Technical fundamentals and application prospects of self-driving vehicles: from sensors to civil and military mobility

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Abstract: Self-driving vehicles represent one of today's most innovative areas of technological development, transforming transportation, logistics, and warfare simultaneously. The aim of this study is to present the technical content of autonomous systems, with a particular focus on development milestones, key technologies, and the strategies of leading industry players. We analyze in detail the role of sensors—LiDAR, radar, cameras, and ultrasound—as well as the importance of sensor fusion and artificial intelligence-driven decision-making. We also discuss navigation and localization solutions, which are essential for safe transportation. In the field of civilian use, the main areas of focus are improving transport safety, sustainable urban mobility, and logistics optimization, while military applications are opening up new horizons in the areas of logistics convoys, reconnaissance systems, and autonomous combat vehicles. The analysis emphasizes that the future success of autonomous technologies will be determined by the combined development of technical advances, regulatory frameworks, and public trust.y

Keywords: autonomous vehicles, sensor reliability, artificial intelligence, cybersecurity, technical challenges

1 Introduction

Autonomous vehicles (AVs) represent one of the most significant technological developments of our time, fundamentally reshaping the future of transportation and mobility. In recent decades, the increasingly close integration of the automotive industry and information technology has led to the creation of complex systems capable of continuously sensing the traffic environment, processing data, and autonomously making decisions and controlling vehicles. The technical background behind self-driving technologies is multidisciplinary: robotics, artificial intelligence, sensor technology, remote sensing, and communication networks are all key elements in the operation of these systems (Thrun, 2010; Anderson et al., 2016). Several factors are driving these developments. On the one hand, improving road safety and reducing the number of road accidents is a priority, as a significant proportion of road accidents are attributable to human error (Fagnant & Kockelman, 2015). On the other hand, increasing mobility needs, social expectations for sustainable transport, and the need to improve logistical efficiency are also key factors. In addition, technology is playing an increasingly important role not only in civilian transport, but also in military and industrial applications, for example in the form of autonomous logistics convoys or reconnaissance vehicles (Lin, 2016). The aim of this study is to analyze the technical content and development of self-driving vehicles, with a particular focus on key technologies, manufacturer strategies, the functioning of sensor systems, and civil and military applications. The structure of the material first reviews the milestones and technological levels of development, then analyzes the technical components—sensors, navigation systems, and artificial intelligence. This is followed by a presentation of the global manufacturing environment and industry players, and the study concludes with a summary of the opportunities and challenges presented by civilian and military applications. The aim of the analysis presented is to provide a comprehensive picture of how self-driving vehicles will shape the future of transportation and what technical, economic, and social issues will arise during their introduction..

2 Development and technological milestones

The development of self-driving vehicles is the result of decades of research and industrial effort, closely linking robotics, computer science, and transportation engineering. Initial experiments began in the 1980s, when research teams at Carnegie Mellon University and Mercedes-Benz developed prototypes that were capable of limited lane tracking and obstacle avoidance (Dickmanns & Zapp, 1987). These early systems still relied heavily on simplified models of the environment and a combination of image processing and rule-based algorithms. Development gained new momentum in the early 2000s with the DARPA Grand Challenge competitions, which aimed to encourage the development of autonomous vehicle applications in the field. In the first competition in 2004, none of the vehicles were able to complete the course, but even then, the integration of sensors, navigation, and control algorithms represented a significant step forward (Thrun et al., 2006). During the 2005 and 2007 competitions, the participating vehicles were already capable of traveling tens of kilometers in complex environments, demonstrating the reality of autonomous driving. Starting in 2010, development focused on the automation levels (0–5) defined by the SAE, which provide a uniform framework for evaluating the technology. Level 2 systems (partial automation) were already capable of controlling acceleration and steering simultaneously, but driver supervision was still required. Level 3 (conditional automation) and above allow the vehicle to drive autonomously under certain conditions, while level 5 represents full autonomy without human intervention (SAE International, 2021). Among the industry milestones, the Google/Waymo project plays a prominent role, as it was one of the first companies to demonstrate the feasibility of self-driving systems in a real-world environment, having already covered millions of kilometers in road conditions (Waymo, 2020).

