinguishes systems in which the human driver remains responsible for monitoring the driving environment from those in which the automated driving system performs the entire dynamic driving task under defined conditions. This distinction determines who is expected to monitor the environment and who must act when the system reaches the limits of its capabilities. Functional safety is addressed by ISO 26262 [7], which provides a framework for identifying hazards caused by malfunctions of electrical and electronic systems and for assigning safety requirements according to the risk involved. However, an AI-based perception module can also be unsafe without any hardware or software fault, for example when a neural network fails to detect an unusual object or when a sensor operates beyond its performance limits. This class of risk is covered by ISO 21448 (SOTIF) [8], which addresses hazards arising from the intended functionality and its performance limitations. It is particularly relevant for machine-learning components, whose behavior cannot be fully specified in advance and whose interpretability and robustness remain open issues [1], [2].

Connected and automated vehicles also introduce new attack surfaces, as they depend on communication interfaces, software updates, and continuous sensor data. ISO/SAE 21434 [9] addresses this by requiring cybersecurity to be managed throughout the lifecycle of road vehicles, including the analysis of threats and the assessment of associated risks, while the NHTSA best practices [10] recommend a layered, risk-based approach to protecting vehicle systems. Cybersecurity is closely related to privacy, since continuously collect camera, location, and sensor data about their occupants and surroundings. Empirical research indicates that cybersecurity regulation, data sharing, and data usage influence individuals' intentions to use autonomous vehicles [14].

The EU AI Act [11] introduces a risk-based regulatory framework in which high-risk AI systems are subject to requirements such as risk management, data governance, transparency, human oversight, robustness, and cybersecurity. Accountability for the behavior of an autonomous vehicle is not, however, a purely technical question. When decisions are made by a learned model, responsibility may be shared among developers, manufacturers, owners, and operators, and the limited interpretability of deep models [1], [2] makes this allocation more difficult. Safety, cybersecurity, privacy, and accountability are therefore the aspects examined from the users' perspective in the survey presented in the following section.

3. The study: Survey of User Perceptions of Artificial Intelligence and Autonomous Vehicles

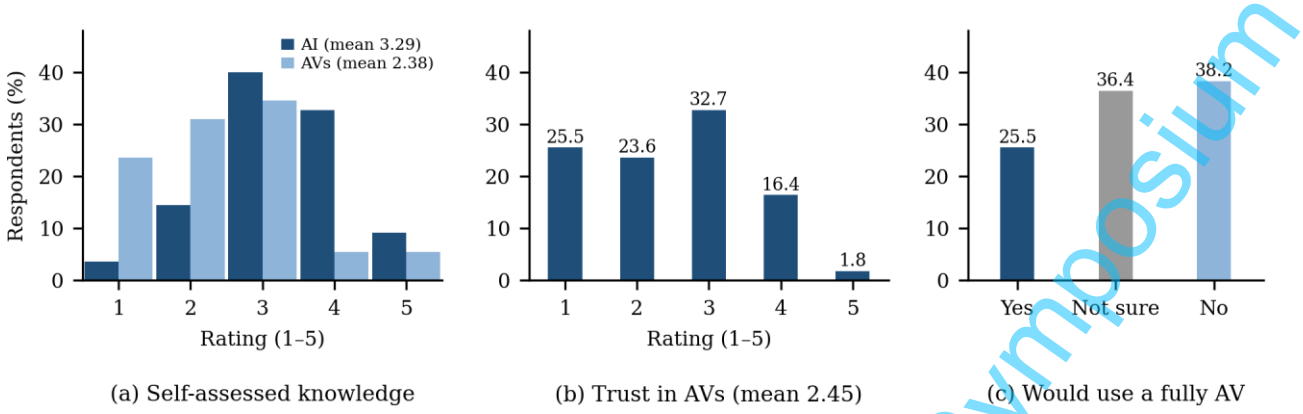
The empirical part of this study was conducted through a survey, designed to complement the literature-based analysis of the preceding sections with user-centered evidence. It was organized into thematic blocks covering demographic data, prior familiarity with the concept of an autonomous vehicle, self-assessed knowledge of AI and autonomous vehicles, attitudes toward the societal impact of AI, willingness to use autonomous vehicles, trust in their safety, familiarity with sensor technologies, perceived cybersecurity and privacy risks, and expectations regarding future adoption. Several items allowed multiple responses; for these, the reported percentages reflect the share of respondents selecting each option within the observed sample rather than a distribution summing to 100%.