Similarly significant is Tesla's Autopilot system, which has made Level 2 driver assistance features widely available, although its operation is accompanied by safety concerns and legal disputes (Favarò et al., 2017). Uber and other mobility service providers have also conducted significant experiments in the field of robotaxi technologies, which, however, have raised serious ethical and regulatory challenges. Another key element of development is the evolution of the regulatory and legal environment. While experimental permits and legal frameworks for self-driving tests have gradually emerged in the United States and Europe, China and other Asian countries are encouraging development through large-scale government programs (Liu & Xu, 2021). However, issues of standardization, data security, and liability remain unresolved. Future developments will be determined by deeper integration of artificial intelligence and machine learning. Self-driving systems are increasingly capable of making real-time decisions based on the processing of large data sets and adapting to changes in the traffic environment in an adaptive manner. Cloud-based infrastructure, 5G communications, and vehicle-to-everything (V2X) technologies will also play a key role in the coming decade, as they enable cooperation between vehicles and the optimization of traffic systems (Campolo et al., 2017). The development of self-driving vehicles has progressed in recent decades from prototype-level experiments to widely tested systems that are partially available on the commercial market. These technological milestones not only signal advances in technical capabilities, but also indicate that autonomous transport is moving closer to mass adoption, although the timing of this remains dependent on a number of technological, regulatory, and societal factors.

The development of autonomous vehicles (AVs) has made spectacular progress in recent years, both in academia and industry. This development covers several key areas: end-to-end architectures, environment perception and representation, path planning and decision-making algorithms, and simulation and validation methods. Foundation models and systems based on historical prediction are also becoming increasingly prominent. The following summary provides an overview of the most important technical achievements and challenges based on ten studies published between 2023 and 2025.

The goal of end-to-end (E2E) systems is to guide the flow of information from raw sensor data to control commands through a single learning architecture. This significantly reduces the number of interface errors arising from modular designs and enables global optimization. Lan and Hao's (2023) review shows how this is being applied by industry players such as Tesla FSD V12 and Momenta, as well as in academic research. Common features include the use of Bird's Eye View (BEV) representation and occupancy networks, which transform data from various sensors (camera, lidar, radar) into a unified map. The main challenges are handling rare traffic situations, minimizing computational requirements, and verifying safety. Research presented at CVPR 2025 further expanded the capabilities of end-to-end models by integrating historical sensor data. This enables the system to not only infer from the current environment, but also take into account past dynamics, resulting in more accurate predictions and more natural path planning (Bridging Past and Future, 2025).

The development of environmental representation is key to the safe operation of AVs. 2D BEV models are effective but limited in their handling of vertical structures. 3D occupancy perception offers a new approach that models the environment in voxelized space. Xu et al. (2024) have detailed how information fusion techniques can be applied to combine camera, lidar, and radar data. Advanced architectures, such as 3D convolutional networks and transformer modules, enable the system to create a probabilistic map of the environment's occupancy. Challenges include high computational requirements, annotation costs, and sensor limitations (e.g., poor lighting conditions, occlusion).

Collaborative perception has opened up new perspectives in environmental sensing. Technologies such as Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Everything (V2X) communication enable vehicles to exchange data with each other and with infrastructure to detect obstacles that their own sensors cannot see. The 2024 review highlights the importance of open datasets and benchmarks, which are essential for developing and comparing algorithms (Collaborative Perception Datasets, 2024).

In the field of path planning, in addition to classic algorithms such as Dijkstra and A*, sampling-based methods such as RRT and PRM, as well as machine learning-based approaches, have gained greater prominence. According to a 2024 review by Reda et al. (2024), the goal of newer systems is to integrate path planning with motion prediction so that vehicles can anticipate the behavior of other road users (Path Planning Algorithms, 2024). Waymo's ModeSeq system, developed for the 2024 challenge, presents a multimodal approach to motion prediction. Using a transformer-based architecture, it generates multiple possible future trajectories whose diversity and accuracy exceed those of traditional RNN-based models. This capability is particularly useful in congested urban environments, where multiple future scenarios must be considered (ModeSeq, 2024). Closely related to this, the BehaviorGPT model simulates the behavior of traffic agents using generative methods. This allows realistic scenarios to be created in which autonomous systems can be stress tested. Traffic simulation is thus not only a validation tool, but also an active area of research (BehaviorGPT, 2024).

Decision-making in autonomous vehicles is developing along two main lines. Rule-based and optimization-based methods, such as Markov Decision Processes or search algorithms, are explainable and deterministic, but have limited adaptability to dynamic environments. Data-driven methods, such as imitation and reinforcement learning, are more flexible but require large amounts of data and extensive simulation environments. The 2023 review article highlights that the three levels of decision-making—strategic, tactical, and operational—require different approaches (Zhang, Li, & Wang, 2023). According to a more detailed summary from 2025, the future lies in hybrid systems that combine the transparency of rule-based methods with the adaptability of data-driven models (Hu, Zhang, Li, & Zhao, 2025). Validation and verification remain a key issue: systems must be tested not only in average situations, but also in rare, safety-critical scenarios.

The use of foundation models in autonomous vehicle research promises a paradigm shift. These large-scale, multimodal models are capable of integrating knowledge from different sources, such as sensor data, traffic situations, and simulations. According to the review study, the strength of foundation models lies in their adaptability and generalization, which enable systems to operate robustly even in new environments (Foundation Models in Autonomous Driving, 2025). The biggest challenges are computational resource requirements, lack of transparency, and safety verification. It is clear that self-driving vehicle technology is on an integrated development path. End-to-end systems simplify the architecture, 3D occupancy perception offers more accurate environmental models, the integration of path planning and motion prediction improves safety, while collaborative perception and generative models open up new possibilities for validation. In decision-making, hybrid approaches and foundation models are the future, capable of balancing explainability, flexibility, and robustness. The main challenges in the coming years will be scalability, meeting real-time requirements, and compliance with safety standards.

3 Technical content and key technologies

The operation of self-driving vehicles is based on complex hardware and software architectures that enable continuous environmental sensing, data processing, and real-time decision-making. The most important components of the system include sensors, algorithms for sensor fusion and data processing, navigation and localization solutions, and control systems based on artificial intelligence. The goal of self-driving vehicle sensor systems is to cover the entire spectrum of the traffic environment. One of the most important sensor types is LiDAR (Light Detection and Ranging), which uses laser beams to create a highly accurate, three-dimensional map of the vehicle's surroundings. The advantage of LiDAR is its high resolution and reliable distance measurement, but its disadvantages are its high cost and sensitivity to adverse weather conditions (Svoboda et al., 2016, Ghraizi, 2023). Radar technology is used to determine distance and speed and is particularly reliable in poor visibility conditions. Ultrasonic sensors provide support at short range, primarily in parking and low-speed maneuvering situations. Cameras provide visual information that is key to object recognition, traffic sign and signal identification, and lane marking detection. The disadvantage of cameras is that they require high computing power and are sensitive to changes in lighting conditions (Janai et al., 2020).

Autonomous driving systems do not rely on a single sensor, but use a sensor fusion approach that combines data from different sensors to increase redundancy and reliability. Sensor fusion allows the vehicle to create a more accurate and robust environmental model, reducing errors caused by the weaknesses of individual sensors (Khaleghi et al., 2013). Based on the processed data, the system is able to detect and track objects and predict their movement, which is essential for safe maneuvering. Accurate positioning is one of the biggest challenges for self-driving vehicles. Global positioning systems (GPS) alone do not provide sufficient accuracy, so a combination of HD (high-definition) maps and real-time localization algorithms (e.g., SLAM – simultaneous localization and mapping) is required. Such systems are capable of determining the position of a vehicle with centimeter accuracy, while continuously updating the map of the environment to reflect changing traffic and infrastructure conditions (Levinson et al., 2007).