Data were analyzed using descriptive statistics: percentage shares for categorical variables and mean scores (on a 1–5 scale) for items assessing self-reported knowledge and trust. Given the non-probabilistic sampling method and the resulting demographic composition, the results are not intended to be representative of the general population; they describe the attitudes of the specific group of respondents who participated in this survey (N = 55).

The gender distribution of the sample was relatively balanced. The age structure was skewed toward younger respondents, with older age groups less represented, which should be considered when interpreting the results. Regarding education, undergraduate students formed the largest group, followed by graduate students and respondents with completed secondary education. Technical sciences and economics were the most frequently reported fields of study.

Working Paper of 37th DAAAM Symposium

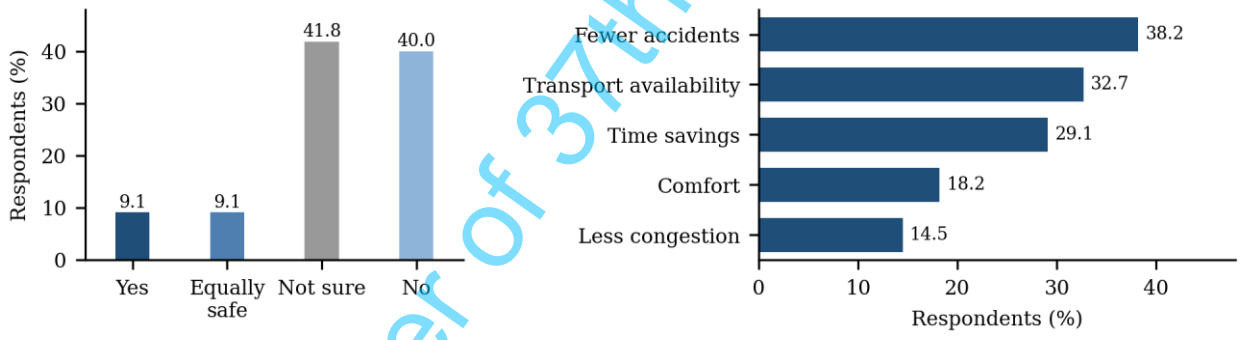
Most participants were students, followed by employed individuals, while unemployed respondents accounted for the smallest share.



(a) Self-assessed knowledge (b) Trust in AVs (mean 2.45) (c) Would use a fully AV

Fig. 1. (a) Self-assessed knowledge of AI and AVs; (b) trust in AVs; (c) willingness to use a fully autonomous vehicle.

Regarding respondents' knowledge and trust, most participants had heard of autonomous vehicles before the survey, but they rated their knowledge of AVs considerably lower than their knowledge of AI. Fig. 1a compares the two self-assessments. Self-assessed knowledge of AI was moderate (mean 3.29/5): the most frequent rating was 3 (40.0%), followed by 4 (32.7%) and 2 (14.5%), while the highest rating of 5 was given by only 9.1% and the lowest rating of 1 by 3.6% of respondents. The distribution for AVs is shifted toward lower ratings (mean 2.38/5): ratings of 3 (34.5%), 2 (30.9%) and 1 (23.6%) dominate, whereas ratings of 4 and 5 account for only 5.5% each. Trust in AVs was similarly low (mean 2.45/5), with the distribution shown in Fig. 1b. Rating 3 was the most common (32.7%), while ratings of 1 (25.5%) and 2 (23.6%) together accounted for 49.1% of respondents. Rating 4 was given by 16.4%, and the highest rating by only 1.8%. This pattern was also reflected in respondents' willingness to use fully autonomous vehicles: as shown in Fig. 1c, only 25.5% of respondents would use a fully autonomous vehicle if it were available, while 36.4% were unsure and 38.2% would not.



(a) Will AVs be safer than humans? (b) Perceived advantages of AVs

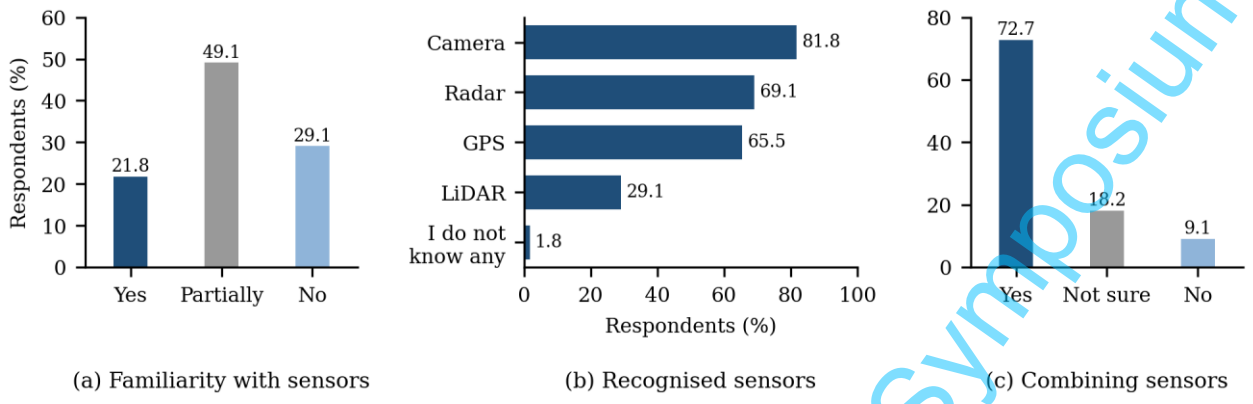
Fig. 2. (a) Expectation of whether AVs will be safer than human-driven vehicles; (b) perceived advantages of AVs.