The central element of autonomous driving systems is the application of artificial intelligence (AI) and machine learning. Neural networks, especially convolutional neural networks (CNNs), play a key role in image processing, object recognition, and interpreting traffic situations (Grigorescu et al., 2020). Decision-making modules are responsible for planning responses to different traffic situations, including route planning, obstacle avoidance, and safe vehicle control. Real-time control requires high-performance hardware platforms. Manufacturers such as Nvidia and Intel/Mobileye have developed special chip architectures capable of processing large amounts of sensor data and running AI algorithms in real time. This hardware-software integration enables the responsiveness and safe operation of self-driving vehicles. It can be concluded that the technological background of self-driving vehicles is extremely complex and relies on the close cooperation of various sensors, algorithms, and control systems. The direction of development is determined by the ever-deeper integration of artificial intelligence, the development of sensor fusion solutions, and the application of high-precision navigation systems. The synergy of the technical components ensures that self-driving vehicles will be able to operate safely and efficiently in both civil and military transport systems in the future.

4 Manufacturers and industry players

The development of self-driving vehicles has led to global industry competition, in which car manufacturers, technology companies, and startups all play a decisive role. The market is characterized by the fact that traditional automotive companies are constantly expanding their research and development activities, while players in the technology sector are shaping the competitive environment with new approaches and innovative software solutions. Among traditional car manufacturers, Tesla stands out with its Autopilot and Full Self-Driving (FSD) systems, which provide the most widely available, commercially available partial self-driving functions (Shladover, 2018). Although Tesla's system represents level 2 automation according to the SAE classification, the company is seeking to gradually expand the range of functions through continuous software updates. Among European manufacturers, Mercedes-Benz was the first to receive official approval in Germany in 2021 for the introduction of a Level 3 autonomous driving system (Drive Pilot) on public roads, which can be considered a milestone in terms of legal and technological recognition (Mercedes-Benz, 2021). Volkswagen and BMW are also pursuing ambitious development programs focused on shared mobility and robotaxi services. In the US market, General Motors is developing self-driving vehicles through its subsidiary Cruise, which are already in test operation in several major cities.

In the technology sector, Waymo is considered one of the market's biggest innovators. The company, which spun off from Google, was among the first to complete millions of kilometers of autonomous test drives and currently operates robotaxi services in the United States (Waymo, 2020). The Baidu Apollo program plays a similar role in China, with extensive government support and strategic partnerships (Liu & Xu, 2021). Although Apple officially releases little information, it has been actively testing its self-driving systems for years, which are linked to the company's development program known as Project Titan. Nvidia and Intel/Mobileye tend to offer hardware- and software-based solutions, such as high-performance AI processors and driver assistance algorithms, which enable OEMs to integrate autonomous systems (Gavrilut et al., 2020). Startups play a key role in the global technology ecosystem. Aurora, Zoox (acquired by Amazon), and Nuro are developing specialized self-driving solutions that focus specifically on freight and urban logistics. These companies are often more agile and risk-taking than large corporations, enabling them to respond more quickly to new market demands. Players involved in the development of autonomous vehicles have also emerged in the military sector. The US Department of Defense (DoD) is funding several projects targeting self-driving logistics convoys and reconnaissance vehicles (Defense Science Board, 2016). Israeli and European companies are also actively working on autonomous vehicles for military use, such as unmanned combat vehicles. The industry is highly globalized, with American and Chinese players dominating, but Europe and Japan are also active participants. The competition is not only technological, but also has economic and geopolitical significance, as self-driving vehicles are strategic pillars of the mobility infrastructure of the future. According to market forecasts, the global market for self-driving vehicles could reach hundreds of billions of dollars by 2030 (MarketsandMarkets, 2020). This industry is not only transforming car manufacturing, but also logistics, urban transport, the insurance sector, and the regulatory environment.

5 Possibilities and uses (civilian and military)

The development of self-driving vehicles is not only a technological innovation, but also offers comprehensive social, economic, and safety opportunities. Autonomous systems, which are used in both civilian transportation and military applications, have the potential to transform mobility structures, improve efficiency, and increase safety. At the same time, both areas present serious challenges and risks that affect the widespread introduction of the technology.

One of the greatest promises of self-driving vehicles is improved road safety. More than 90% of road accidents are attributable to human error, so autonomous systems have the potential to significantly reduce the number of deaths and injuries (National

Highway Traffic Safety Administration [NHTSA], 2017). Self-driving vehicles are capable of making the right decisions in situations where human drivers would hesitate or make mistakes, thanks to the rapid response times provided by sensors and algorithms. In urban transport, autonomous systems can contribute to the development of mobility services, for example through the introduction of robotaxi fleets and self-driving buses. These solutions can reduce traffic congestion, increase the utilization of transport infrastructure, and support sustainable urban mobility concepts (Litman, 2020). Self-driving logistics vehicles can also revolutionize the freight transport sector by optimizing route planning, reducing labor requirements, and improving energy efficiency. Their environmental potential is also of particular importance. Autonomous vehicles can optimize the entire transport network, reducing fuel consumption and pollutant emissions. For example, convoys controlled by self-driving systems can use "platooning" technology, in which multiple vehicles drive closely behind each other, minimizing air resistance and increasing energy efficiency (Tsugawa, 2016). In military applications, the development of autonomous vehicles is of strategic importance. One of the most important areas is the automation of logistics convoys, which can significantly reduce human casualties on dangerous supply routes. Autonomous convoys are capable of operating in a coordinated manner with minimal human supervision, while increasing the mobility and supply security of the army (Gow & Carpenter, 2016). Reconnaissance and surveillance vehicles also play an important role in modern warfare. Autonomous systems are capable of real-time data collection in hostile environments, reducing the risk to human soldiers. In addition, the development of unmanned combat vehicles and drones is intensifying, and their deployment on the battlefield could provide a strategic advantage (Singer, 2009).

At the same time, military use raises serious ethical and legal dilemmas. The use of autonomous weapon systems—especially when they make decisions without human intervention—is the subject of significant international debate, as it is unclear who would be responsible for any damage or violations of the laws of war (Lin, 2016). Particular attention must be paid to cybersecurity in both civilian and military applications, as the network vulnerability of autonomous systems can pose a serious security risk. A successful cyberattack can cause not only material damage but also endanger human lives (Petit & Shladover, 2015). Social acceptance, regulatory frameworks, and liability issues pose further challenges, all of which determine the pace of widespread adoption of the technology. The civilian use of self-driving vehicles can contribute to increased traffic safety, sustainable mobility, and more efficient logistics processes. In the military sphere, autonomous systems offer strategic advantages in logistics and reconnaissance, but also raise new ethical and security dilemmas. A common feature of civilian and military applications is that the technological advantages can only be realized if appropriate responses to security, regulatory, and social challenges are found.

Conclusions

Over the past few decades, self-driving vehicle technology has evolved from the level of research prototypes to the threshold of commercial application. In this study, we reviewed the milestones of this development, from early experiments and DARPA competitions to modern, large-scale robotaxi services. The automation levels defined by SAE provide a framework for measuring technological advancement and also indicate further directions for research and development (SAE International, 2021). An examination of the technical content revealed that the operation of autonomous vehicles is based on various sensor systems, sensor fusion, high-precision localization, and artificial intelligence-based decision-making. These components work closely together to ensure that the vehicle is able to perceive, interpret, and respond in real time in complex traffic environments. Analysis of industry players has shown that traditional car manufacturers, technology companies, and agile startups are all present in the global competition. Tesla, Mercedes-Benz, Waymo, and other key players are pursuing different strategies, but all of them aim to introduce safe, commercial-grade autonomous systems. The market has enormous growth potential, which also has significant economic and geopolitical implications (MarketsandMarkets, 2020). Civilian applications include improving transport safety, optimizing urban mobility, and improving the efficiency of logistics processes. Military applications also hold great potential, particularly in the areas of logistics and reconnaissance. At the same time, regulatory, ethical, and safety challenges are of paramount importance in both spheres and must be addressed in order to achieve widespread social acceptance (Lin, 2016). Overall, self-driving vehicles are not just a technological novelty, but are fundamentally transforming the future of mobility, transport safety, environmental protection, and warfare. In the coming decades, the key to success will be the harmonious balance between technological developments, regulatory frameworks, and social trust.