With respect to perceived safety and benefits, respondents were cautious about whether AVs will be safer than human-driven vehicles, as shown in Fig. 2a: 41.8% were unsure and 40.0% answered "no", while only 9.1% answered "yes" and a further 9.1% expected equal safety. Nevertheless, respondents recognized several advantages of AVs, as shown in Fig. 2b. The reduction of traffic accidents was selected most frequently (38.2%), followed by greater availability of transport (32.7%), time savings (29.1%), greater travel comfort (18.2%), and less traffic congestion (14.5%). Multiple answers were allowed, while only a very small share of respondents recognized none of the advantages offered. Overall, a reduction in accidents is recognized as a potential benefit by a substantial minority of respondents, but only a small share expects AVs to actually outperform human drivers, suggesting that perceived potential alone does not establish trust in the final system.

Regarding sensors and technical understanding, respondents showed relatively limited familiarity with the sensing technologies used in AVs. As shown in Fig. 3a, only 21.8% of respondents reported being familiar with these sensors, while 49.1% were partially familiar and 29.1% were not familiar with them. When asked to identify specific sensors, as shown in Fig. 3b, cameras were the most widely recognized (81.8%), followed by radar (69.1%) and GPS (65.5%). In contrast, LiDAR was recognized by only 29.1% of respondents, while just 1.8% were unfamiliar with all the listed sensors. Despite this limited technical familiarity, a clear majority of respondents (72.7%) believed that combining multiple

Working Paper of 37th DAAAM Symposium

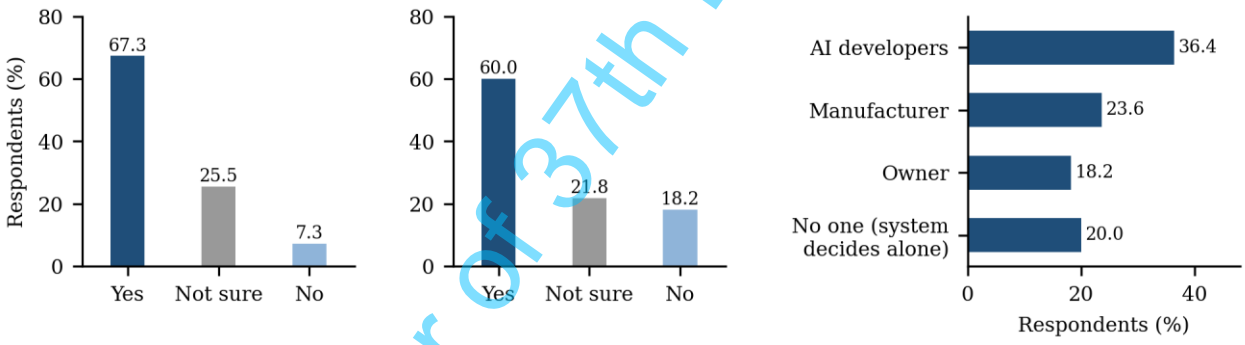
sensors improves the safety of AVs. As shown in Fig. 3c, 18.2% were unsure and 9.1% disagreed with this statement, suggesting an intuitive understanding of the importance of sensor redundancy and complementarity even among respondents with limited detailed technical knowledge.



(a) Familiarity with sensors (b) Recognised sensors (c) Combining sensors

Fig. 3. (a) Familiarity with the sensors used in AVs; (b) recognition of individual sensors (multiple answers); (c) belief that combining several sensors increases safety.

Concerning security, privacy and responsibility, 67.3% of respondents were concerned about a possible hacker attack, as shown in Fig. 4a, 25.5% were unsure and only 7.3% were not concerned. Similarly, 60.0% believe that AVs may threaten privacy through data collection, as shown in Fig. 4b, 21.8% were unsure and 18.2% do not consider the risk significant. Both concerns are thus shared by a clear majority of the sample, whereas only a small minority dismisses them. When asked who should be responsible for an accident, as shown in Fig. 4c, the largest share named AI developers (36.4%), followed by the vehicle manufacturer (23.6%) and the vehicle owner (18.2%), while 20.0% held that no one is directly responsible because the system decides on its own. Several open-ended answers emphasized that responsibility should be determined according to the specific circumstances.

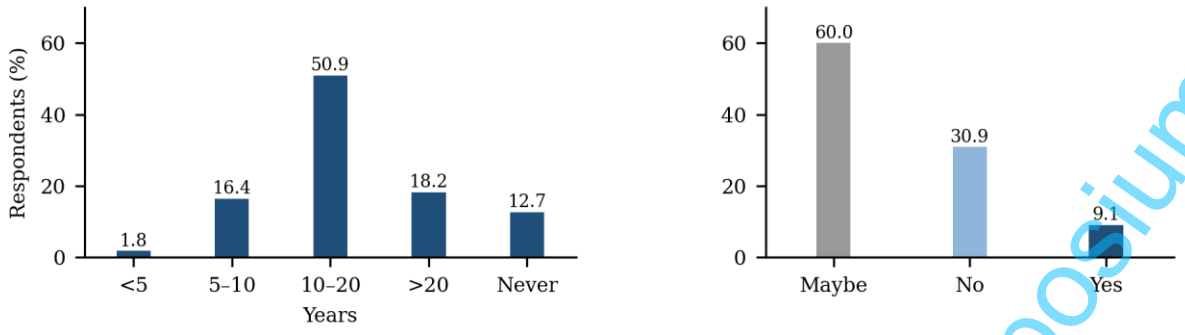


(a) Hacking concern (b) Privacy concern (c) Responsibility

Fig. 4. (a) Concern about a hacker attack; (b) perceived risk to privacy; (c) responsibility for an accident.

Looking at expectations of future adoption, as shown in Fig. 5a, half of the respondents (50.9%) expect wide adoption of fully autonomous vehicles in 10–20 years, 18.2% in more than 20 years and 16.4% in 5–10 years, while 12.7% do not expect it at all and only 1.8% expect it within five years. The prevailing expectation is therefore a medium- to long-term horizon rather than imminent adoption. When asked whether they would recommend AVs to others, as shown in Fig. 5b, 60.0% answered “maybe”, 30.9% “no” and only 9.1% “yes”. Open-ended comments reflect a mixture of interest (practicality, time savings, accessibility of transport) and caution (cost, distrust, insufficient research and a wish for humans to retain control over driving).

Working Paper of 37th DAAAM Symposium



(a) Expected wide adoption

(b) Would recommend AVs

Fig. 5. (a) Expected time of wide adoption of fully autonomous vehicles; (b) willingness to recommend AVs.

4. Discussion

The results show that the safety potential of AI is recognized by part of the respondents but does not translate into trust. Fewer traffic accidents was the most frequently selected benefit (38.2%), yet only 9.1% of respondents expected AVs to be safer than human-driven vehicles, only 25.5% would use a fully autonomous vehicle, and 49.1% gave low trust ratings (1 or 2). Recognizing a possible benefit therefore does not imply confidence in the technology; between technical capability and acceptance lies a layer of perceived risk, responsibility and personal safety.

The strong concern about hacking (67.3%) and privacy (60.0%) is consistent with the growing connectivity of modern vehicles, which makes cybersecurity and data protection part of the overall safety of the system. The distribution of answers on responsibility, with the largest share assigned to AI developers and manufacturers but a notable share holding that no one is responsible, points to the importance of transparent development, testing and a clear allocation of responsibility. Users are likely to need understandable information on what the system can do, under which conditions it operates and how it behaves when it reaches the limits of its capabilities. Interestingly, although only 21.8% felt well informed about sensors, 72.7% believe that combining several sensors increases safety, which indicates an intuitive understanding of redundancy and complementarity, the principle on which sensor fusion in AV perception is based.

The study has several limitations. The sample is small (N = 55) and not demographically balanced: younger respondents, students and respondents from technical fields and economics predominate, which may affect both their interest in the topic and their self-assessed knowledge. The results therefore cannot be generalized to the whole population. In addition, the survey is based on attitudes and self-assessments, which are not equivalent to an objective test of technical knowledge, and attitudes toward technology may change after direct experience with a concrete system. Only descriptive statistics were used, so relationships between knowledge, trust and willingness to use AVs were not tested, and the questionnaire did not ask separately about individual levels of driving automation. Future research should use a larger and more representative sample, compare age groups, include questions on levels of automation and apply inferential analysis. It would also be useful to complement attitudes with measurable technical indicators, such as detection accuracy, execution time and robustness of perception and sensor-fusion models on publicly available datasets.