References

[1] Anderson, J. M., Kalra, N., Stanley, K. D., Sorensen, P., Samaras, C., & Oluwatola, O. A. (2016). Autonomous vehicle technology: A guide for policymakers (RR-443-2). RAND Corporation. https://doi.org/10.7249/RR443-2

[2] Zhou, Z., Hu, H., Chen, X., Wang, J., Guan, N., Wu, K., Li, Y.-H., Huang, Y.-K., & Xue, C. J. (2024). BehaviorGPT: Technical report for the 2024 Waymo Open Sim Agents Challenge – 1st Place. Waymo Research. https://storage.googleapis.com/waymo-uploads/files/research/2024%20Technical%20Reports/2024%20WOD%20Sim%20Agents%20Challenge%20-%201st%20Place%20-%20BehaviorGPT.pdf

[3] Zhang, B., Song, N., Jin, X., & Zhang, L. (2025). Bridging Past and Future: End-to-End Autonomous Driving with Historical Prediction and Planning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). arXiv:2503.14182. https://arxiv.org/abs/2503.14182

[4] Campolo, C., Molinaro, A., Iera, A., & Menichella, F. (2017). 5G network slicing for vehicle-to-everything services. IEEE Wireless Communications, 24(6), 38–45. https://doi.org/10.1109/MWC.2017.1700114

[5] Yazgan, M., Akkanapragada, M. V., & Zoellner, J. M. (2024). Collaborative perception datasets in autonomous driving: A survey. arXiv:2404.14022. https://arxiv.org/abs/2404.14022

[6] Defense Science Board. (2016). Autonomy. Office of the Under Secretary of Defense for Acquisition, Technology, and Logistics. https://apps.dtic.mil/sti/citations/AD1002727

[7] Dickmanns, E. D., & Zapp, A. (1987). Autonomous high speed road vehicle guidance by computer vision. IFAC Proceedings Volumes, 20(5), 221–226. https://doi.org/10.1016/S1474-6670(17)54968-4

[8] Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. Transportation Research Part A: Policy and Practice, 77, 167–181. https://doi.org/10.1016/j.tra.2015.04.003

[9] Favarò, F. M., Nader, N., Eurich, S. O., Tripp, M., & Varadaraju, N. (2017). Examining accident reports involving autonomous vehicles in California. PLOS ONE, 12(9), e0184952. https://doi.org/10.1371/journal.pone.0184952

[10] Gao, Y., Piccinini, M., Zhang, Y., Wang, D., Moller, K., Brusnicki, R., … Betz, J. (2025). Foundation Models in Autonomous Driving: A Survey on Scenario Generation and Scenario Analysis. arXiv:2506.11526. https://arxiv.org/abs/2506.11526

[11] Gavrilut, D., Arif, A., & Törngren, M. (2020). A survey on autonomous vehicle development platforms. In Proceedings of the 2020 IEEE International Conference on Connected Vehicles and Expo (ICCVE) (pp. 157–162). IEEE. https://doi.org/10.1109/ICCVE45908.2020.9365975

[12] Gow, J., & Carpenter, T. (2016). Autonomy in military logistics: The case of convoy operations. Defense & Security Analysis, 32(4), 290–304. https://doi.org/10.1080/14751798.2016.1238659

[13] Grigorescu, S., Trasnea, B., Cocias, T., & Macesanu, G. (2020). A survey of deep learning techniques for autonomous driving. Journal of Field Robotics, 37(3), 362–386. https://doi.org/10.1002/rob.21918

[14] Hu, J., Wang, Y., Cheng, S., Xu, J., Wang, N., Fu, B., … Zhang, Y. (2025). A survey of decision-making and planning methods for self-driving vehicles. Frontiers in Neurorobotics, 19, 1451923. https://doi.org/10.3389/fnbot.2025.1451923

[15] Janai, J., Güney, F., Behl, A., & Geiger, A. (2020). Computer vision for autonomous vehicles: Problems, datasets and state of the art. Foundations and

Trends in Computer Graphics and Vision, 12(1–3), 1–308. https://doi.org/10.1561/0600000079

[16] Khaleghi, B., Khamis, A., Karray, F. O., & Razavi, S. N. (2013). Multisensor data fusion: A review of the state-of-the-art. Information Fusion, 14(1), 28–44. https://doi.org/10.1016/j.inffus.2011.08.001

[17] Lan, G., & Hao, Q. (2024). End-to-end planning of autonomous driving in industry and academia: 2022–2023. arXiv:2401.08658. https://arxiv.org/abs/2401.08658

[18] Levinson, J., Montemerlo, M., & Thrun, S. (2007). Map-based precision vehicle localization in urban environments. In Robotics: Science and Systems III (pp. 121–128). MIT Press.