5. Conclusion

This study examined how respondents perceive artificial intelligence and autonomous vehicles. Self-assessed knowledge of AI was moderate (3.29/5), whereas knowledge of AVs was lower (2.38/5), and trust in AVs remained low (2.45/5). Respondents recognize the potential benefits of AVs, above all fewer traffic accidents, greater availability of transport and time savings, but only a quarter would use a fully autonomous vehicle, and most were unsure or skeptical about whether AVs will be safer than human drivers.

Concerns about cybersecurity (67.3%) and privacy (60.0%), together with unresolved views on who is responsible for an accident, show that acceptance depends not only on technical performance but also on transparency, data protection and clearly defined responsibility. The results therefore only partially support the hypothesis: respondents recognize that AI could improve the safety and efficiency of autonomous vehicles and are clearly aware of the associated technical and ethical challenges, but most do not yet expect AVs to be safer than human drivers. As the technical review indicates, such improvements do not follow from the use of AI itself, but from the whole system of sensors, algorithms, safety mechanisms, testing and responsible use. Given the limitations of the sample, the findings should be treated as indicative. Wide adoption is most often expected in 10–20 years (50.9%), which suggests a gradual rather than abrupt introduction of automated functions, accompanied by growing user trust and suitable regulatory frameworks.

6. References

Working Paper of 37th DAAAM Symposium

[1] S. Grigorescu, B. Trasnea, T. Cocias, and G. Macesanu, "A survey of deep learning techniques for autonomous driving," *J. Field Robot.*, vol. 37, no. 3, pp. 362–386, Nov. 2019, doi: 10.1002/rob.21918.
[2] J. Zhao, Y. Wu, R. Deng, S. Xu, J. Gao, and A. Burke, "A Survey of Autonomous Driving from a Deep Learning Perspective," *ACM Comput. Surv.*, vol. 57, no. 10, pp. 1–60, Oct. 2025, doi: 10.1145/3729420.
[3] J. Janai, F. Güney, A. Behl, and A. Geiger, "Computer Vision for Autonomous Vehicles: Problems, Datasets and State of the Art," Mar. 2021.
[4] Y. Cui *et al.*, "Deep Learning for Image and Point Cloud Fusion in Autonomous Driving: A Review," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 2, pp. 722–739, 2022, doi: 10.1109/TITS.2020.3023541.
[5] K. Huang, B. Shi, X. Li, X. Li, S. Huang, and Y. Li, "Multi-modal Sensor Fusion for Auto Driving Perception: A Survey," Dec. 2024.
[6] T. SAE, "Definitions for terms related to driving automation systems for on-road motor vehicles," *SAE Standard J*, vol. 3016, p. 2016, 2016.
[7] ISO 26262, *Road Vehicles—Functional Safety*. ISO: Geneva, 2011.
[8] ISO 21448, *Road Vehicles—Safety of the Intended Functionality*. ISO: Geneva, 2022.
[9] ISO/SAE 21434, "Road vehicles — Cybersecurity engineering," Geneva, 2021.
[10] NHTSA, "Cybersecurity Best Practices for the Safety of Modern Vehicles," Washington, D.C., 2022.
[11] European Parliament and Council of the European Union, "Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (AI Act)," Brussels, 2024.
[12] T. Zhang, W. Zeng, Y. Zhang, D. Tao, G. Li, and X. Qu, "What drives people to use automated vehicles? A meta-analytic review," *Accid. Anal. Prev.*, vol. 159, p. 106270, 2021, doi: https://doi.org/10.1016/j.aap.2021.106270.
[13] S.-A. Kaye, K. Somoray, D. Rodwell, and I. Lewis, "Users' acceptance of private automated vehicles: A systematic review and meta-analysis," *J. Safety Res.*, vol. 79, pp. 352–367, 2021, doi: https://doi.org/10.1016/j.jsr.2021.10.002.
[14] S. Khalid Khan, N. Shiwakoti, P. Stasinopoulos, Y. Chen, and M. Warren, "Exploratory factor analysis for cybersecurity regulation and consumer data in autonomous vehicle acceptance: Insights from four OECD countries," *Transp. Res. Interdiscip. Perspect.*, vol. 25, p. 101084, 2024, doi: https://doi.org/10.1016/j.trip.2024.101084.
[15] S. J. . Russell *et al.*, *Artificial intelligence : a modern approach*. Pearson, 2021.

Working Paper of 37th DAAAM Symposium