[19] Lin, P. (2016). Why ethics matters for autonomous cars. In M. Maurer, J. C. Gerdes, B. Lenz, & H. Winner (Eds.), Autonomous driving: Technical, legal and social aspects (pp. 69–85). Springer. https://doi.org/10.1007/978-3-662-48847-8_4

[20] Litman, T. (2020). Autonomous vehicle implementation predictions: Implications for transport planning. Victoria Transport Policy Institute. http://www.vtpi.org/avip.pdf

[21] Liu, P., & Xu, Z. (2021). Autonomous vehicle testing and deployment in China: Policies and practices. Journal of Advanced Transportation, 2021, 1–12. https://doi.org/10.1155/2021/6639162

[22] Market Research Future. (2020). Autonomous vehicles market research report by type, vehicle type and region – Forecast to 2035 (Report ID: MRFR/SEM/0514-CR). https://www.marketresearchfuture.com/reports/autonomous-vehicles-market-1020

[23] Mercedes-Benz. (2021, December 9). Mercedes-Benz is the world’s first automobile manufacturer to receive internationally valid system approval for conditionally automated driving (SAE Level 3). Daimler Media. https://media.mercedes-benz.com

[24] Zhou, Z., Wang, J., Li, Y.-H., & Huang, Y.-K. (2024). ModeSeq: Technical Report for 2024 Waymo Open Motion Prediction Challenge – Motion Prediction. Waymo Research. https://storage.googleapis.com/waymo-uploads/files/research/2024%20Technical%20Reports/2024%20WOD%20Motion%20Prediction%20Challenge%20-%202nd%20Place%20-%20ModeSeq.pdf

[25] National Highway Traffic Safety Administration. (2017). Automated driving systems 2.0: A vision for safety. U.S. Department of Transportation. https://www.nhtsa.gov/

[26] Reda, M., Onsy, A., Haikal, A. Y., & Ghanbari, A. (2024). Path planning algorithms in the autonomous driving system: A comprehensive review. Robotics and Autonomous Systems, 174, 104630. https://doi.org/10.1016/j.robot.2024.104630

[27] Petit, J., & Shladover, S. E. (2015). Potential cyberattacks on automated vehicles. IEEE Transactions on Intelligent Transportation Systems, 16(2), 546–556. https://doi.org/10.1109/TITS.2014.2342271

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

[29] 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

[30] Singer, P. W. (2009). Wired for war: The robotics revolution and conflict in the 21st century. Penguin Press.

[31] Thrun, S. (2010). Toward robotic cars. Communications of the ACM, 53(4), 99–106. https://doi.org/10.1145/1721654.1721679

[32] Thrun, S., Montemerlo, M., Dahlkamp, H., Stavens, D., Aron, A., Diebel, J., … Mahoney, P. (2006). Stanley: The robot that won the DARPA Grand Challenge. Journal of Field Robotics, 23(9), 661–692. https://doi.org/10.1002/rob.20147

[33] Tsugawa, S. (2016). An overview on driverless truck platoons for energy saving. Proceedings of the IEEE, 104(6), 1138–1166. https://doi.org/10.1109/JPROC.2016.2545681

[34] Svoboda, P., Hradis, M., Marsik, L., & Zemcik, P. (2016). CNN for license plate motion deblurring. arXiv:1602.07873. https://arxiv.org/abs/1602.07873

[35] Waymo. (2020). On the road to fully self-driving. Waymo. https://waymo.com/research/

[36] Xu, H., Chen, J., Meng, S., Wang, Y., & Chau, L. P. (2025). A survey on occupancy perception for autonomous driving: The information fusion perspective. Information Fusion, 114, 102671. https://doi.org/10.1016/j.inffus.2024.102671

[37] Ghraizi, D., Talj, R., & Clovis, F. (2023). An overview of decision-making in autonomous vehicles. IFAC-PapersOnLine, 56(2), 10971–10983. https://doi.org/10.1016/j.ifacol.2023.10.793